From Local to Global: Offshoring and Asset Prices *

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Abstract

Industries differ in the extent to which they can offshore their production. I document that industries with low offshoring potential have 7.31% lower stock returns per year compared to industries with high offshoring potential, suggesting that the possibility to offshore affects industry risk. This risk premium is concentrated in manufacturing industries that are exposed to foreign import competition. Put differently, the option to offshore effectively serves as insurance against import competition. A two-country general equilibrium dynamic trade model in which firms have the option to offshore rationalizes the return patterns uncovered in the data: industries with low offshoring potential carry a risk premium that is increasing in foreign import penetration. Within the model, the offshoring channel is economically important and lowers industry risk up to one-third. I find that an increase in trade barriers is associated with a drop in asset prices of model firms. The model thus suggests that the loss in benefits from offshoring outweighs the benefits from lower import competition. Importantly, the model prediction that offshorability is negatively correlated with profit volatility is strongly supported by the data.

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1 Introduction

"The typical 'Made in' labels in manufactured goods have become archaic symbols of an old era. These days, most goods are 'Made in the World'." Antras (2015)

Over the recent decades, the world economy has seen a gradual dispersion of the production process across borders. Firms increasingly organize their production on a global scale and choose to offshore parts, components, or services to producers in foreign countries. The revolution in information and communication technology (ICT) and the dismantling of trade barriers allow firms to engage in global production networks, or global sourcing strategies, in order to cut costs.[1] For this reason, the choice of production location is a potentially valuable decision tool at the firm level. However, firms/industries differ in their ability to engage in offshoring due to the nature of their products and tasks involved in the production process. In short, in the era of globalization, the possibility to take a business from local to global has heterogenous implications for the cross-section of industries.

In this paper, I exploit cross-sectional heterogeneity in the ability to offshore to study how the possibility to relocate the production process affects industries' cost of capital. In particular, I focus on industries' ability to offshore the employed labor force and examine whether this is reflected in the cross-section of returns.[2] To this end, I construct a measure of labor offshorability at the industry level. The measure is calculated in two steps. In the first step, using data from the O*NET program of the U.S. Department of Labor, I calculate an offshorability score at the occupation level, as in Acemoglu and Autor (2011).[3] In the second step, I aggregate occupation offshorability scores by industry, weighting them by the product of employment and the wage bill associated with each occupation. The resulting data set covers an average of 331 industries per year during the period 1990 to 2016.[4]

I sort industries in five offshorability quintiles and find that the strategy that is long the low and short the high offshorability quintile portfolios, L-H, yields average annual excess returns of 7.31 percent and a Sharpe ratio of 0.48. This premium is not spanned by well-known risk factors such as Fama and French (2015) and Carhart (1997). Even after controlling for the five factors of Fama and French (2015), L-H generates positive average annual excess returns of 4.18 percent.

[1] In addition to the ICT revolution and lower trade barriers, political developments have led to an increase in the fraction of world population that actively participates in the process of globalization (Antras (2015)).

[2] In a related paper, Donangelo (2014) shows that industries that employ many workers with transferable skills are more exposed to aggregate shocks.

[3] A strand of literature in labor economics studies offshoring of tasks at the occupation level. See, for example, Jensen and Kletzer (2010), Goos and Manning (2007), Goos, Manning, and Salomons (2010), Acemoglu and Autor (2011), and Firpo, Fortin, and Lemieux (2013).

[4] Industries are defined at the three-digit Standard Industry Classification (SIC) from 1990 to 2001 and at the four-digit North American Industry Classification System (NAICS) level thereafter.

Furthermore, I split the sample into manufacturing and service industries. In univariate sorts, the L-H excess return spread in manufacturing is two to three times larger in magnitude compared to services. Moreover, for service industries, the premium is explained by the CAPM and a positive loading on the market. For manufacturing industries, on the other hand, common linear factor models fail to explain the returns generated by L-H. Consistent with this, in annual panel regressions at the firm level, I find that lagged industry offshorability significantly predicts annual excess returns for manufacturing but not for service industries. The results for manufacturing firms are economically meaningful: a one standard deviation increase in offshorability is associated with 4% to 5% lower annual excess stock returns. These results are robust to controlling for firm characteristics known to predict excess returns.

A first-order question is what drives the heterogeneity between manufacturing and services. A potential explanation is based on the degree of foreign import competition. While manufacturing industries have seen a sharp increase in foreign competition, mainly from low-wage countries, this is not the case for service industries.[5] I relate my results to foreign import competition in manufacturing industries using conditional double sorts of excess returns on proxies of import competition and offshorability. I find that the L-H premium is monotonically increasing in import competition.[6] The results are robust to different proxies of import competition: First, I use a direct measure of import penetration from low-wage countries defined as the imports from low-wage countries divided by the sum of domestic production and net exports in a given industry (see Bernard, Jensen, and Schott (2006a)). Second, I use industry-specific shipping costs as a proxy for barriers to trade.[7] These results are consistent with the U.S. having a comparative advantage in providing services but not in manufacturing (see also Jensen (2011)).[8]

In a related paper, Barrot, Loualiche, and Sauvagnat (2017) focus on manufacturing industries and document that industries more exposed to foreign competition have higher excess returns. While their work establishes that import competition poses risks for an industry, my findings document that offshoring allows industries to hedge these risks. Intuitively, being able to offshore allows firms to fight import competition from low-wage countries by reducing costs through relocating production. Consistent with this argument, a recent paper by Magyari (2017) shows that offshoring enables U.S. firms to reduce costs and outperform peers that cannot offshore.

[5] This can be seen from U.S. trade balances. While the trade balance in goods is negative and has decreased sharply over the last 25 years, the trade balance for services is positive and has been stable over time.

[6] In line with this, many recent empirical studies, such as Autor, Dorn, and Hanson (2013, 2016) and Pierce and Schott (2016), stress the importance of imports from low-wage countries for understanding the dynamics in U.S. manufacturing industries.

[7] Shipping costs are calculated as the markup of the Cost-Insurance-Freight value over the Free-on-Board value, as in Bernard, Jensen, and Schott (2006b).

[8] The principle of comparative advantage was first elaborated by Ricardo (1821) and formalized by Heckscher (1919) and Ohlin (1933). They argue that countries have a comparative advantage in activities that are intensive in the use of factors that are relatively abundant in the country.

To further improve understanding of the mechanism, I embed the option to offshore in a two-country general equilibrium dynamic trade model similar to Ghironi and Melitz (2005) and Barrot, Loualiche, and Sauvagnat (2017) with multiple industries and aggregate risk. I will refer to the two countries as East and West. My model departs from previous work by allowing firms to offshore part of the production, as in Antras and Helpman (2004). Moreover, I assume that the East has a comparative cost advantage over the West in performing offshorable labor tasks. As a result, offshoring to the East allows Western firms to reduce production costs and diversify aggregate risks. In addition, firms in both countries can export and sell their products abroad.

The model successfully matches industry- and trade-related moments and generates return patterns qualitatively, in line with the data. First, it generates a return spread between low and high offshorability industries. Second, the spread is increasing in the degree of import penetration. Third, excess returns of multinational companies are higher than for domestic firms. Fourth, industry excess returns are increasing in import penetration.

Asset price movements in the model are governed by shocks to aggregate productivity in each of the two countries. The responses of equilibrium quantities to the two aggregate productivity shocks are related because quantities react to changes in the ratio of aggregate productivity of the two countries: upon arrival of a positive (negative) productivity shock in the East (West), more Eastern firms find it profitable to export, which results in an increase in import penetration and competition in the West. As a result, Western firms experience losses in market share and lower profits. At the same time, offshoring allows Western firms to reduce production costs, which renders them more competitive towards new market entrants. Consequently, industries with a higher offshoring potential have smoother profits and dividends. Put differently, high (low) offshorability industries are less (more) exposed to aggregate productivity shocks in the model. This difference in exposure to aggregate risk results in an L-H return spread in industry excess returns, as observed in the data.

To further validate the model, I test three of its main predictions in the data. First, the model predicts that profit volatility is decreasing in industry offshorability, which is strongly supported by the data: a one standard deviation increase in industry offshorability is associated with an up to 19.7% lower profit volatility for the median firm. Second, the model predicts that the offshorability premium is largest in industries with more price-sensitive consumers. Conditional double sorts of monthly excess returns on U.S. trade elasticities from Broda and Weinstein (2006) and offshorability confirm this prediction in the data: the L-H spread is roughly double in magnitude for industries with high compared to low U.S. trade elasticities. Finally, within the model, low (high) offshorability industries have high (low) covariance with consumption. Consistent with this, I find that the strategy that is long low and short high offshorability industries has a positive and significant consumption beta in the data.

To quantify the importance of the offshorability channel in the model, I study industry moments in absence of offshorable labor tasks. The counterfactual indicates that an industry with no offshorability exhibits substantially higher risk premia (up to 33% or 3.14 percentage points) and lower equity valuations (a reduction of up to 17%). Hence, offshoring is an economically important channel in the model.

Finally, within the context of my model, I examine the consequences of a sudden increase in trade costs on goods shipped from East to West. Alternatively, this could be interpreted as a sudden increase in trade barriers for all goods imported by the West. Intuitively, higher barriers to trade lead to a decrease in import penetration in the model, which reduces industry risk. However, an increase in trade barriers also renders offshoring less valuable, since shipment of intermediate goods becomes more costly. Interestingly, within the model, the loss in benefits from offshoring outweighs the positive effects from lower import penetration. As a result, consumption and asset prices in the West fall.

The rest of the paper is organized as follows. After the literature review, section 2 details the data and discusses the construction of the labor offshorability measure. In section 3, I discuss the empirical findings. Section 4 presents a theoretical model with a calibration. Finally, section 5 concludes.

Literature Review

This paper relates to four main strands of literature. First, the paper relates to the literature that studies the interaction between labor and asset prices. Danthine and Donaldson (2002) and Favilukis and Lin (2016) document that operating leverage induced by rigid wages is a quantitatively important channel in matching financial moments in general equilibrium models.[9] More recently, a growing body of papers focus on different forms of labor heterogeneity and the cross-section of stock returns.[10] In particular, Zhang (2016) finds a real option channel for firms that have the possibility to substitute routine-task labor with machines. Moreover, Donangelo (2014) shows that industries with mobile workers are more exposed to aggregate shocks, since mobile workers can walk away for outside options in bad times, making it difficult for capital owners to shift risk to workers. This paper contributes to the literature by studying a new dimension of labor heterogeneity, i.e., whether or not a task can be offshored.

Second, this study relates to the literature on the effects of competition and international trade for asset pricing. Among others Loualiche (2015), Corhay, Kung, and Schmid (2017) and Bustamante and

[9] Gomes, Jermann, and Schmid (2017) investigate the rigidity of nominal debt, which creates long-term leverage that works in a similar way to operating leverage induced by labor.

[10] See, among others, Gourio (2007), Ochoa (2013), Eisfeldt and Papanikolaou (2013), Belo, Lin, Li, and Zhao (2015), Kuehn, Simutin, and Wang (2017), Donangelo, Gourio, Kehrig, and Palacios (2016) and Tuzel and Zhang (2017)

Donangelo (2016) show that the risk of entry is priced in the cross-section of expected returns. In a recent and closely related paper, Barrot, Loualiche, and Sauvagnat (2017) focus on risks associated with import competition and find that firms more exposed to import competition command a sizeable positive risk premium. Furthermore, Fillat and Garetto (2015) document that multinational firms exhibit higher excess returns than purely domestic firms. This is rationalized in a model in which selling abroad is a source of risk exposure to firms: following a negative shock, multinationals are reluctant to exit the foreign market because they would forgo the sunk cost they paid to enter. While their model shows how firms' revenues relate to risk in multinationals, my paper focuses on the relation between firm risk and labor costs.

Third, a recent line of research studies the consequences of the surge in international trade over the last decades at the establishment and firm level. Among others, Autor, Dorn, and Hanson (2013) and Pierce and Schott (2016) show that U.S. manufacturing establishments more exposed to growing imports from China in their output markets exhibit a sharper decline in employment relative to the less exposed ones.[11] Other studies use tariff cuts to instrument for import competition and find that it affects firms' capital structure (Xu (2012) and Valta (2012)) and capital budgeting decisions (Bloom, Draca, and Van Reenen (2015) and Frésard and Valta (2016)). My paper complements this literature by studying asset pricing implications instead of firm quantities. I find that offshoring allows firms to allocate resources more efficiently and lowers risks associated with foreign import competition.[12] Therefore, my paper also contributes to the growing body of empirical trade literature that documents that manufacturing firms have benefited from offshoring. Hummels, Jørgensen, Munch, and Xiang (2016), Chen and Steinwender (2016) and Bloom, Draca, and Van Reenen (2015) document that offshoring fosters firms' productivity and innovation activity. Magyari (2017) shows that offshoring enables U.S. firms to reduce their costs. She also finds that firms that are able to offshore actually increase their total firm-level employment both in manufacturing and headquarter service jobs.[13]

Fourth, this paper relates to the literature that examines the relationship between firm and plant organization and performance. Empirically, Atalay, Hortaçsu, and Syverson (2013) examine the domestic sourcing by U.S. plants, and Ramondo, Rappoport, and Ruhl (2016) study foreign sourcing by U.S. multinational firms. These papers show that firms and plants tend to source a large share of their material inputs from third-party suppliers. My paper documents how sourcing decisions affect asset prices.

[11] See also Autor, Dorn, and Hanson (2016), Acemoglu, Autor, Dorn, Hanson, and Price (2016), Amiti, Dai, Feenstra, and Romalis (2016).

[12] Related papers show that firms suffer less from import competition if they have larger cash holdings (Frésard (2010)) or higher R&D expenses (Hombert and Matray (2017)).

[13] Compared to other related papers, Magyari (2017) focuses on employment at the firm level rather than at the establishment level.

Theoretically, Antras and Helpman (2004) formulate a model in which firms decide whether to integrate the production of intermediate inputs or outsource them with incomplete contracts. Both decision can either take place domestically or abroad. More recently, Antras, Fort, and Tintelnot (2016) develop a quantifiable multi-country sourcing model in which global sourcing decisions interact through the firm's cost function, and Bernard, Jensen, Redding, and Schott (2016) present a theoretical framework that allows firms to decide simultaneously on the set of production locations, export markets, input sources, products to export, and inputs to import. In contrast, my model focuses on the interaction of offshoring and industry risk. To do so, I incorporate the possibility to offshore into a dynamic trade model with multiple industries, as in Ghironi and Melitz (2005), Chaney (2008) and Barrot, Loualiche, and Sauvagnat (2017).[14]

2 Data

In this section, I first outline the data and the method to construct a measure of labor offshorability at the occupation level and the industry level. Second, I discuss the financial and accounting as well as international trade data used in the empirical analysis.

2.1 Measuring Labor Offshorability

As a first step, I calculate a measure of offshorability at the occupation level. To do so, I follow the recent literature in labor economics and use data from the U.S. Department of Labor's O*NET program on the task content of occupations.[15] , [16] This program classifies occupations according to the Standard Occupational Classification (SOC) system and has information on 772 different occupations.[17] O*NET contains information about the tools and technology, knowledge, skills, work values, education, experience and training needed for a given occupation.[18] I follow Acemoglu and Autor (2011) and Blinder (2009) and calculate an offshorability score at the occupation level.

Acemoglu and Autor (2011) argue that an occupation that requires substantial face-to-face interaction and needs to be carried out on site is unlikely to be offshored. To capture this notion of offshorability,

[14] Melitz (2003) and Bernard, Jensen, Eaton, and Kortum (2003) also allow for firm heterogeneity and heterogenous gains from trade.

[15] For papers that rely on the O*NET data base, see, among others, Jensen and Kletzer (2010), Goos and Manning (2007), Goos, Manning, and Salomons (2010), Firpo, Fortin, and Lemieux (2013), and Acemoglu and Autor (2011).

[16] I use O*NET 20.3, available from https://www.onetonline.org/

[17] Some of the 772 occupations are further detailed into narrower occupation definitions. The total number of more-detailed occupations in O*NET is 954.

[18] The O*NET content model organizes these data into six broad categories: worker characteristics, worker requirements, experience requirements, occupational requirements, labor market characteristics, and occupation-specific information.

they focus on seven individual occupational characteristics, which are tabulated in Panel A of table 1. Compared with alternative occupation offshorability scores (see Firpo, Fortin, and Lemieux (2013), for example), Acemoglu and Autor (2011) base their calculations on fewer occupation characteristics to mitigate a high correlation with the routine-task content of an occupation.[19]

[Insert Table 1 here.]

The O*NET database organizes characteristics in work activities or work context (see column 3 of Panel A in table 1). For work activities, O*NET provides information on "importance" and "level". I follow Blinder (2009) and assign a Cobb-Douglas weight of two-thirds to "importance" and one-third to "level" to calculate a weighted sum for work activities.[20] Since there is no "importance" score for work context characteristics, I simply multiply the relative frequency by the level.[21] Thus, the offshorability score for occupation j, off_j, is defined as

$$off_j = \frac{1}{\sum_{l=1}^{A} I_{jl}^{\frac{2}{3}} \times L_{jl}^{\frac{1}{3}} + \sum_{m=1}^{C} F_{jm} \times L_{jm}} \tag{1}$$

where A is the number of work activities, I_{jl} is the importance and L_{jl} is the level of a given work activity in occupation j, C is the number of work context elements, F_{jm} is the frequency and L_{jm} is the level of a given work context in occupation j.[22] Finally, I take the inverse to obtain a score that is increasing in an occupation's offshorability.[23]

In a second step, I aggregate the occupation offshorability scores at the industry level using industry-level occupation data from the Occupational Employment Statistics (OES) program of the BLS. This data set contains information on the number of employees in a given occupation, industry and year. The data set is based on surveys that track employment across occupations and industries in approximately 200,000 establishments every six months over three-year cycles, representing roughly 62% of non-farm employment in the U.S. Each industry in the sample was surveyed every three years until 1995 and every year from 1997 onwards. For the period before 1997, I follow Donangelo (2014) and use the same industry

[19] As a robustness check, I also calculate occupation offshorability according to Firpo, Fortin, and Lemieux (2013). They base their calculations on 16 different occupation characteristics, which are organized into three categories: face-to-face contact, on-site and decision-making. The characteristics are tabulated in an online appendix. The results of the paper remain qualitatively the same when the measure of Firpo, Fortin, and Lemieux (2013) is employed and are available upon request.

[20] The results are robust to different Cobb-Douglas weights. For example, taking simple averages between importance and level scores does not change any of the results in the paper.

[21] For example, the level of the work context element "frequency of decision-making" is a number between one and five: 1 = never; 2 = once a year or more but not every month; 3 = once a month or more but not every week; 4 = once a week or more but not every day; or 5 = every day.

[22] Note that importance and level scores are all rescaled to be between zero and one. Relative frequencies F_{jm} lie, by definition, between zero and one.

[23] The occupation offshorability for Acemoglu and Autor (2011) ranges between one-sixth and one.

data for three consecutive years to ensure continuous coverage of the full set of industries. For example, the data used in 1992 combine survey information from 1990, 1991, and 1992. Unfortunately, the OES did not conduct a survey in 1996. To avoid a gap, I follow Ochoa (2013) and Donangelo (2014) and rely on survey information from the years 1993, 1994, and 1995.

The data set employs the OES taxonomy with 258 broad occupation definitions before 1999, the 2000 Standard Occupational Classification (SOC) system with 444 broad occupations between 1999 and 2009, and the 2010 SOC afterwards. To merge the occupation level offshorability with the OES data set, I bridge different occupational codes using the crosswalk provided by the National Crosswalk Service Center. Industries are classified using three-digit Standard Industrial Classification (SIC) codes until 2001 and four-digit North American Industry Classification System (NAICS) codes thereafter.[24]

The OES/BLS data set also includes estimates of wages since 1997. For the 1990 to 1996 period, I use estimates of wages from the BLS/U.S. Census Current Population Survey (CPS) obtained from the Integrated Public Use Microdata Series of the Minnesota Population Center.[25] I aggregate the occupation level offshorability measure, off_j, by industry, weighting by the wage expense associated with each occupation:

$$OFF_{i,t} = \sum_j off_j \times \frac{emp_{i,j,t} \times wage_{i,j,t}}{\sum_j emp_{i,j,t} \times wage_{i,j,t}} \tag{2}$$

where $emp_{i,j,t}$ is the employment in industry i, occupation j and year t, and $wage_{i,j,t}$ measures the annual wage paid to workers. Using wages at this stage is consistent with placing more weight on occupations with greater impact on cash flows.[26] Lastly, $OFF_{i,t}$ is standardized in each year, i.e., the cross-sectional mean and standard deviation of the offshorability measure are set to zero and one, respectively. The resulting data set covers the years 1990 to 2016, with an average of 331 industries.

[24] While the OES data set is designed to create detailed cross-sectional employment and wage estimates for the U.S. by industry, because of changes in the occupational classification, it might be challenging to exploit its time series variation. For this reason, I focus predominantly on cross-sectional analyses of the data.

[25] These data are available from https://www.ipums.org/. For more information, see King, Ruggles, Alexander, Flood, Genadek, Schroeder, Trampe, and Vick (2010)

[26] I also test for robustness of the empirical analysis by using an industry measure of offshorability that does not rely on wages, i.e.,

$$OFF^{\star}_{i,t} = \sum_j off_j \times \frac{emp_{i,j,t}}{\sum_j emp_{i,j,t}}.$$

The results remain qualitatively unchanged and are available upon request.

2.2 Financial and Accounting Data

For the empirical analysis, I use monthly stock returns from the Center for Research in Security Prices (CRSP) and annual accounting information from the CRSP/COMPUSAT Merged Annual Industrial Files. The sample of firms includes all NYSE-, AMEX-, and NASDAQ-listed securities that are identified by CRSP as ordinary common shares (with share codes 10 and 11) for the period between January 1990 and December 2016. I follow the literature and exclude regulated (SIC codes between 4900 and 4999) and financial (SIC codes between 6000 and 6999) firms from the sample. I also exclude observations with negative or missing sales, book assets and observations with missing industry classification codes. Firm-level accounting variables are winsorized at the 1% level in every sample year to reduce the influence of possible outliers. All nominal variables are expressed in year-2009 USD.[27] I also use historical segment data from COMPUSTAT to classify firms in multinationals and domestic firms as in Fillat and Garetto (2015). Finally, I use COMPUSTAT quarterly to calculate the volatility of sales and profits, as in Minton and Schrand (1999). A detailed overview of the variable definitions can be found in the online appendix.

2.3 International Trade Data

I use product-level U.S. import and export data for the period 1989 to 2015 from Peter Schott's website. For every year, I obtain the value of imports as well as a proxy for shipping costs at the product level that can be aggregated to the industry level. I follow Hummels (2007) and approximate shipping costs with freight costs, i.e., the markup of the Cost-Insurance Freight value over Free-on-Board value. Moreover, I use data on US trade elasticities at the product level from Broda and Weinstein (2006). Finally, data on U.S. trade balances are from the Bureau of Economic Analysis.

3 Empirical Evidence

In this section, I present the empirical results of the paper. First, I examine the validity of the offshorability measures. Second, I report that average portfolio excess returns are decreasing in offshorability. Third, I show that the premium that can be earned by going long low and short high offhsorability industries is concentrated in manufacturing industries and is not explained by a wide range of linear asset pricing models. Finally, I offer further empirical evidence that links the offshorability premium to the recent surge in foreign import competition from low-wage countries.

[27] I use the GDP deflator (NIPA table 1.1.9, line 1) and the price index for non-residential private fixed investment (NIPA Table 5.3.4, line 2) to convert nominal into real variables.

3.1 Validity and Summary Statistics of Labor Offshorability

I start by examining whether the measures discussed in section 2 deliver reasonable rankings of occupations and industries in terms of offshorability. Panels B and C of table 1 report the top and bottom ten occupations by offshorability. Occupations with high offshorability are not restricted with respect to location or immediacy to the final consumer. Conversely, occupations at the bottom are either closely related to the location, such as "tree trimming", or to customers, such as "dentists". Unfortunately, off_j is, by construction, constant throughout time. Therefore, occupation offshorability is unable to capture how technological progress has affected the offshorability of individual occupations.[28] To the extent that technological progress has affected offshorability symmetrically across occupations, this is not a concern for my cross-sectional analysis.

In contrast, industry offshorability inherits some time variation from the changes in the occupation-industry composition of the U.S. labor force. To gain a better sense of the time-variation in $OFF_{i,t}$, I examine the industry rankings for manufacturing and services industries separately.[29] Table 2 reports the top and bottom ten industries by offshoring potential in the years 1992 and 2015 (Panels A and B) and the transition probabilities (Panel C) between offshorability quintiles for manufacturing industries.[30] In 1992, the top industries are predominantly apparel industries, whereas the bottom industries are related to mining and construction. The 2015 rankings reveal that there is not much variation over time during the sample period. In fact, even though industries are now classified according to the NAICS system, the top and bottom ten are similar to 1992.[31]

Another way to examine the persistence of $OFF_{i,t}$ over time is to look at transition probabilities. I do so by sorting industries into quintiles of offshorability each year and calculating the transition probabilities across quintiles. Panel C of table 2 reports the one- and five-year transition probabilities.[32] For industries in the top or bottom quintiles of labor offshorability, the probability of being in the same quintile the next year (in five years) is close to 90% (80%). For the middle quintiles, the persistence is slightly lower, approximately 75%, over one year and 60% over five years. To sum up, industry offshorability is very persistent over time, consistent with offshoring being a slow-moving response to changes in the economic

[28] Several authors note that recent technological advances have substantially increased the offshorability of occupations. See, among others, Antras (2015) for manufacturing occupations and Jensen (2011) for service industry occupations.

[29] Manufacturing industries contain all industries with SIC codes between 2011 and 3999 and NAICS codes between 311111 and 339999, respectively. Conversely, service industries encompass all industries that are not classified as manufacturing industries.

[30] An analogous table with industry rankings for the full sample can be found in an online appendix.

[31] Note that the industries with NAICS code 3341xx correspond to SIC industry 3570, which ranks 18th in 1992.

[32] I calculate transition probabilities for the period 1991 to 2001 (SIC codes) and 2002 to 2016 (NAICS codes) separately and report the average of the two. The transition probabilities are very similar for the two subsamples.

environment.

[Insert Tables 2 and 3 here.]

Table 3 reports analogous industry rankings and transition probabilities for service industries. I find that legal and financial services and computer software programming are high in offshorability, whereas mining, labor unions and other personal services are not.[33] Overall, the findings are very much in line with those for manufacturing. Again, the top and bottom ten industries in 1992 and 2015 suggest that $OFF_{i,t}$ does not exhibit much variation over time. The transition probabilities in Panel C confirm this impression. The probability of remaining in the same quintile over the next year (next five years) ranges between 83% and 91% (61% and 82%). Moreover, there are only very few changes, other than to the neighboring quintile, even over five years.

Next, I examine how offshorability correlates with other labor- and trade-related variables. Panel A of table 4 reports correlations at the occupation level. Interestingly, off_j is positively and significantly related to skill (correlation coefficient of .31), which is driven by the large number of service occupations that are both offshorable and skill-intense.[34] This is in line with Jensen (2011), Blinder (2009) and Amiti and Wei (2009), who discuss that recent advances in communication technologies increasingly allow for the offshoring of service jobs. Importantly, the correlation between offshorability and routine-task occupations is statistically indistinguishable from zero (correlation coefficient of .04). Hence, occupation level offshorability does not solely capture occupations that can be substituted with machines. This is consistent with Zhang (2016), who finds an insignificant empirical correlation coefficient of -.02 between offshorability and routine-task labor at the firm level. In panel B, I report the overlap in occupations that rank in the top tercile for the different measures. I find that the percentage overlap is close to 33%, which is what one would expect in case of no correlation. This suggests that there is little correlation in the highest-ranked occupations across measures.

[Insert Table 4 here.]

Panel C reports time-series averages of annual Spearman rank sum correlations of different variables at the industry level both for manufacturing and services. The correlation with skill is positive and significant for both manufacturing and service industries. While the point estimate for manufacturing is very similar to that at the occupation level (.29), it is slightly higher for services (.44). The correlation

[33] Related to this finding, Alan Blinder writes in *Foreign Affairs* in 2006 that "...changing trade patterns will keep most personal-service jobs at home while many jobs producing goods and impersonal services migrate to the developing world...".

[34] Examples of such occupations include legal support workers or paralegals, computer programmers, and radiologists.

with routine is statistically indistinguishable from zero for both sectors (the point estimates are .10 for manufacturing and .14 for services). Interestingly, the correlation with the labor mobility measure of Donangelo (2014) is negative (-.22) and weakly statistically significant for manufacturing and is positive (.11) but insignificant for services. The weak relationship with labor mobility is not surprising. Labor mobility is intended to capture the transferability of occupation-specific skills across industries, which is conceptually very different from offshorability.

Furthermore, I find that the correlation coefficient with product tradability from Jensen (2011) is positive (.13) but insignificant for manufacturing and positive and highly statistically significant for services (.23).[35] The insignificant correlation coefficient in manufacturing is not surprising. While offshorability captures the "tradability" of the labor force, the measure by Jensen (2011) captures the tradability of the product.

Finally, I also analyze the relation between $OFF_{i,t}$ and industry shipping costs, a variable often employed in studies of international trade. I document a negative and weakly significant correlation coefficient (-0.16) between offshorability and shipping costs paid by importers for manufacturing industries. For services, the lack of import data makes it impossible to calculate shipping costs at the industry level.

3.2 Portfolio Analysis

3.2.1 Offshorability Portfolios and Excess Returns

To study the characteristics of sample industries and realized excess returns, I construct five offshorability portfolios. For each sample year, I assign industry offshorability in the previous year to individual stocks. I then obtain monthly industry returns by value-weighting monthly stock returns. Again, industries are defined at the 3-digit SIC level between 1990 and 2001 and at the 4-digit NAICS level between 2002 and 2016. In every year, at the end of June, I sort industry returns into five portfolios based on industry offshorability quintiles. Finally, industry returns within each offshorability portfolio are either equal- or value-weighted. To obtain value-weighted portfolio returns, I use an industry's market capitalization as a weight. In what follows, in the interest of brevity, I refer to industry excess returns simply as excess returns. Panel A of table 5 reports the equal- and value-weighted excess returns of the five portfolios. L (H) stands for the portfolio consisting of industries with low (high) offshorability, and L-H refers to the strategy that is long L and short H.

[Insert Table 5 here.]

[35] I thank J. Bradford Jensen for sharing his data on industry tradability. Jensen (2011) measures of industry tradability are based on geographic concentration/dispersion of production.

Industries with low offshorability have average equal-weighted (value-weighted) monthly excess returns that are .61% (.80%) higher compared to high offshorability industries. The magnitude of the spread is economically meaningful: 7.31% (9.64%) per year for equal-weighted (value-weighted) returns with an annualized Sharpe ratio of .48 (.47). I also consider unlevered equity returns to ensure that the results are not driven by leverage. I follow Donangelo (2014) and Zhang (2016) and calculate unlevered stock returns as

$$r_{i,y,m}^{unlevered} = r_{y,m}^{f} + (r_{i,y,m} - r_{y,m}^{f}) \times (1 - lev_{i,y-1})$$

where $r_{i,y,m}$ denotes the monthly stock return of firm i over month m of year y, $r_{y,m}^{f}$ denotes the one-month risk-free rate in month m of year y, and $lev_{i,y-1}$ denotes the leverage ratio, defined as the book value of debt over the sum of book value of debt plus the market value of equity at the end of year $y-1$ for firm i. The unlevered excess returns (.51% equal-weighted and .73% value-weighted) and corresponding Sharpe ratios (.46 equal-weighted and .43 value-weighted) are slightly lower in magnitude.

Despite the relatively short sample period, t-tests using Newey-West standard errors confirm that the L-H spread is statistically significant both in equal- and value-weighted portfolios. Notably, the results are slightly stronger for value-weighted returns. While traditional t-tests only compare returns of the L and H portfolios, the "monotonic relationship (MR)" test by Patton and Timmermann (2010) tests for monotonicity in returns relying on information from all five portfolios. Next to the L-H spread in table 5, I report in parentheses the p-value from the MR test, which considers all possible adjacent pairs of portfolio returns. The bootstrapped p-value is studentized, as advocated by Hansen (2005) and Romano and Wolf (2005). The p-values indicate that the null hypothesis of non-monotonic portfolio returns is rejected both for equal- and value-weighted returns.

To test whether the L-H spread reflects industries' exposure to risk factors irrespective of the ability to relocate production, I estimate linear factor regression models. Panels B and C of table 5 report time-series regressions across the five offshorability portfolios for the four- and five-factor models of Carhart (1997) and Fama and French (2015).[36] Even after controlling for the various factors, the estimated alphas show a nearly (one exception) strictly monotonic pattern for both equal- and value-weighted returns.[37] Moreover, the alpha of the L-H portfolio remains statistically significant in three out of four specifications. L-H loads positively on SMB in all specifications. Moreover, for equal-weighted portfolios, L-H is positively related to HML. Even though the magnitude of the L-H alpha is smaller than the spread in univariate

[36] The risk-free rate and the market, size, value, momentum, profitability and investment factors are obtained from Kenneth French's website.

[37] The results are very similar for the unconditional CAPM, the conditional CAPM and the three-factor model of Fama and French (1992). The corresponding regressions are tabulated in an online appendix.

portfolio sorts, it is economically meaningful: the annualized alphas range between 3.82% and 6.49%, with Sharpe ratios from .35 to .41.

3.2.2 Offshorability premium: Manufacturing vs Service Industries

Due to limited data availability, most empirical papers that study the effects of offshoring focus on U.S. manufacturing firms or European data.[38] Hence, having a measure of offshorability both for manufacturing and services industries, it is interesting to see how the results differ among these two broad sectors. To this end, I first split the sample into manufacturing and services and then conditionally sort industries into five offshorability portfolios, as discussed above.[39]

Table 6 reports univariate portfolio sorts and CAPM regression results for manufacturing (Panel A) and services (Panel B). The univariate sorts show that portfolio excess returns are decreasing in offshorability in both sectors, which suggests that the relocation of production is a desirable option in manufacturing and service industries. This is consistent with Jensen and Kletzer (2010), Blinder (2009) and Amiti and Wei (2009), among others, who discuss the increasing importance of offshoring in service industries.

However, the annualized mean excess return of L-H in manufacturing is two to three times the magnitude of that in services: 12.37% versus 6.66% for equal-weighted levered returns and 12.43% versus 4.15% for equal-weighted unlevered returns. This is also true for value-weighted excess returns. Hence, having the option to offshore seems to affect the risk profile of manufacturing and services industries differently. This conclusion finds further support in sector-specific CAPM regression results. For manufacturing, the L-H strategy is not spanned by the market, and the resulting alphas are highly statistically and economically significant. For services, on the other hand, the alphas are insignificant and are only roughly one-third in magnitude compared to manufacturing. In short, while differential exposures to the market across the five offshorability portfolios explain the offshorability spread in services, this is not the case in manufacturing.[40]

[Insert Tables 6 and 7 here.]

Panel C of table 6 shows portfolio characteristics of the five portfolios in manufacturing and services, respectively. For manufacturing, firms with low offshorability tend to be large, have a low book to market

[38] See Harrison and McMillan (2011) and Ebenstein, Harrison, McMillan, and Phillips (2014) for studies on U.S. data and Hummels, Jørgensen, Munch, and Xiang (2016) for a study with Danish data.

[39] Manufacturing includes all industries with SIC codes between 2011 and 3999 and NAICS codes between 311111 and 339999. Conversely, services encompass all industries that are not classified as manufacturing.

[40] These results also hold for the three-factor model of Fama and French (1992): the L-H for manufacturing loads positively on size, and the L-H for services loads positively on the market and size. The corresponding results are tabulated in an online appendix.

ratio, low market leverage and low labor intensity compared to high offshorability firms. For services, on the other hand, the five portfolios show no clear patterns in terms of book to market ratio and market leverage.

As a more restrictive test of the offshorability premium in manufacturing, I employ the four- and five-factor models by Carhart (1997) and Fama and French (2015), respectively. The results are reported in table 7. The alpha of the L-H strategy remains highly statistically and economically significant across all specifications: the annualized alphas range between 8.05% and 9.94% with Sharpe ratios from .55 to .81. Moreover, L-H positively loads on size and momentum.

To gain an idea of the performance of L-H in each sector over time, I plot the evolution of a one USD investment on a log-scale in the left panel figure 1. The figure plots L-H separately for manufacturing and service industries along the market, size and value. Both L-H portfolios significantly outperform the size and value strategies over the period from July 1991 until June 2016.

[Insert Table 8 and Figure 1 here.]

Interestingly, the L-H strategy in manufacturing does not generally correlate strongly with the market except during the financial crisis, when both investments lose value. The right panel of figure 1 plots the realized equal-weighted excess returns of the L-H strategy in manufacturing along with average monthly excess returns for the first and second half of the sample period. The two averages are similar in magnitude (1.19% during 1991 and 2004 and 0.86% during 2004 and 2016), which suggests that the L-H strategy delivers a stable return over time.

To further investigate the offshorability premium in manufacturing, I report portfolio sorts for different time subsamples in table 8. The sample is split into four subsamples - one for each decade plus one that excludes the financial crisis. The offshorability premium is, with one exception, positive and significant in all subsamples. This is true both for equal- and value-weighted portfolios. For most subsamples, the premium is significant at the 10% level due to the relatively small sample size and the corresponding loss of statistical power. Moreover, the MR-test rejects the null hypothesis of non-monotonic portfolio returns for all but the most recent subsample that runs from 2010:01 to 2016:06.[41]

In a next step, I investigate the predictive power of offshorability in the cross-section of returns. To do so, I run annual panel regressions at the firm level. The regressions are of the following form:

$$r_{i,t} = a + b_{j,t} + c * OFF_{i,t-1} + d * controls_{i,t-1} + \epsilon_{i,t}, \tag{3}$$

[41] In a robustness test, I test whether the results are driven by the time variation in the $OFF_{i,t}$ measure. I find that keeping industry offshorability fixed over time (i.e., fixing it to the first observation for each industry classification period) results in very similar full and subsample results. The corresponding results are tabulated in an online appendix.

where $r_{i,t}$ is the firm's i annual stock return, a is a constant term, $b_{j,t}$ is an industry×year fixed effect, $OFF_{i,t-1}$ is lagged labor offshorability and $controls_{i,t-1}$ are lagged firm-level characteristics.[42] I include firm size, book-to-market ratio, market leverage ratio, hiring rate, investment rate, one-year lagged stock return, operating leverage, and profitability to control for characteristics known to predict expected excess returns. Standard errors are clustered at the firm and year level.

Table 9 reports the regression results for manufacturing in Panel A and services in Panel B. All variables are standardized with mean zero and variance one, which makes the coefficients directly comparable. For manufacturing, the coefficient of offshorability is negative and statistically significant across all specifications. Moreover, the coefficients are only marginally affected by adding control variables individually (compare regression specifications (1) to (9)), which is reassuring.[43] The estimated slopes range from -4.64 to -5.06 and are economically meaningful: a one standard deviation increase in offshorability is associated with a 4% - 5% lower annual excess stock return.

[Insert Table 9 here.]

Regression specification (10) includes all control variables at once, which results in a reduction in sample size. Nevertheless, the coefficient on OFF_{t-1} stays negative and highly statistically significant.[44] For services, the coefficients on offshorability are negative throughout all specifications. However, the coefficients are statistically significant only in two regression specifications, which suggests that for services, OFF_{t-1} does not have much predictive power once controlled for other firm characteristics. This is consistent with the findings of table 6.

3.3 Manufacturing Industries and the Surge in International Trade

Technological advances such as the revolution in information and communication technologies and the dismantling of trade barriers have contributed to an increase in international trade activity over the recent past. The left panel of figure 2 shows that the ratio of imports to U.S. Gross Domestic Product (GDP) has increased by a factor of 1.5 over the sample period. Interestingly, this increase in imports/GDP is mostly due to imports from low-wage countries, which have increased by a factor of 4.5 since 1990. By contrast, high-wage country imports have increased by a factor of 1.2 only.[45] These growth patterns are

[42] Note that offshorability is measured at the industry level only. Hence, firms in a given industry and year share the same offshorability.

[43] I run similar monthly panel regressions following Belo, Lin, Li, and Zhao (2015) and find that the results are nearly identical. The results are available upon request.

[44] These results are robust to various industry definitions. The corresponding results are tabulated in an online appendix.

[45] I follow Bernard, Jensen, and Schott (2006a) and label a country as low-wage in year t if its GDP per capita is less than 5% of the GDP per capita of the U.S. A list of countries that were classified as low-wage in every year of the sample period can be found in an online appendix.

illustrative of the change in the composition of U.S. imports, consistent with the principle of comparative advantage first elaborated by Ricardo (1821) and continued by Heckscher (1919) and Ohlin (1933).[46] They argue that countries have a comparative advantage in activities that are intensive in the use of factors that are relatively abundant in the country. As a result, countries that have an abundance of low-cost labor have an advantage in producing labor-intense products, and countries with an abundance of skilled labor specialize in skill-intense products.

[Insert Figure 2 here.]

Another way of illustrating the change in the composition of U.S. imports is to look at the trade balances for goods and services separately, as reported in the right panel of figure 2. While the trade balance in goods has decreased sharply over the last 25 years, the trade balance in services has been positive and slightly increasing since 1960. Hence, the United States is a net exporter in services.[47] Consistent with this, Jensen (2011) argues that providing services is consistent with the U.S.'s comparative advantage. On the other hand, international specialization has led to fierce import competition in manufacturing industries.[48] In fact, many recent empirical studies stress the importance of international trade for understanding the dynamics in U.S. manufacturing industries. In particular, the rise in import penetration from low-wage countries has been emphasized as the key driving force of the decrease in manufacturing employment (see, among others, Autor, Dorn, and Hanson (2013, 2016), Pierce and Schott (2016)).[49]

Motivated by this evidence, I examine how my results relate to import competition from low-wage countries. I follow Bernard, Jensen, and Schott (2006a) and calculate import penetration from low-wage countries at the industry level. Panel A of table 10 reports conditional double sorts on import penetration and offshorability.[50] Indeed, the L-H spread is monotonically increasing with import penetration both for equal- and value-weighted returns. This finding is consistent with the interpretation that the ability to relocate production is most valuable in industries that are exposed to fierce import competition from low-wage countries.[51]

[46] The figure that plots value shares of imports instead of real value of imports looks nearly identical. The corresponding figure can be found in the online appendix of the paper.

[47] In fact, the United States is the global leader in business service exports. The OECD reports that the United States accounts for approximately 22 percent of the OECD total.

[48] The increase in imports is either due to new market entrants or imports of intermediate production inputs. Antras (2015) reports that between 2000 and 2011, close to 50% of imports were intra-firm transactions, i.e., either intermediate production inputs or final goods manufactured entirely abroad. The other half of imports were either third-party intermediate goods or final products of foreign competitors. Hence, the surge of imports from low-wage countries over the past 25 years brought cheaper intermediate production inputs but also more fierce competition to the U.S.

[49] While US total imports as a share of GDP have increased from 4.19% to 15.48% since 1960, US manufacturing employment as a percent share of nonagricultural employment has fallen from 28.43% to 8.69%. A corresponding figure can be found in the online appendix.

[50] I first sort on import penetration and then on offshorability.

[51] The results are very similar for double sorts on offshorability and import penetration from China, as reported

[Insert Tables 10 and 11 here.]

I also run cross-sectional return predictability regressions conditional on import penetration being lower (higher) than the median, which allows me to control for various firm characteristics. The results are reported in Panel B. Consistent with the double sorts, I find that coefficients on offshorability are negative and significant only for firms in industries with high import penetration. Moreover, the absolute values of the estimated coefficients on OFF_{t-1} are double the magnitude for high compared to low import penetration industries.

A potential concern is that realized U.S. imports from low-wage countries may be correlated with industry import demand shocks. To mitigate this concern, I instrument for import competition with industries' average shipping costs paid on imports, which serves as a proxy for barriers to trade. In the data, industries with low shipping costs are associated with high imports and exports. Panel A of table 11 reports average returns of conditional double sorts on shipping costs and offshorability. The L-H spread is monotonically decreasing with shipping costs, consistent with the findings in table 10. Panel B tabulates the results of conditional panel regressions. Offshorability negatively predicts firms' annual excess returns only in industries with lower-than-median shipping costs.

Barrot, Loualiche, and Sauvagnat (2017) document that industries with low shipping costs face higher import competition and have higher excess returns. This premium originates from the risk of displacement of least efficient firms triggered by import competition. Given that the offshorability premium is increasing in import penetration from low-wage countries and decreasing in shipping costs, my findings suggest that offshoring helps protect industries from foreign competition. In particular, being able to offshore allows firms to reduce their labor costs upon increases in competition. This argument is consistent with Magyari (2017), who finds that offshoring enables US firms to reduce costs and outperform peers that cannot offshore.

Table 4 shows that offshorability is slightly negatively related to shipping cost. Hence, one might be concerned whether sorting on offshorability is similar to sorting on shipping costs. To mitigate this concern, I replicate the findings of Barrot, Loualiche, and Sauvagnat (2017) for my sample period and control for the return of the portfolio that is long firms in low shipping cost industries and short firms in high shipping cost industries (henceforth, SC). The explanatory power of SC is very limited. In fact, neither the monotonic relationship in the offshorability portfolio alphas nor the highly statistically significant alpha of the L-H portfolio is impaired.[52]

in an online appendix.

[52] In a first step, I replicate the findings of Barrot, Loualiche, and Sauvagnat (2017). Despite different sample periods, the resulting portfolio sorts look very similar to those in their paper. Portfolio sorts and the regression results are reported in the online appendix of this paper.

Approximately half of the manufacturing firms in my sample are multinational companies that have sales in at least one country other than the United States. Fillat and Garetto (2015) have documented that multinational firms experience higher stock returns compared to domestic firms. To understand how their results relate to mine, I first split the sample into multinational and domestic manufacturing firms and then conditionally sort them into five offshorability portfolios in each subsample. The results are reported in panel A of table 12.

[Insert Table 12 here.]

In line with Fillat and Garetto (2015), I find that equal-weighted excess returns for multinationals are higher than for domestic firms. Moreover, the L-H spread is positive, significant and of very similar magnitude for both groups. This suggests that sorting on offshorability is different from sorting on a firm's location of sales. In addition, the non-monotonicity of portfolio excess returns can only be rejected for firms with multinational operations. Panel B confirms that even after controlling for other firm characteristics, offhsorability negatively predicts future annual excess returns both for multinational and domestic firms.

Finally, given the large number of multinationals in manufacturing industries, another potential concern is that L-H is related to differential foreign exchange exposures across industries. To address this, I estimate three two-factor models including the U.S. market excess return and either the dollar factor, the carry factor (both from Verdelhan (2017)) or the excess return of high interest rate currencies minus low interest rate currencies (from Lustig, Roussanov, and Verdelhan (2011)). I find that the three factors related to foreign exchange are insignificant in most specifications. Moreover, the L-H alphas are positive and statistically different from zero in all specifications. The corresponding results are tabulated in an online appendix.

4 Model

In this section, I develop a two-country dynamic general equilibrium trade model with multiple industries that are heterogenous in their ability to offshore.

The model builds on existing work on trade models with aggregate risk by Ghironi and Melitz (2005) and Barrot, Loualiche, and Sauvagnat (2017), who also focus on asset prices. To discuss my empirical results through the lens of the model, I additionally embed firm-level offshoring, as in Antras and Helpman (2004), in the model. Consequently, firms not only decide whether or not to export but also where to produce their goods.

The model features two countries, West and East. To distinguish between the two countries, quantities that refer to the East are labeled with a $\star$. Each country is inhabited by a continuum of homogenous households and two industrial sectors that are spanned by $S+1$ industries. The first sector consists of one industry and a single homogenous good, and the corresponding sector quantities are labeled with a 0. The second sector encompasses S industries, which each consist of a continuum of differentiated goods that are produced by a continuum of firms.

4.1 Demand Side: The Households Problem

Homogenous households have the following Epstein-Zin preferences over the consumption stream $\{C_t\}$:

$$U_t = \left\{ (1-\beta)\, C_t^{\frac{1-\gamma}{\nu}} + \beta \left(\mathbb{E}_t \left[U_{t+1}^{1-\gamma} \right] \right)^{\frac{1}{\nu}} \right\}^{\frac{\nu}{1-\gamma}}$$

where C_t is an aggregate consumption index, β is the subjective time discount factor, γ is the coefficient of risk aversion, ψ is the elasticity of intertemporal substitution and $\nu \equiv \frac{1-\gamma}{1-1/\psi}$ is a parameter defined for notational convenience. Each period, households derive utility from consuming goods in $S+1$ industries. C_t is given by the following aggregator:

$$C_t = c_{0,t}^{1-a_0} \left[\sum_s \delta_s^{\frac{1}{\theta}} \left(\int_{\Omega_{s,t}} c_{s,t}(\varphi)^{\frac{\sigma_s - 1}{\sigma_s}} d\varphi \right)^{\frac{\sigma_s}{\sigma_s - 1} \frac{\theta - 1}{\theta}} \right]^{\frac{\theta}{\theta - 1} a_0},$$

where $c_{0,t}$ and $1-a_0$ denote, respectively, the consumption and the expenditure share in the homogenous good sector; $c_{s,t}(\varphi)$ denotes the consumption of differentiated good variety φ in industry s; δ_s is an industry taste parameter (where $\sum_s \delta_s = 1$); θ is the elasticity of substitution between industries; σ_s is the elasticity of substitution among good varieties within industry s; and $\Omega_{s,t}$ is the set of firms that sell their goods at time t in industry s in the West.

The aggregation over industry-specific consumption and over varieties is based on constant elasticity of substitution with elasticities θ and σ_s, respectively. This results in Dixit and Stiglitz (1977) demand schedules at both the industry and the product level. Detailed derivations can be found in appendix A of the paper.

Finally, households obtain revenues L_t from inelastic labor supply and from ownership of firms, resulting in the following budget constraint:[53]

$$\sum_s \int_{\Omega_{s,t}} p_{s,t}(\varphi) c_{s,t}(\varphi) d\varphi \leq L_t + \Pi_t,$$

[53] Wages in each country are equal to the numeraire and are set to 1 as discussed below.

with Π_t being profits from firm ownership.[54] In what follows, I suppress the time index t for ease of notation.

4.2 Supply Side: Firms' Production and Organizational Decision

Homogenous good sector - The homogenous good 0 is produced under constant returns to scale (CRS) and a production function that is linear in labor.[55] Moreover, the good is freely traded across countries. Its price is used as a numeraire in each country and is set to one.[56]

Differentiated goods sector - This sector encompasses S industries that each consist of a continuum of differentiated goods that are produced by a continuum of monopolistically competitive firms. Each firm produces a different product variety, φ. Intuitively, firms possess a product variety-specific blueprint that determines their idiosyncratic productivity. In what follows, φ not only serves as an identifier of product variety but also stands for idiosyncratic productivity. Following Antras and Helpman (2004), I model firms' production function as a Cobb-Douglas function that aggregates two tasks: non-offshorable **h**eadquarter tasks, $h(\varphi)$, and **o**ffshorable tasks, $o(\varphi)$:[57]

$$y_s(\varphi) = A \left[\frac{h_s(\varphi)}{\alpha_s}\right]^{\alpha_s} \left[\frac{o_s(\varphi)}{1-\alpha_s}\right]^{1-\alpha_s},$$

where $y_s(\varphi)$ is the amount of product variety φ produced in industry s, A is aggregate productivity and α_s is the headquarter-intensity in industry s. Importantly, $1 - \alpha_s$ measures to what extent a firm can offshore its production. Since α_s is identical for all firms in industry s, firm offshorability is identical to industry offshorability in the model. Furthermore, I assume that aggregate productivity follows an autoregressive process of order one in each country:

$$a_t = \rho_a a_{t-1} + \epsilon_t^a \qquad a_t^\star = \rho_{a^\star} a_{t-1}^\star + \epsilon_t^{a^\star},$$

where a_t ($a_t^\star$) is the logarithm of A_t ($A_t^\star$), $\epsilon_t^a \sim N\left(0, \sigma_a^2\right)$ $\left(\epsilon_t^{a^\star} \sim N\left(0, \sigma_{a^\star}^2\right)\right)$ and $cov\left(\epsilon_t^a, \epsilon_t^{a^\star}\right) = 0$.

Production is costly. Firms are subject to production costs as well as fixed organizational costs. The total production costs consist of wages or salaries paid for time actually worked, w, and other labor costs,

[54] Households can have ownership both in Eastern and Western firms, as will become clear in the section on asset prices below. Alternatively, one can think of households owning a share in a world mutual fund that redistributes profits of firms from the two countries, as discussed in Barrot, Loualiche, and Sauvagnat (2017).

[55] In other words, one unit of labor produces one unit of good 0. Because of the CRS technology, there are no profits to be distributed from sector 0.

[56] Consequently, wages are equal to one in both countries.

[57] The task-specific technology is linear in labor: for every unit of labor, each task produces φ units of task-specific output.

c, such as payments to pension plans, unemployment insurance fees, legal costs and accruals for possible severance payments. I assume that other labor costs are proportional to the amount of labor hired such that the marginal costs of labor equals $w + c$. I further assume that any unit of labor can be employed either as headquarter or offshorable tasks. In other words, within a country, there is no separation of the labor force. For clarity of exposition, in what follows, I will be explicit about the total costs associated with one unit of headquarter and offshorable labor employed in industry s. I call them $w_{h,s}$ and $w_{o,s}$, respectively.

Throughout the paper, I further assume that the East has a comparative cost advantage in offshorable labor over the West. In particular, I assume that $c > c^{\star}$. That is, within the context of the model, the East can be associated with a low-wage country such as China and the West with a highly developed economy such as the U.S. Intuitively, the wedge $c - c^{\star}$ can be interpreted as differences in unemployment benefits and other social insurances, strength of labor unions and severance payments across the two countries. This cost wedge provides an incentive to Western firms to offshore and, as such, is a key ingredient for the model to generate results consistent with the empirical evidence.

Given the comparative cost advantage of the East over the West, firms decide on their organizational strategy along two dimensions. First, they decide whether to produce domestically or offshore part of their production. Second, they choose whether to sell their output only domestically or, alternatively, both on the domestic and export market. In what follows, I detail the optimal sorting of firms into the different strategies.

Domestic Production vs Offshoring

Firms operate in monopolistically competitive industries and set their prices at a markup over marginal costs. The monopolistic competition markup $\frac{\sigma_s}{\sigma_s - 1}$ is determined by the elasticity of substitution among product varieties within an industry, σ_s.[58] Hence, the price set by firms that produce domestically is given by

$$p_{s,D}(\varphi) = \frac{\sigma_s}{\sigma_s - 1} \frac{(w_{h,s})^{\alpha_s} (w_{o,s})^{1-\alpha_s}}{A\varphi},$$

[58] The higher the σ_s, the lower the markup $\frac{\sigma_s}{\sigma_s - 1}$.

where $w_{h,s}$ ($w_{o,s}$) are total wage costs for headquarter (offshorable) tasks. Firm profits in industry s are defined as the difference between sales and total costs, $\Gamma_{s,D}(y_{s,D}(\varphi), \varphi)$:

$$\begin{aligned}
\pi_{s,D}(\varphi) &= p_{s,D}(\varphi) y_{s,D}(\varphi) - \Gamma_{s,D}(y_{s,D}(\varphi), \varphi) \\
&= \frac{1}{\sigma_s} p_{s,D}(\varphi) \left[\frac{p_{s,D}(\varphi)}{P_s} \right]^{-\sigma_s} C_s \\
&= B_s \left((w_{h,s})^{\alpha_s} (w_{o,s})^{1-\alpha_s} \right)^{1-\sigma_s} (A\varphi)^{\sigma_s - 1},
\end{aligned}$$

where $B_s = \frac{1}{\sigma_s} \left[\frac{\sigma_s}{\sigma_s - 1} \right]^{1-\sigma_s} P_s^{\sigma_s} C_s$. Without loss of generality, fixed organizational costs for a purely domestic firm are set to 0.[59] Consequently, all firms in an industry are productive, since domestic production is profitable for all values of φ.

Firms decide whether or not to offshore tasks of type o. On the one hand, firms that offshore can benefit from potentially lower total production costs and from risk diversification.[60] On the other hand, offshoring is costly due to trade costs, $\tau^\star$, and per-period fixed organizational costs of offshoring, f_O. [61]

Trade costs are often associated with the costs of transporting intermediate inputs across countries. Alternatively, $\tau^\star$ can be interpreted more broadly to reflect other technological barriers related to international fragmentation, such as language barriers, communication or search costs.

As in Antras and Helpman (2004), fixed organizational costs, f_O, can be interpreted as the joint management cost of final and intermediate goods production, such as supervision, quality control, accounting, and marketing, which depend on the organizational form and location of production. These costs are expressed in units of effective labor. I assume that firms hire workers from their respective domestic labor markets to cover these fixed costs. Hence, profits with offshoring are equal to

$$\pi_{s,O}(\varphi) = B_s \left((w_{h,s})^{\alpha_s} (w_{o,s}^\star \tau^\star)^{1-\alpha_s} \right)^{1-\sigma_s} \left(A^{\alpha_s} (A^\star)^{1-\alpha_s} \varphi \right)^{\sigma_s - 1} - \frac{f_O}{A}.$$

Profit-maximizing firms in industry s decide to offshore whenever profits from doing so are larger than

[59] Alternatively, I could set the fixed costs for domestic production to a value different from zero. Consequently, firms with sufficiently low idiosyncratic productivity would decide to shut down production entirely. In the absence of fixed costs for domestic production, fixed costs of offshoring, f_O, can be interpreted as the excess cost of offshoring in comparison to domestic production.

[60] More formally, the total costs of producing y units of a final good of variety φ associated with **D**omestic sourcing and **O**ffshoring can be written as

$$\begin{aligned}
\Gamma_{s,D}(y_{s,D}(\varphi), \varphi) &= \frac{y_{s,D}(\varphi)}{A\varphi} (w_{h,s})^{\alpha_s} (w_{o,s})^{1-\alpha_s} \\
\Gamma_{s,O}(y_{s,O}(\varphi), \varphi) &= \frac{f_O}{A} + \frac{y_{s,O}(\varphi)}{A^{\alpha_s} (A^\star)^{1-\alpha_s} \varphi} (w_{h,s})^{\alpha_s} (w_{o,s}^\star \tau^\star)^{1-\alpha_s}
\end{aligned}$$

[61] Notation: $\tau^\star$ labels trade costs for shipments from East to West and τ labels trade costs for shipments from West to East.

profits from domestic production, $\pi_{s,O}(\varphi) \geq \pi_{s,D}(\varphi)$. $\varphi_{s,O}$ is defined as the idiosyncratic productivity level for which the profits from the two strategies are equalized, such that $\pi_{s,O}(\varphi_{s,O}) = \pi_{s,D}(\varphi_{s,O})$:

$$\varphi_{s,O} = \left[\frac{f_O (A)^{-1}}{B_s \left[\left[(w_{h,s})^{\alpha_s} \left(w^{\star}_{o,s} \tau^{\star} \right)^{1-\alpha_s} \right]^{1-\sigma_s} \left[A^{\alpha_s} (A^{\star})^{1-\alpha_s} \right]^{\sigma_s - 1} - \left[(w_{h,s})^{\alpha_s} (w_{o,s})^{1-\alpha_s} \right]^{1-\sigma_s} A^{\sigma_s-1} \right]} \right]^{\frac{1}{\sigma_s - 1}}$$

$\varphi_{s,O}$ is decreasing in $A^{\star}$ and $w_{o,s}$, since $\sigma_s \geq 1$. In other words, the stronger the comparative advantage of the East over the West, the more Western firms decide to offshore. Regardless of the organizational decision, firm profits are monotonically increasing in φ. This can be seen from figure 3, which plots profits of different organizational strategies against idiosyncratic productivity both for Western firms (left panel) and Eastern firms (right panel). Western firm profits from offshoring are negative for low values of φ due to the fixed organizational costs. However, profits from offshoring grow significantly with higher φ, which eventually leads to higher profits compared to domestic production. Consequently, all firms with idiosyncratic productivity larger than $\varphi_{s,O}$ decide to offshore. This implies that large and productive firms offshore. In contrast, Eastern firms abstain from offshoring, since domestic production is more cost-efficient (lower production costs and no trade costs on intermediate inputs). This aspect of the model is discussed in more detail in appendix A.3.

[Insert Figure 3 here.]

Decision to Export

In addition to choosing the location of production, firms decide whether or not to export. Similar to offshoring, exporting is costly and involves variable trade costs, τ, and per-period fixed costs, f_X . Firms choose to export whenever profits from doing so are positive, $\pi_{s,X} \geq 0$. However, the decision to export also depends on the location of production. Consequently, the productivity cutoff for domestic producers is different from the cutoff for firms that offshore.

The cutoff level for firms that produce **domestically** is defined as [62]

$$\varphi_{s,X,D} = \left[\frac{f_X (A)^{-1}}{B^{\star}_s \left[\tau (w_{h,s})^{\alpha_s} (w_{o,s})^{1-\alpha_s} \right]^{1-\sigma_s} A^{\sigma_s - 1}} \right]^{\frac{1}{\sigma_s - 1}}.$$

[62] Note that the corresponding profit expression is equal to

$$\pi_{s,X,D}(\varphi) = B^{\star}_s \left(\tau (w_{h,s})^{\alpha_s} (w_{o,s})^{1-\alpha_s} \right)^{1-\sigma_s} (A\varphi)^{\sigma_s - 1} - \frac{f_X}{A}.$$

Profit maximization implies that all domestically producing firms in the West with idiosyncratic productivity higher than $\varphi_{s,X,D}$ engage in exporting.

In contrast, firms that **offshore** decide to export whenever their productivity level is higher than [63]

$$\varphi_{s,X,O} = \left[\frac{f_X (A)^{-1}}{B_s^\star \left[\tau (w_{h,s})^{\alpha_s} \left(w_{o,s}^\star \tau^\star \right)^{1-\alpha_s} \right]^{1-\sigma_s} \left[A^{\alpha_s} (A^\star)^{1-\alpha_s} \right]^{\sigma_s - 1}} \right]^{\frac{1}{\sigma_s - 1}}.$$

As above, all Western firms that engage in offshoring with idiosyncratic productivity higher than $\varphi_{s,X,O}$ decide to export. Importantly, this productivity cutoff is valid only for firms that offshore. Hence, the fixed costs of offshoring f_O need not be considered again.

Allowing firms to choose the production location and decide whether or not to export is realistic but increases complexity substantially. In fact, the decision to offshore might affect the decision to export and vice versa. Hence, to ensure tractability, I rule out equilibria in which in a given country, firms that produce only domestically and export and firms that offshore and export co-exist.[64] One way to prevent co-existence is to ensure that only firms that offfshore engage in exporting. This can be induced by large-enough fixed costs of exporting, f_X. In particular, it is sufficient that $\varphi_{s,X,O} > \varphi_{s,O}$ holds period by period.[65] This case is illustrated in the left panel of figure 3. $\varphi_{s,X,O}$ is indeed larger than $\varphi_{s,O}$ in this specific equilibrium of the model. As a result, only Western firms that engage in offshoring also export. For the East, the problem is much simpler. Since all firms produce domestically, the relevant cut-off productivity that separates exporters from non-exporters is $\varphi^\star_{s,X,D}$.

4.3 Aggregation

In what follows, I follow Ghironi and Melitz (2005) and assume that firm productivity is distributed according to a Pareto distribution with lower bound φ_{min} and shape parameter $\kappa_s > \sigma_s - 1 : G(\varphi) = 1 - \left(\frac{\varphi_{min}}{\varphi}\right)^{\kappa_s}$. The assumption of a Pareto distribution for productivity induces a size distribution of

[63] Corresponding profits are equal to

$$\pi_{s,X,O}(\varphi) \quad = \quad B_s^\star \left(\tau (w_{h,s})^{\alpha_s} (w_{o,s}^\star \tau^\star)^{1-\alpha_s} \right)^{1-\sigma_s} \left(A^{\alpha_s} (A^\star)^{1-\alpha_s} \varphi \right)^{\sigma_s - 1} - \frac{f_X}{A}.$$

[64] Antras, Fort, and Tintelnot (2016) multi-country sourcing model, in which global sourcing decisions interact through the firm's cost function, and Bernard, Jensen, Redding, and Schott (2016) present a theoretical framework that allows firms to decide simultaneously on the set of production locations, export markets, input sources, products to export, and inputs to import.

[65] To be precise, a large f_X lowers the probability of co-existence to a very small number but does not strictly rule it out. Therefore, when simulating the model, I check ex post that $\varphi_{s,X,O} > \varphi_{s,O}$ holds period by period for all industries s. More details on the computation approach when solving the model can be found in an online appendix.

firms that is also Pareto, which fits well the empirical distribution. The parameter κ_s relates industry output to the cross-section of firms, where high values are associated with more homogenous industries in the sense that more output is concentrated among the smallest and least-productive firms.

Quantities

As in Melitz (2003) and Ghironi and Melitz (2005), it is enough to track the mass and the average productivity for firms that choose the same strategy. In essence, the model is isomorphic to one in which firms within a strategy group all have a productivity equal to the average productivity of the group. Put differently, the average productivity levels per group summarize all information on the productivity distribution relevant for macroeconomic variables.

First, I calculate the fraction of firms in industry s that engage in domestic production, $\zeta_{s,D}$, and offshoring, $\zeta_{s,O}$. Moreover, $\zeta_{s,X,O}$ and $\zeta^{\star}_{s,X,D}$ stand for the fractions of firms that export in the West and East, respectively. These quantities are determined by the cutoff productivity levels and the shape of the Pareto distribution, as detailed in appendices A.2 and A.3.

Second, I derive average productivity levels for the different groups: 1) $\bar{\varphi}_{s,D}$, for purely domestic Western firms; 2) $\bar{\varphi}_{s,O}$, for Western firms that offshore; 3) $\bar{\varphi}_{s,X,O}$, for Western firms that offshore and export; 4) $\bar{\varphi}^{\star}_{s,D}$, for purely domestic Estern firms; and 5) $\bar{\varphi}^{\star}_{s,X,D}$, for Eastern firms that produce domestically and export. These quantities can be calculated as simple conditional averages for the Pareto distribution. Again, detailed derivations can be found in appendices A.2 and A.3.

Industry Profits and Prices

Industry-wide profits and price indices can now be calculated using probability masses and average productivity levels. Industry profits are simply given by the sum of the profits made on the domestic and exporting markets. Therefore, industry profits in the West are given by

$$\Pi_s = N_s \left[\zeta_{s,D}\pi_{s,D}(\bar{\varphi}_{s,D}) + \zeta_{s,O}\pi_{s,O}(\bar{\varphi}_{s,O}) + \zeta_{s,X,O}\pi_{s,X,O}(\bar{\varphi}_{s,X,O})\right]$$

and industry profits in the East are given by

$$\Pi^{\star}_s = N^{\star}_s \left[\pi^{\star}_{s,D}(\bar{\varphi}^{\star}_{s,D}) + \zeta^{\star}_{s,X,D}\pi^{\star}_{s,X,D}(\bar{\varphi}^{\star}_{s,X,D})\right],$$

where N_s ($N^{\star}_s$) is the total mass of firms in the West (East) exogenously set to match the size of the economy.

Finally, the industry price indices in the two countries are equal to

$$P_s = \left[N_s \left[\zeta_{s,D} p_{s,D}(\bar{\varphi}_{s,D})^{1-\sigma_s} + \zeta_{s,O} p_{s,O}(\bar{\varphi}_{s,O})^{1-\sigma_s} \right] + N_s^\star \zeta_{s,X,D}^\star \left(p_{s,X,D}^\star (\bar{\varphi}_{s,X,D}^\star) \right)^{1-\sigma_s} \right]^{\frac{1}{1-\sigma_s}},$$

in the West, and

$$P_s^\star = \left[N_s^\star p_{s,D}^\star (\bar{\varphi}_{s,D}^\star)^{1-\sigma_s} + N_s \zeta_{s,X,O} p_{s,X,O}(\bar{\varphi}_{s,X,O})^{1-\sigma_s} \right]^{\frac{1}{1-\sigma_s}},$$

in the East.

4.4 Equilibrium

In equilibrium, the aggregate budget constraint of the representative household is given in terms of the aggregate price index P, composite consumption C, labor income L and revenues from Western and Eastern industries, Π_s and $\Pi_s^\star$:

$$PC \leq L + \sum_s \Pi_s + \chi \left[\frac{N_s}{N_s + N_s^\star} \Pi_s^\star - \frac{N_s^\star}{N_s + N_s^\star} \Pi_s \right].$$

The exogenous parameter $\chi \in [0,1]$ controls the level of risk sharing across countries in the economy. This formulation embeds both the case of no risk-sharing and perfect or full risk-sharing. Without risk-sharing, $\chi = 0$, households only receive dividends from domestic firms: $\Pi_{no} = \sum_s \Pi_s$. In comparison, with full risk-sharing, $\chi = 1$, households receive a share of total world profits that is proportional to their capital endowments: $\Pi_{full} = \sum_s \frac{N_s}{N_s + N_s^\star} (\Pi_s + \Pi_s^\star)$. Consequently, dividends paid to households are a convex combination of Π_{no} and Π_{full}.

The model is solved with time-invariant mass of firms in each industry. Moreover, the model abstracts from capital or investment. As a result, firms can adjust their production solely by deciding either to offshore or export. The equilibrium is defined as a collection of prices $(p_{s,D}, p_{s,O}, p_{s,X,O}, p_{s,X,D}, P_s, P_T, P)$, output $(y_s(\varphi))$, consumption $(c_s(\varphi))$ and labor demand $(l_s(\varphi))$ such that each firm maximizes profit, consumers maximize their utility, and goods and labor markets clear.

4.5 Asset Pricing

Since the representative household in the West holds Western firms, the firms are priced using her stochastic discount factor (SDF). Therefore, I derive the Euler equation from the portfolio problem faced by the representative household. She maximizes her continuation utility over the consumption stream $\{C_t\}$ subject to her budget constraint. Because there is no capital and investment in the model, firms pay out dividends that are equal to their profits, $\pi_{s,t}(\varphi)$.

$$\begin{aligned}&\max \left\{(1-\beta)\, C_t^{\frac{1-\gamma}{\nu}} + \beta\left(\mathbb{E}_t\left[U_{t+1}^{1-\gamma}\right]\right)^{\frac{1}{\nu}}\right\}^{\frac{\nu}{1-\gamma}} \\ &\text{s.t. } P_tC_t + \sum_s \int_{\Omega_s} x_{s,t+1}(\varphi)\upsilon_{s,t}(\varphi)d\varphi \leq L + \sum_s \int_{\Omega_s} x_{s,t}(\varphi)\left[\upsilon_{s,t}(\varphi) + \pi_{s,t}(\varphi)\right]d\varphi\end{aligned}$$

where $x_{s,t}(\varphi)$ is the investment in the firm in industry s of variety φ and $\upsilon_{s,t}(\varphi)$ is the corresponding firm valuation.

The resulting Euler equation reads as follows:

$$\upsilon_{s,t} = \mathbb{E}_t\left[M_{t,t+1}\left(\upsilon_{s,t+1}(\varphi) + \pi_{s,t+1}(\varphi)\right)\right],$$

where $M_{t,t+1} = \beta^{\nu}\Delta C_t^{-\frac{\nu}{\psi}} R_{c,t}^{\nu-1}$ is the stochastic discount factor (SDF) and $R_{c,t}$ is the return on the consumption claim.

4.6 Calibration

To calibrate my model, I associate the West with the United States and the East with China. Moreover, where possible, I calibrate the model using parameters from the literature, as reported in table 13. In particular, I use elasticities across industries from Loualiche (2015) and across goods from Broda and Weinstein (2006). The firm distribution is governed by the parameter κ_s, which is set to 3.4, as in Ghironi and Melitz (2005). The industry taste parameter δ_s is equal to 0.5. Hence, households do not have a preference for a certain industry.

[Insert Table 13 here.]

Wage costs other than pay for time in the West, c, are chosen to match the empirical counterpart in the United States. According to the Bureau of Labor Statistics (BLS), 24.35% of the total wage costs in manufacturing accounted for social insurance payments and 8.92% for directly paid benefits.[66] Hence, 33.27% of the total wage bill consisted of payments other than wages and salaries for time actually worked. To reflect this in the model, I calibrate c to 0.32 and $c^{\star}$ to 0, assuming absence of social insurance costs in the East.

L and $L^{\star}$ are determined by the ratio of the working age population in the U.S. and China. The Federal Reserve Bank of St. Louis reports a working age population of 205 millions by the end of 2015 in the U.S. and 1'004 million in China. The mass of firms in each country, N_s and $N_s^{\star}$, is chosen to match

[66] Directly paid benefits are primarily pay for leave time, bonuses, and pay in kind.

the ratio of the market capitalization in the U.S. and China. The World Bank states the total market capitalization of listed domestic companies in 2015 as 25.068 trillion USD in the U.S. and 8.19 trillion USD in China. To match the ratio between the two, I calculate the model-implied ratio of the sum of market values of all firms in the West and East, respectively.

The headquarter intensities of the two industries, α_s, are set to 0.55 and 0.95, respectively. This implies that a high (low) offshorability industry has an offshoring potential of 45% (5%) and that the average offshoring potential in the model economy is 25%. For comparison, the OECD estimates that close to 20% of jobs in OECD countries are offshorable, while Blinder's (2009) estimates for the U.S. lie between 22% and 29%.[67]

Variable trade cost and fixed cost parameters are set to the values in Ghironi and Melitz (2005) and Barrot, Loualiche, and Sauvagnat (2017), respectively. The subjective discount factor is 0.99, and the intertemporal elasticity of substitution is 1.5, as in Bansal and Yaron (2004). I calibrate the risk aversion parameter to match the U.S. equity premium. Finally, parameters related to aggregate productivity in the West (East) are chosen to reflect GDP in the U.S. (Chinese imports to the U.S.), as in Barrot, Loualiche, and Sauvagnat (2017).

4.7 Model Mechanism

Consumption Response - To examine what drives asset prices in the model, it is necessary to understand how aggregate consumption and the SDF respond to aggregate productivity shocks in the model.

The elasticity of consumption in the West to a productivity shock in the East, $\eta^{\star}(C)$[68], is

$$\eta^{\star}(C) = \underbrace{-\eta^{\star}(P)}_{\text{price effect}} + \underbrace{\frac{\Pi}{L+\Pi}\eta^{\star}(\Pi)}_{\text{wealth effect}} \tag{4}$$

The elasticity consists of a price and a wealth effect. As will be discussed later, the elasticity of the price index with respect to $A^{\star}$ is negative. As a result, the sign of the first term is unambiguously positive. On the other hand, the sign of the wealth effect depends on the degree of international risk sharing. With full risk-sharing, the wealth effect is positive, as is the elasticity of consumption with respect to a foreign productivity shock: Western households benefit from (1) lower domestic prices due to increases in imports and (2) higher capital income due to higher world profits.

However, with a sufficiently high degree of home bias in capital income (low χ), the wealth effect is

[67] The OECD also reports the offshoring potential for NACE 2-digit industries. For the year 2003, the numbers lie between 79.5% and 1.8%.
[68] Notation: $\eta(X) = \frac{\partial \log X}{\partial \log A}$ and $\eta^{\star}(X) = \frac{\partial \log X}{\partial \log A^{\star}}$.

negative and dominates the positive price effect. As an illustration, the first row of figure 4 plots impulse response functions of consumption for different values of χ. In the baseline parametrization, $\chi < 0.75$ is sufficient to generate a negative consumption response. $\chi = 0.75$ implies that Western households overweigh their investments in domestic firms by 18.62% compared to domestic firms' share of the world market. Hence, a fairly moderate home bias is sufficient to generate a negative elasticity of consumption with respect to a positive productivity shock in the East. In comparison, Coeurdacier and Rey (2012) empirically find a home bias for equity investments of 44.6% in the U.S. in 2008.[69] To simplify the exposition, I impose no international risk sharing (i.e., $\chi = 0$) in my benchmark specification; I then discuss the implications thereof.

[Insert Figures 4 and 5 here.]

The elasticity of consumption to productivity shocks in the West looks identical to equation 4. For shocks to A, however, the elasticity of consumption is unambiguously positive. In particular, both price and wealth effect carry a positive sign.

In what follows, I separately discuss how shocks to $A^\star$ and A affect the equilibrium. The discussion mostly focuses on the West as the main country of interest and starts with the analysis of aggregate productivity shocks in the East.

Shocks to $A^\star$ - To facilitate the discussion, figure 4 plots impulse response functions of model quantities to a positive one standard deviation shock to $A^\star$ in the absence of risk sharing. As discussed, consumption in the West (East) decreases (increases) upon arrival of a shock. Moreover, due to higher productivity, more Eastern firms find it profitable to export, which results in an increase in import penetration. Higher import penetration in turn leads to an increase in product variety, a decrease in industry prices and a loss in market share and profits of Western firms.

Higher productivity in the East, however, also renders offshoring more attractive. Doing so allows firms to lower costs, which goes hand in hand with a larger market share and higher profits. Hence, offshoring effectively acts as partial insurance against adverse consequences associated with foreign productivity shocks.

The response of the fraction of firms that offshore is more pronounced in high offshorability industries. The reason is simple: in the model, industries with higher offshoring potential are able to replace more workers/tasks, which results in a larger cost reduction and makes it more likely for firms to overcome the fixed costs of offshoring. As a result, profits drop less in industries with high offshorability.

[69] For further empirical evidence of home bias in the U.S., see, among others, French and Poterba (1991) and Coval and Moskowitz (1999); and for rational explanations of the home bias puzzle, see, for example, Glassman and Riddick (2001), Ahearne, Griever, and Warnock (2004), Nieuwerburgh and Veldkamp (2009) and Bretscher, Julliard, and Rosa (2016).

What does this mean for asset prices? The heterogenous response of industry profits maps into differential asset price and excess return dynamics across industries. The last row plots the response of the SDF, asset prices and excess returns for the case of no and full risk sharing, respectively. Consistent with the consumption response in the first row, the SDF increases under no risk sharing but decreases with full risk sharing. However, the qualitative response of asset prices and returns is not altered by the degree of risk sharing. In both cases, the responses are negative and more pronounced for the low offshorability industry.

Shocks to A - Figure 5 plots the impulse responses to a *negative* one standard deviation shock to A. I plot the responses to a negative productivity shock to facilitate comparison with the impulse response functions after a shock to $A^{\star}$. Upon arrival of the shock, Western consumption drops, which affects firms through a decrease in product demand. Moreover, because the production function of Eastern firms that export to the West is not directly affected by shocks to A, their productivity and, hence, their prices remain unchanged. This gives Eastern exporters a competitive advantage over Western firms whenever a negative shock to A happens. As a result, Western firms lose market share to these exporters.

As above, offshoring presents itself as a valuable alternative in order to mitigate the adverse consequences of the shock. Again, offshoring results in a larger cost reduction for high compared to low offshorability industries. Consequently, the response of the fraction of firms that offshore is more pronounced in high offshorability industries, which ultimately leads to smoother industry profits. Asset prices and excess returns follow from industry profits and look very similar to figure 4 (not shown).

To sum up, the ability to offshore protects industries against losses associated with import competition. Differences in offshorability across industries contribute to a spread in excess returns similar to the L-H spread observed in the data.

4.8 Model Simulation Results

To quantify the model and investigate the contribution of the two productivity shocks, I calculate moments from simulated data. As discussed in section 4.6, I target the ratios of market capitalization and working age populations in the U.S. and China as well as the average import competition from China to discipline my calibration exercise. In particular, matching these moments constrains the choice of parameters N_s, $N_s^{\star}$, L, $L^{\star}$ and $f_X^{\star}$. The model matches the targeted moments well, as can be seen in panel A of table 14.

[Insert Table 14 here.]

Panel B of the same table reports model-implied macro moments. Similar to Barrot, Loualiche, and Sauvagnat (2017), aggregate consumption is too volatile in the model. While the mean of the risk-free rate is close to the data, the model implied standard deviation is too low. Interestingly, the model-implied U.S. labor share aligns quite well with the data. The Bureau of Labor Statistics reports a labor share of 58.4% as of the third quarter in 2016. In comparison, the model-implied labor share is 60.54%.

The moments of industry quantities are reported separately for high and low offshorability industries in panel C. The level of import penetration is slightly higher in the industry with low offshoring potential. Intuitively, because Eastern firms face less resistance upon entering in this industry, it is optimal to do so to a higher extent in equilibrium. Moreover, import penetration is more volatile because the response to productivity shocks is more pronounced, as can be seen from figures 4 and 5. For industry profits, the standard deviation and covariance with aggregate productivity shocks and consumption are decreasing in offshorability. In other words, the possibility to offshore allows firms to smooth their profits, which renders them less exposed to shocks.

Panel D of table 14 reports moments of model asset prices and excess returns. The model-implied annualized market risk premium is 4.52%.[70] Since the model does not feature financial leverage, this is the unlevered risk premium. To make the model premium comparable to the data, I calculate the model-implied levered market risk premium assuming a leverage ratio equal to the sample median of 23.8%. The model market risk premium of 5.93% is quantitatively in line with the annualized excess return of the S&P 500 of 5.72% during the sample period. As in the data, model excess returns are lower for high compared to low offshorability industries. The levered (unlevered) annualized L-H spread between the two model industries is equal to 3.82% (2.91%), which is clearly lower than the risk-adjusted annualized spread of 8.05% for manufacturing industries in the data. I will discuss different reasons for the relatively low L-H spread in the model in section 4.10. This section will also discuss how the magnitude of the spread depends on model parameters and endogenous model quantities.

$$\eta^\star\left(\Pi^X\right) = \underbrace{-\sigma_s\left[1+\frac{\kappa_s-(\sigma_s-1)}{\sigma_s-1}\right]\left[-\eta^\star\left(P_s^\star\right)\right]}_{\text{price effect}} + \underbrace{\left[1+\frac{\kappa_s-(\sigma_s-1)}{\sigma_s-1}\right]\eta^\star\left(C_s^\star\right)}_{\text{demand effect}} + \underbrace{(1-\alpha_s)\,\kappa_s}_{\text{productivity effect}} \tag{5}$$

Within the model, it is possible to separate the domestic profits from profits from exporting. Equation 5 shows the elasticity of profits from exporting with respect to a productivity shock in the East, $A^\star$. The elasticity consists of three parts: (1) price effect (negative): the industry price index, $P_s^\star$, decreases and causes a loss in market share and profits; (2) demand effect (positive): demand increases and leads to an increase in profits; (3) productivity effect (positive): since all exporters also offshore, productivity shocks in the offshoring country directly affect profits through gains in productivity. Hence, the elasticity of export profits is negative whenever the price effect dominates.

[70] I calculate the model market risk premium as the value-weighted excess return across industries.

Panel D of table 14 shows that profits from exporting are riskier than total industry profits, which results in higher excess returns for exporters compared to the industry as a whole. Intuitively, all exporters have exercised their offshoring option, which leaves them unable to smooth profits going forward. Consequently, the model implies that multinational firms whose profits stem from domestic and exporting markets exhibit higher excess returns than purely domestic firms. This is consistent with the empirical evidence in Fillat and Garetto (2015).

To quantify the contribution of the two productivity shocks, I simulate the model with just one stochastic productivity process at a time. Panel A of table 15 reports simulated moments in the model economy for industry profits and excess returns. In the model, 89% of the L-H spread is due to shocks to $A^{\star}$, while only 11% is due to shocks to A.

[Insert Table 15 here.]

In an extension discussed in section A.4 of the appendix, I introduce international bond trading to the model, as in Ghironi and Melitz (2005). Not surprisingly, the standard deviation of consumption decreases compared to the baseline model, as bonds allow households to smooth their consumption intertemporally. As a result, the overall risk premium is lower. Importantly, however, the L-H spread is unaffected by the introduction of international bond trading. Since risk-free bonds are a state independent savings technology, trading them does not help mitigate state-specific risks.[71]

4.9 Testable Model Implications

The model delivers several predictions that can be tested in the data. Within the model, the possibility to offshore allows firms and industries to lower their exposure to aggregate productivity shocks. As a result, profits are less volatile for high compared to low offshorability industries. To test this model implication, I calculate profit and sales volatility as in Minton and Schrand (1999) and regress these volatilities on lagged offshorability, other firm controls (Tobin's Q, leverage and investment) and year fixed effects.[72] Standard errors are clustered at the year and firm level. The regression results are tabulated in Panel B of table 15.

Consistent with the theory, the coefficients on $OFF_{i,t-x}$ for profit volatility are negative and highly statistically and economically significant both for one- and five-year lags. Interestingly, the coefficient on $OFF_{i,t-5}$ is double the magnitude of the coefficient on the first lag. A one standard deviation increase in

[71] Relevant moments of simulated data of the model with international bond trading are reported in table A1 of the appendix.

[72] I adapt the methodology proposed by Minton and Schrand (1999) to calculate cash flow volatility both for profit and sales volatility.

industry offshorability is associated with an 8.9% (one-year lag) to 19.7% (five-year lag) decrease in the profit volatility for the median firm. Regression coefficients for several lags with 90% and 95% confidence bands are plotted in figure 6. I find that the coefficient on $OFF_{i,t-x}$ is monotonically increasing in magnitude with the horizon. This is consistent with offshoring being a process that takes time to be fully incorporated.

[Insert Figure 6 here.]

The results for sales volatility are very similar as for profit volatility. While the coefficients on $OFF_{i,t-x}$ are negative in all specifications, they are statistically different from zero at a 90% (95%) confidence level only for horizons larger or equal to three (four) years. Intuitively, offshoring allows for a cost reduction that affects profits with higher immediacy than sales.

Furthermore, the model allows one to form predictions about the cross-sectional dispersion of the L-H premium. Households become more price-sensitive when the elasticity of substitution among product varieties, σ_s, increases. Put differently, in industries with high elasticities, all else being equal, the drop in Western firms' market share is more pronounced upon arrival of an adverse productivity shock - both in low and high offshorability industries. This can be seen from the elasticity of domestic profits with respect to a productivity shock in the East:

$$\begin{aligned}\eta^{\star}\left(\Pi^{D}\right) &= \underbrace{-\left(\sigma_s-\theta\right)\left(-\eta^{\star}\left(P_s\right)\right)}_{\text{competition effect}} + \underbrace{\eta^{\star}\left(C_s\right)+\frac{1-a_0-\theta}{a_0}\left(-\eta^{\star}\left(P\right)\right)}_{\text{expenditure effect}} + \\ &\left[\underbrace{\kappa_s\frac{\zeta_{s,O}\left(\pi_{s,O}-\pi_{s,D}\right)}{\Pi^{D}}}_{\text{relative benefits from offshoring}} \underbrace{-\left(\sigma_s-1\right)\frac{\zeta_{s,D}\pi_{s,D}\Phi+\zeta_{s,O}\pi_{s,O}}{\Pi^{D}}}_{\text{industry composition effect}}\right]\left(-\eta^{\star}\left(\varphi_{s,O}\right)\right) + \\ &\underbrace{\frac{\zeta_{s,O}\pi_{s,O}}{\Pi^{D}}\left(\sigma_s-1\right)\left(1-\alpha_s\right)}_{\text{productivity gain from offshoring}}, \end{aligned} \tag{6}$$

where $\Phi>0$ and $\frac{\partial\Phi}{\partial\varphi_{s,O}}>0$.[73] Irrespective of an industry's offshorability, the elasticity is more negative with higher σ_s because the *competition effect* is amplified. Competition leads to a decrease in industry prices, which results in a decrease in market share. Moreover, the effect of an increase in σ_s depends on the industry equilibrium in the West (*industry composition effect*). A higher elasticity of substitution

[73] φ is defined as follows:

$$\Phi=\frac{\varphi_{s,min}^{\kappa_s}}{\sigma_s-1}\left[\frac{\varphi_{s,O}^{\sigma_s-\kappa_s}\left[\kappa_s-\left(\sigma_s-1\right)\right]}{\varphi_{s,min}^{\sigma_s-1}-\varphi_{s,min}^{\kappa_s}\frac{1}{\varphi_{s,O}^{\kappa_s-\left(\sigma_s-1\right)}}}-\frac{\kappa_s}{\varphi_{s,O}^{\kappa_s}-\varphi_{s,min}^{\kappa_s}}\right]$$

harms firms that have already offshored. These firms cannot decrease costs further, and their profits are adversely affected by increases in competition.[74]

Lastly, *productivity gains from offshoring* increase the elasticity of domestic profits with respect to a productivity shock in the East. Intuitively, firms that offshore benefit from positive productivity shocks in the offshoring country. As a result, this productivity effect shows up in the elasticity of profits. Interestingly, the productivity gain is multiplied by the term $(\sigma_s - 1)$, which implies that being able to offshore is more valuable when the elasticity of substitution is high. Hence, a testable implication of the model is that excess return spreads between high and low offshorability industries are larger in industries with high elasticity of substitution with respect to imported goods.

[Insert Table 16 here.]

To test this implication in the data, I use U.S. trade elasticities estimated by Broda and Weinstein (2006) from 1990 to 2001. Table 16 reports average returns for double sorts on offshorability and US trade elasticities. The results are consistent with the model. The L-H spread is increasing in trade elasticities. In fact, for low elasticity industries, the spread is no longer statistically significant.

Finally, the model implies that the covariance of industry excess returns with consumption is decreasing in offshorability. In other words, low (high) offshorability industry excess returns have a high (low) covariance with domestic consumption. To test this model implication in the data, I calculate consumption betas for offshorability portfolios both in the model and in the data. It is well known that differences in the covariance of returns and contemporaneous consumption growth do not explain the expected returns observed in the U.S. stock market.[75] However, Parker and Julliard (2005) show that considering the ultimate risk to consumption, defined as the covariance of quarterly portfolio returns and consumption growth over the quarter of the return and many following quarters, can largely explain the cross-sectional pattern of expected portfolio returns. Ultimate consumption risk is likely to be a better measure of the true risk of an asset if consumption is slow to adjust to returns. Alternatively, Brainard, Nelson, and Shapiro (1991) and Bandi and Tamoni (2017) show that measuring both portfolio returns and consumption growth at a lower than quarterly frequency improves the performance of the consumption CAPM (CCAPM). Given that my model does not feature a slow adjustment of consumption to returns, I follow the latter approach and calculate portfolio returns and consumption growth over four and eight quarters both in the model and in the data.[76]

[74] Note that σ_s is multiplied by the share of profits that come from companies that offshore.
[75] See, among others, Mankiw and Shapiro (1986), Breeden, Gibbons, and Litzenberger (1989), Campbell (1996), Cochrane (1996), and Lettau and Ludvigson (2001)
[76] See Lynch (1996), Marshall and Parekh (1999) and Gabaix and Laibson (2002) for models that implement slow or delayed adjustment of consumption.

[Insert Table 17 here.]

Panel A of table 17 reports the regression results for the simulated data. As discussed above, the consumption beta is higher for low compared to high offshorability industries. As a result, L-H has a positive and significant consumption exposure in the model. The R^2 is close to one, since the CCAPM holds within the model. Panel B reports corresponding regressions for my sample of manufacturing industries. Consistent with the model, the consumption beta is positive and significant for the L-H portfolio for four-, six- and eight-quarter returns. This is true both for equal- and value-weighted returns.

4.10 Comparative Statics and Model Counterfactuals

This section explores the role of model parameters using comparative statics analyses and discusses model counterfactuals. First, I explore comparative statics with respect to differences in headquarter intensity across industries. Figure 7 shows that the model L-H premium is increasing in the difference in headquarter intensity of low and high offshorability industries, $\alpha_L - \alpha_H$. An increase in the difference in headquarter intensity across industries maps into an increase in the difference in offshoring potential across industries (i.e., $\alpha_L - \alpha_H = (1 - \alpha_H) - (1 - \alpha_L)$). Hence, a larger difference in offshoring potential implies a larger difference in industry risk premia.

[Insert Figures 7 and 8 here.]

Second, the left panel of figure 8 plots annualized industry returns for different values of risk aversion, γ. The L-H spread is increasing in risk aversion. To generate returns in line with market returns over the sample period, a relatively high risk aversion coefficient of roughly 80 is needed.[77] The right panel of figure 8 plots the returns of the two industries for different levels of import penetration.[78] In line with the findings of Barrot, Loualiche, and Sauvagnat (2017), returns in both industries are increasing in import penetration. Importantly, the model-implied L-H spread is increasing in import penetration. This is consistent with the excess return double sorts from tables 10 and 11. Moreover, the figure shows that import penetration is a quantitatively important driver of the L-H spread: an increase in import penetration from 6.26% (benchmark calibration) to 11.12% leads to an increase in the levered L-H spread from 3.82% to 5.73%. This is intuitive, given that offshoring protects industries against foreign import competition. Consequently, a reason for the relatively low model L-H spread compared to the data is that the calibration only accounts for import penetration from China. In fact, over the sample period, the

[77] For comparison, the annualized return (excess return) of the S&P 500 over the sample period is equal to 8.25% (5.72%).

[78] Average import penetration is defined as $IP = \left[\sum_s \eta_s IP_s^{1-\theta}\right]^{\frac{1}{1-\theta}}$, where IP_s is the import penetration of a single industry.

average import penetration from all countries is equal to 24.95%. Therefore, allowing for a higher level of import penetration could help in matching the L-H spread.

Having established that import competition drives returns, one might wonder whether the L-H spread is predominantly driven by the difference in the level of import penetration across the two industries (see panel C of table 14). To explore this possibility, I simulate the model such that both industries have the same mean of import penetration. To do so, I slightly increase the mass of Eastern firms in the high offshorability industry. Panel C of table 15 reports the results. Industry excess returns slightly increase because overall import penetration has increased. Moreover, the levered L-H spread decreases slightly from 3.82% to 3.45%. Hence, the difference in equilibrium means of import penetration across industries matters, but it only accounts for 9.7% of the L-H spread in the benchmark calibration. Therefore, the model-implied L-H spread cannot be explained by differences in import penetration across industries.

Next, I explore the quantitative importance of the offshorability channel within the model. To do so, I simulate the baseline model and set the offshorability in both industries to zero, i.e., $(1 - \alpha_s) = 0$. Consequently, firms can no longer offshore. Moreover, by setting $(1 - \alpha_s) = 0$, the two industries become identical to each other, since differences in headquarter intensity are the only source of industry heterogeneity. Panel C of table 15 reports the moments for valuations and excess returns. In comparison with the baseline low (high) offshorability industry, the excess returns are 2.65 (5.27) percentage points higher. This remarkable increase in risk premium is due to a higher exposure of firm profits to aggregate shocks. To further assess the importance of the channel in absence of industry heterogeneity, I compare the no offshorability case with a counterfactual in which both industries have an offshorability of 20%, $(1 - \alpha_s) = 0.2$ (not shown): offshoring allows the industry risk premium to be lowered by 33% or 3.14 percentage points. Moreover, higher implied discount rates result in 17% lower equity valuations in the model without offshoring. To sum up, the offshoring channel is economically important in the model. Being able to offshore significantly lowers the risk of an industry, which manifests in lower excess returns and higher equity valuations.

Furthermore, I use the model to explore the response to a sudden increase in trade costs when shipping goods from East to West. This could be interpreted as the introduction of a new tax in the West on all imported goods. To do so, I simply replace the trade cost parameter, $\tau^\star$, with an autoregressive process of order one with the mean equal to 1.1 and a persistence of .95. This allows me to generate impulse response functions for model variables upon a shock in trade costs, as shown in figure 9. The figure shows responses after a one percent increase in $\tau^\star$. In the model, an increase in trade costs leads to lower import penetration from Eastern firms, which reduces the risk for Western industries. However, higher trade costs also render offshoring less attractive, since shipment of intermediate goods is more costly.

Consistent with this, figure 9 shows that both import penetration and the fraction of firms that offshore fall upon an increase in $\tau^{\star}$. Interestingly, the asset prices of Western firms also decrease in the model. Hence, the reduction in the benefits from offshoring outweigh the positive effects from lower import penetration. Consistent with this, asset prices drop more for the high compared to low offshorability industry.

[Insert Figures 9 and 10 here.]

Finally, I explore through the lens of the model what would happen if the comparative cost advantage of the East over the West were to fade away. This is an important counterfactual, given that hourly manufacturing wages in China have risen by an average of 12% per year since 2001.[79] In particular, I assume that the comparative cost advantage of the East decreases to half of its initial magnitude. Figure 10 reports impulse responses to a positive productivity shock in the East, $A^{\star}$, for the benchmark and the low comparative cost advantage economies. As the comparative advantage becomes smaller, the East loses its relative cost competitiveness over the West. This leads to lower import penetration and exposure of Western firms to aggregate productivity shocks in the East. As a result, industry profits and asset prices drop less compared to the benchmark economy, and the unconditional risk premium is lower. Importantly, the L-H spread is also smaller, with a low comparative advantage.[80] Intuitively, offshoring provides insurance against a risk that is less severe compared to the benchmark economy.

5 Conclusion

This paper studies how the possibility to relocate production affects industries' cost of capital. Using a new measure of offshorability at the industry level, I find that industries with low offshoring potential carry an annualized 7.31 percent risk premium over industries with high offshoring potential. This suggests that the option to offshore is an important driver of industry risk. The offshorability premium for services is only half that of manufacturing. For manufacturing industries, traditional factor models fail to explain the offshorability premium. For service industries, on the other hand, the premium is explained by the CAPM and a positive loading on the U.S. market.

An explanation based on the recent surge in international trade and specialization is consistent with various return patterns in the data. Intuitively, being able to reduce production costs through offshoring allows firms to compete against foreign competitors from low-wage countries. Consistent with this, double

[79] See the article "A tightening grip" in the Economist from March 12, 2015.

[80] The annualized market risk premium and the L-H spread in the low comparative advantage economy are equal to 4.54% and 2.52%, respectively.

sorts of monthly excess returns on industry import penetration from low-wage countries and offshorability show that the offshorability premium is increasing in import penetration from low-wage countries.

A two-country general equilibrium trade model that embeds the option to offshore is able to rationalize a number of stylized facts: (1) there is a positive excess return spread between low and high offshorability industries; (2) the offshorability spread is increasing in import penetration; (3) excess returns for multinational companies are higher than for domestic firms; and (4) industry excess returns are increasing in import penetration. Moreover, within the model, counterfactuals indicate that the offshorability channel is economically important, as it allows industries to lower risk premia by 33% and increase equity valuations by 17%.

Importantly, three main model predictions are strongly supported by the data. First, the model predicts a negative relationship between offshorability and profit volatility. In the data, a one standard deviation increase in industry offshorability is associated with an up to 19.7% lower profit volatility for the median firm. Second, the model predicts that the offshorability premium is the largest in industries that have high elasticities of substitution with respect to imported goods. Double sorts of monthly industry excess returns on U.S. trade elasticities and offshorability confirm this prediction. Finally, within the model, low (high) offshorability industries have high (low) covariance with consumption. Consistent with this, I find that the strategy which is long low and short high offshorability industries has a positive and significant consumption beta in the data.

Finally, the model implies that a sudden tax increase on all imported goods results in a decrease in consumption and asset prices. Put differently, losing access to international specialization and offshoring benefits outweighs the benefits from lower import competition.

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Appendix

A Model

A.1 Demand Side

1st Layer - Sector Demand

In the first layer, households decide how to optimally allocate consumption between homogenous and differentiated goods:

$$\max c_0^{1-a_0} C_T^{a_0}, \text{ s.t. } P_T C_T + p_0 c_0 \leq Y,$$

where C_T is the consumption index aggregated from consumption in the S industries consisting of differentiated goods, P_T is the corresponding price index, c_0 and p_0 are the consumption and price of the homogenous good, and Y is the total income of consumers. First-order conditions imply the following demand functions and the aggregate price index, P:

$$\begin{aligned}
c_0 &= (1-a_0)\frac{PC}{p_0} \\
C_T &= a_0 \frac{PC}{P_T} \\
P &= \left(\frac{P_T}{a_0}\right)^{a_0} \left(\frac{p_0}{1-a_0}\right)^{1-a_0}
\end{aligned}$$

The good 0 is produced under constant returns to scale and a production function that is linear in labor.[81] Moreover, the good is freely traded and used as a numeraire in each country. Its price is set to 1.[82] Consequently, productivity changes across countries can be interpreted as real productivity changes.

2nd Layer - Industry Demand

The aggregation over industry consumption is constant elasticity of substitution with elasticity θ. The optimization problem is as follows:

$$\max \left[\sum_s \delta_s^{\frac{1}{\theta}} C_s^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}, \text{ s.t. } \sum_s P_s C_s \leq P_T C_T,$$

where P_s are industry price levels and η_s are industry taste parameters such that $\sum_s \eta_s = 1$. First-order conditions imply demand functions and price indices:

$$\begin{aligned}
C_s &= \delta_s \left(\frac{P_s}{P_T}\right)^{-\theta} C_T \\
P_T &= \left[\sum_s \delta_s P_s^{1-\theta}\right]^{\frac{1}{1-\theta}}
\end{aligned}$$

3rd Layer - Product Demand

Demand for the product variety, ω, produced by firms:

$$c_s(\varphi) = \left(\frac{p_s(\varphi)}{P_s}\right)^{-\sigma_s} C_s$$

[81] In other words, one unit of labor produces one unit of good 0.
[82] This normalization also leads to wages being equal to 1 in both countries.

Price index in industry s:

$$P_s = \left[\int_{\Omega_s} p_s(\varphi)^{1-\sigma_s} d\varphi \right]^{\frac{1}{1-\sigma_s}}$$

A.2 Aggregation - Western Firms

Domestic Production

The fraction of firms that choose not to offshore is:

$$\zeta_{s,D} = Prob\{\varphi < \varphi_{s,O}\} = G(\varphi_{s,O}) = 1 - \left(\frac{\varphi_{s,O}}{\varphi_{min}} \right)^{-\kappa_s}$$

The average productivity of firms with productivity higher than the minimum productivity $\varphi_{s,min}$ but lower than the cutoff value $\varphi_{s,O}$ is equal to:

$$\bar{\varphi}_{s,D} = \left[\frac{\int_{\varphi_{s,min}}^{\varphi_{s,O}} \varphi^{\sigma_s - 1} dG_s(\varphi)}{G(\varphi_{s,O})} \right]^{\frac{1}{\sigma_s - 1}} = \nu_s \left[\frac{\varphi_{min}^{\sigma_s - 1} - \varphi_{min}^{\kappa_s} \varphi_{s,O}^{(\sigma_s - 1) - k_s}}{1 - \left(\frac{\varphi_{s,min}}{\varphi_{s,O}} \right)^{k_s}} \right]^{\frac{1}{\sigma_s - 1}}$$

where $\nu_s = \left[\frac{\kappa_s}{k_s - (\sigma_s - 1)} \right]^{\frac{1}{\sigma_s - 1}}$.

Partially Offshored Firms

The fraction of firms that choose to offshore is:

$$\zeta_{s,O} = Prob\{\varphi > \varphi_{s,O}\} = 1 - G(\varphi_{s,O}) = \left(\frac{\varphi_{s,O}}{\varphi_{s,min}} \right)^{-\kappa_s}$$

The average productivity of firms with productivity higher than cutoff value $\varphi_{s,O}$ is equal to:

$$\bar{\varphi}_{s,O} = \left[\frac{\int_{\varphi_{s,O}}^{\infty} \varphi^{\sigma_s - 1} dG_s(\varphi)}{1 - G(\varphi_{s,O})} \right]^{\frac{1}{\sigma_s - 1}} = \nu_s \varphi_{s,O}$$

Export: Partially Offshored Firms

This is the relevant case for firms with headquarter in the West. The average productivity of firms with productivity higher than the cutoff $\varphi_{s,X,O}$ is equal to:

$$\bar{\varphi}_{s,X,O} = \left[\frac{\int_{\varphi_{s,X,O}}^{\infty} \varphi^{\sigma_s - 1} dG_s(\varphi)}{1 - G(\varphi_{s,X,O})} \right]^{\frac{1}{\sigma_s - 1}} = \nu_s \varphi_{s,X,O}$$

The fraction of firms that choose to offshore is:

$$\zeta_{s,X,O} = Prob\{\varphi > \varphi_{s,X,O}\} = 1 - G(\varphi_{s,X,O}) = \left(\frac{\varphi_{s,X,O}}{\varphi_{s,min}} \right)^{-\kappa_s}$$

A.3 Aggregation - Eastern Firms

Domestic Production

All firms engage in domestic production. Hence, the fraction is equal to 1. The average productivity of firms with productivity higher than the minimum productivity $\varphi_{s,min}$ but lower than the cutoff value

$\varphi_{s,O}$ is equal to:

$$\tilde{\varphi}^{\star}_{s,D} = \left[\int_{\varphi^{\star}_{s,min}}^{\infty} \varphi^{\sigma_s - 1} dG_s(\varphi) \right]^{\frac{1}{\sigma_s - 1}} = \nu_s \varphi^{\star}_{s,min}$$

Export: Purely Domestic Firms

The fraction of firms that choose to export is:

$$\zeta^{\star}_{s,X,D} = Prob\{\varphi > \varphi^{\star}_{s,X,D}\} = 1 - G(\varphi^{\star}_{s,X,D}) = \left(\frac{\varphi^{\star}_{s,X,D}}{\varphi^{\star}_{s,min}} \right)^{-\kappa_s}$$

The average productivity of firms with productivity higher than the cutoff $\varphi^{\star}_{s,X,D}$ is equal to:

$$\tilde{\varphi}^{\star}_{s,X,D} = \left[\frac{\int_{\varphi^{\star}_{s,X,D}}^{\infty} \varphi^{\sigma_s - 1} dG_s(\varphi)}{1 - G(\varphi^{\star}_{s,X,D})} \right]^{\frac{1}{\sigma_s - 1}} = \nu_s \varphi^{\star}_{s,X,D}$$

A.4 Model Extension: International Bond Trading

In this section, I allow for international sovereign bond trading as in Ghironi and Melitz (2005). Allowing for bond trading is an important model extension because it allows model households to smooth consumption intertemporally. In addition, introducing bonds allows one to study current accounts for the two countries in the model.

Households can trade bonds domestically and internationally. Western (Eastern) bonds are issued by Western (Eastern) households and denominated in Western (Eastern) currency. Hence, bonds issued by each country provide a risk-free real return in units of that country's consumption basket. International asset markets, however, are incomplete, as only risk-free bonds are traded across countries. This would imply indeterminacy of steady-state net foreign assets and non-stationarity. As a remedy, I assume that agents must pay a convex adjustment cost when adjusting their bond holdings, which can be interpreted as a fee paid to financial intermediaries. This is sufficient to uniquely pin down the steady state, and it leads to stationary dynamics of responses to shocks.

Additional Model Equations

Bond trading affects the households' budget constraints, which become

$$\begin{aligned} P_t Q_{D,t+1} + & P_t F_t Q_{X,t+1} + P_t \frac{\xi}{2} Q^2_{D,t+1} + P_t \frac{\xi}{2} F_t Q^2_{X,t+1} + P_t C_t \\ & \leq (1 + r_{f,t}) P_t Q_{D,t} + (1 + r^{\star}_{f,t}) F_t P_t Q_{X,t+1} + T^f_t + \Pi_t(\alpha) \\ P^{\star}_t Q^{\star}_{D,t+1} + & P^{\star}_t \frac{Q^{\star}_{X,t+1}}{F_t} + P^{\star}_t \frac{\xi}{2} \left(Q^{\star}_{D,t+1}\right)^2 + P^{\star}_t \frac{\xi}{2} \frac{\left(Q^{\star}_{X,t+1}\right)^2}{F_t} + P^{\star}_t C^{\star}_t \\ & \leq (1 + r^{\star}_{f,t}) P^{\star}_t Q^{\star}_{D,t} + (1 + r_{f,t}) P^{\star}_t \frac{Q^{\star}_{X,t+1}}{F_t} + T^{\star,f}_t + \Pi^{\star}_t(\alpha), \end{aligned}$$

where $F_t = \frac{P^{\star}_t}{P_t}$ denotes the real exchange rate, $Q_{D,t+1}$ ($Q_{X,t+1}$) denote Western households' bond holdings of the Western (Eastern) bond, $(\xi/2)\, Q^2_{D,t+1}$ is the cost of adjusting holdings of the Western bonds, $(\xi/2)\, F_t Q^2_{X,t+1}$ is the cost of adjusting holdings of the Eastern bonds and T^f_t is the fee rebate, taken as given by the household (note $T^f_t = (\xi/2) \left[F_t Q^2_{X,t+1} + F_t Q^2_{X,t+1} \right]$ in equilibrium). Symmetry implies analogous equations for Eastern quantities. For simplicity, I assume that the cost parameter ξ is identical for Western and Eastern bonds and set it to a value of 0.0025, as in Ghironi and Melitz (2005).

Western and Eastern households maximize their respective intertemporal utility functions subject to the respective constraints. Taking first-order conditions leads to two Euler equations for the risk-free rate in each country:

$$\begin{aligned}
1+\xi Q_{D,t+1} &= (1+r_{f,t+1})\,\mathbb{E}\left[M_{t,t+1}\right] \\
1+\xi Q_{X,t+1} &= \left(1+r^{\star}_{f,t+1}\right)\mathbb{E}\left[M_{t,t+1}\frac{F_{t+1}}{F_t}\right] \\
1+\xi Q^{\star}_{D,t+1} &= \left(1+r^{\star}_{f,t+1}\right)\mathbb{E}\left[M^{\star}_{t,t+1}\right] \\
1+\xi Q^{\star}_{X,t+1} &= (1+r_{f,t+1})\,\mathbb{E}\left[M^{\star}_{t,t+1}\frac{F_t}{F_{t+1}}\right]
\end{aligned}$$

The terms related to the stock of bonds on the left-hand side of the Euler equations are key for determinacy of the steady state and model stationarity. Basically, they ensure that zero holdings of bonds are the unique steady state in which the product of the SDF and the gross interest rate equals one in each country such that the economy returns to this initial position after temporary shocks.

Moreover, equilibrium requires that Western and Eastern bonds be in global zero net supply:

$$\begin{aligned}
Q_{D,t+1}+Q^{\star}_{X,t+1} &= 0 \\
Q^{\star}_{D,t+1}+Q_{X,t+1} &= 0
\end{aligned}$$

Lastly, current accounts can be introduced to the model. Current accounts are, by definition, equal to the changes in aggregate bond holdings in the two countries:

$$\begin{aligned}
CA_t &= Q_{D,t+1}-Q_{D,t}+F_t\left(Q_{X,t+1}-Q_{X,t}\right) \\
CA^{\star}_t &= Q^{\star}_{D,t+1}-Q^{\star}_{D,t}+\frac{Q^{\star}_{X,t+1}-Q^{\star}_{X,t}}{F_t}
\end{aligned}$$

The global zero net supply conditions for the bond market imply that a country's borrowing must equal the other country's lending, $CA_t + F_t CA^{\star}_t = 0$.

Table A1 reports the results for model simulations with international bond trading. Not surprisingly, the standard deviation of consumption decreases compared to the baseline model, as bonds allow households to smooth their consumption intertemporally. This also leads to a lower overall risk premium, which can be seen from the lower mean of industry excess returns. Importantly, however, the L-H spread is unaffected by the introduction of international bond trading. Effectively, trading risk-free bonds allows households to transfer consumption across time in a state- and industry-independent manner, which does not help mitigate industry-specific exposure to aggregate shocks.

Similar to table 15, Panels C and D of table A1 report the moments related to the two shocks in the model. Also, after introducing bond trading to the model, shocks to $A^{\star}$ make up for roughly 88% of the L-H spread.

Finally, the model with sovereign bonds allows one to examine how productivity shocks affect the balance of current accounts in each country. Figure A1 reports impulse response functions of CA_t and $CA^{\star}_t$ to productivity shocks in the West (first row) and East (second row). As in Ghironi and Melitz (2005), positive productivity shocks in the East (West) are associated with increases (decreases) in consumption, which leads to a current account surplus (deficit) in the East and a current account deficit (surplus) in the West.

A.5 Elasticities

Elasticities related to total, sector and industry consumption:

$$\begin{aligned}
\eta^\star(C) &= -\eta^\star(P) + \frac{\Pi}{L+\Pi}\eta^\star(\Pi) \\
\eta^\star(C_T) &= \eta^\star(C) - (1-a_0)\,\eta^\star(P_T) = \eta^\star(C) - \left(\frac{1}{a_0} - 1\right)\eta^\star(P) \\
\eta^\star(C_s) &= -\theta\eta^\star(P_s) + \theta\eta^\star(P_T) + \eta^\star(C_T) = -\theta\eta^\star(P_s) + \eta^\star(C) + [\theta - (1-a_0)]\,\eta^\star(P_T)
\end{aligned}$$

Elasticities related to total and sector price indices:

$$\begin{aligned}
\eta^\star(P) &= a_0\eta^\star(P_T) \\
\eta^\star(P_T) &= \sum_S \delta_s \left(\frac{P_T}{P_s}\right)^{\theta-1} \eta^\star(P_s)
\end{aligned}$$

Elasticities related to offshoring and exporting cutoffs and fractions:

$$\begin{aligned}
\eta^\star(\zeta_{s,O}) &= -\kappa_s\eta^\star(\varphi_{s,O}) \\
\eta^\star(\bar{\varphi}_{s,O}) &= \eta^\star(\varphi_{s,O}) \\
\eta^\star(\zeta_{s,X,O}) &= -\kappa_s\eta^\star(\varphi_{s,X,O}) \\
\eta^\star(\bar{\varphi}_{s,X,O}) &= \eta^\star(\varphi_{s,X,O})
\end{aligned}$$

The elasticity of total industry profits is driven by the elasticities of domestic profits and profits from exports:

$$\eta^\star(\Pi) = \eta^\star\left(\Pi^D\right) + \eta^\star\left(\Pi^X\right)$$

Elasticity of total domestic profits:

$$\begin{aligned}
\eta^\star\left(\Pi^D\right) = & \underbrace{-(\sigma_s - \theta)(-\eta^\star(P_s))}_{\text{competition effect}} + \underbrace{\eta^\star(C_s) + \frac{1-a_0-\theta}{a_0}(-\eta^\star(P)) +}_{\text{expenditure effect}} \\
& \left[\underbrace{\kappa_s \frac{\zeta_{s,O}(\pi_{s,O} - \pi_{s,D})}{\Pi^D}}_{\text{relative benefits from offshoring}} - \underbrace{(\sigma_s - 1)\frac{\zeta_{s,D}\pi_{s,D}\Phi + \zeta_{s,O}\pi_{s,O}}{\Pi^D}}_{\text{industry composition effect}}\right](-\eta^\star(\varphi_{s,O})) + \\
& \underbrace{\frac{\zeta_{s,O}\pi_{s,O}}{\Pi^D}(\sigma_s - 1)(1-\alpha_s)}_{\text{productivity gain from offshoring}}
\end{aligned}$$

where

$$\Phi = \frac{\varphi_{s,min}^{\kappa_s}}{\sigma_s - 1}\left[\frac{\varphi_{s,O}^{\sigma_s-\kappa_s}\left[\kappa_s - (\sigma_s - 1)\right]}{\varphi_{s,min}^{\sigma_s-1} - \varphi_{s,min}^{\kappa_s}\frac{1}{\varphi_{s,O}^{\kappa_s-(\sigma_s-1)}}} - \frac{\kappa_s}{\varphi_{s,O}^{\kappa_s} - \varphi_{s,min}^{\kappa_s}}\right]$$

and $\Phi > 0$ and $\frac{\partial\Phi}{\partial\varphi_{s,O}} > 0$. This means that the negative response of domestic profits after a shock to $A^\star$ is more pronounced when fewer firms offshore. This result is intuitive, since firms that offshore directly profit from the increase in productivity, which makes them more resistant against increases in competition.

Elasticity of total profits from exports:

$$\eta^{\star}\left(\Pi^{X}\right) = \underbrace{-\sigma_s\left[1+\frac{\kappa_s-(\sigma_s-1)}{\sigma_s-1}\right]\left[-\eta^{\star}\left(P_s^{\star}\right)\right]}_{\text{price effect}} + \underbrace{\left[1+\frac{\kappa_s-(\sigma_s-1)}{\sigma_s-1}\right]\eta^{\star}\left(C_s^{\star}\right)}_{\text{demand effect}} + \underbrace{(1-\alpha_s)\,\kappa_s}_{\text{productivity gain from offshoring}}$$

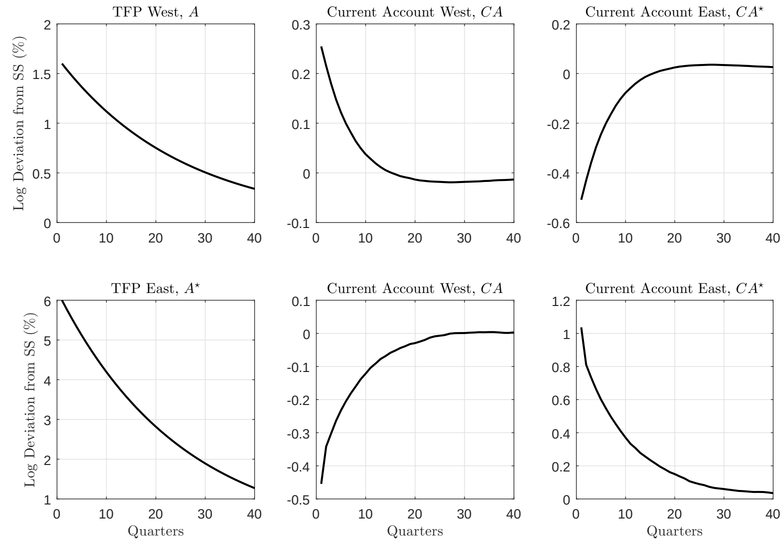

Figure A1: **Responses of Current Accounts**

This figure plots the impulse response functions of current accounts CA_t and $CA_t^{\star}$ to productivity shocks in the West (first row) and East (second row).

Table A1: **Model Simulation Results with International Bond Trading**

The table reports simulated moments of macro variables and industry quantities for the extended model with international bond trading. Column titles "Low" and "High" label low and high offshorability industries. The model is solved using perturbation methods and is approximated to the 3rd-order around the deterministic steady state. Moments are calculated based on simulations over 10'000 periods (with a burn-in period of 1'000 periods).

	Macro Moments				Industry Quantities			
	Consumption		Risk-free Rate		Industry Profits		Excess Returns	
	model	data	model	data	model	data	model	data
mean			4.59%	2.63%	0.28	0.32	4.59%	1.64%
std	8.43%	2.00%	0.29%	2.12%	8.10%	3.72%	14.98%	7.24%
cov(,A)					0.24	0.12	0.07	0.02
cov(,$A^{\star}$)					-1.74	-0.80	-0.88	-0.30
cov(,C)					0.64	0.28	0.06	0.02

Figures

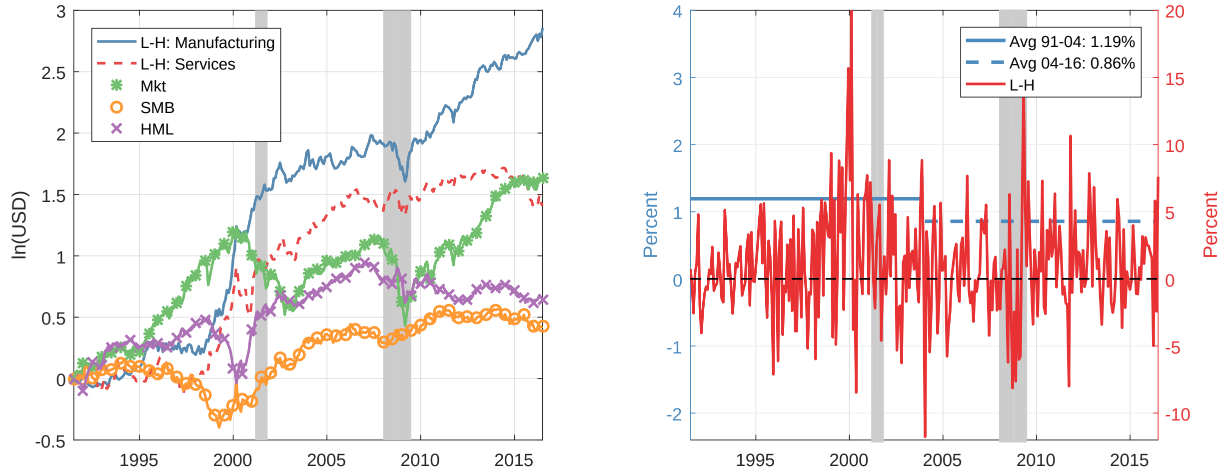

Figure 1: **Investment Strategy and Excess Returns**

The left figure plots the evolution over time of a one USD investment for the L-H strategy in manufacturing and non-manufacturing industries, the excess return on the market (Mkt), small-minus-big (SMB) and high-minus-low (HML). The results are presented on a logarithmic scale. The right panel plots in red the monthly returns of the L-H portfolio in manufacturing. The blue horizontal lines refer to averages over subsamples. The sample period in both figures runs from July 1991 to June 2016.

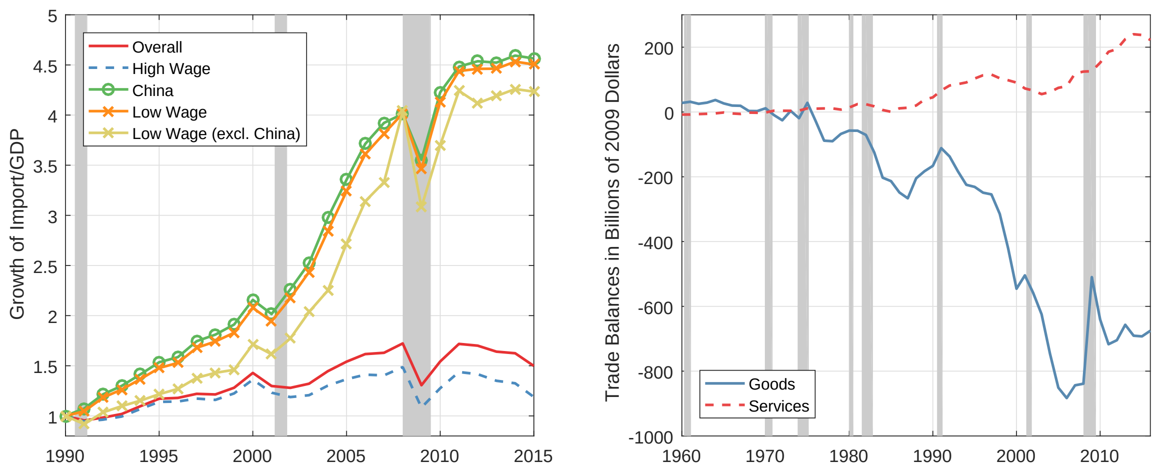

Figure 2: **U.S. Trade Balances and Growth of Imports/GDP**

The left panel plots the U.S. trade balances (i.e., exports minus imports) in goods and services expressed in 2009 Dollars. Data are obtained from the Bureau of Economic Analysis. The sample period runs from 1960 to 2016. The right panel plots the growth of the ratio of imports to the United States from the world, high-wage countries, China, low-wage countries and low-wage countries excluding China to U.S. Gross Domestic Product (GDP). Details about the calculation of the value of imports from a given country or countries can be found in the online appendix. Low-wage countries are defined as in Bernard, Jensen, and Schott (2006a). The sample consists of all imports of manufacturing firms between 1990 and 2015. Trade data are from Schott (2008).

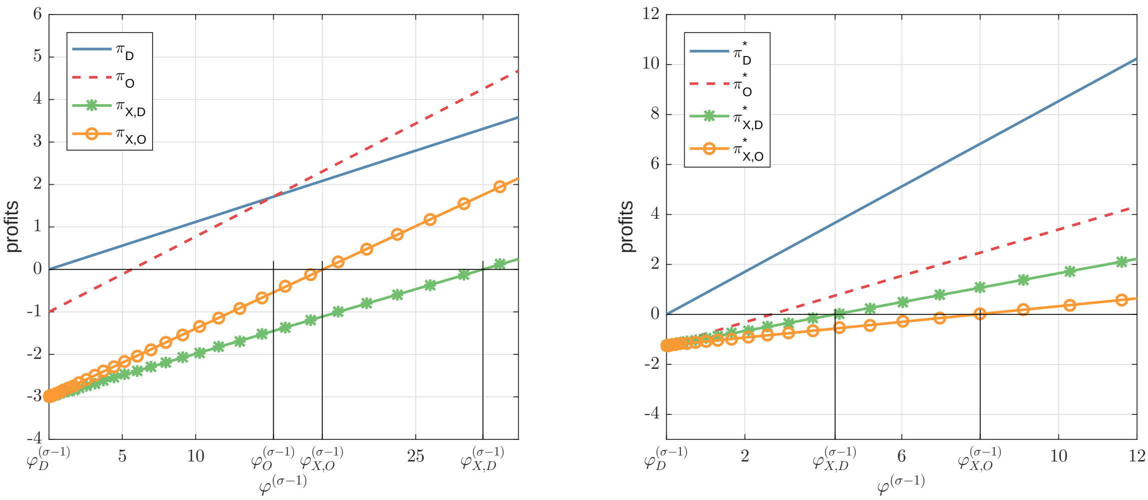

Figure 3: **Profits for Different Organizational Choices**

This figure plots the profits for different organizational choices against a transformation of idiosyncratic firm productivity, $\varphi^{\sigma-1}$. This is convenient, given that firm profits are linear in $\varphi^{\sigma-1}$. The left panel plots profits for Western firms and the right panel profits for Eastern firms, assuming that the East has a comparative cost advantage in producing offshorable tasks.

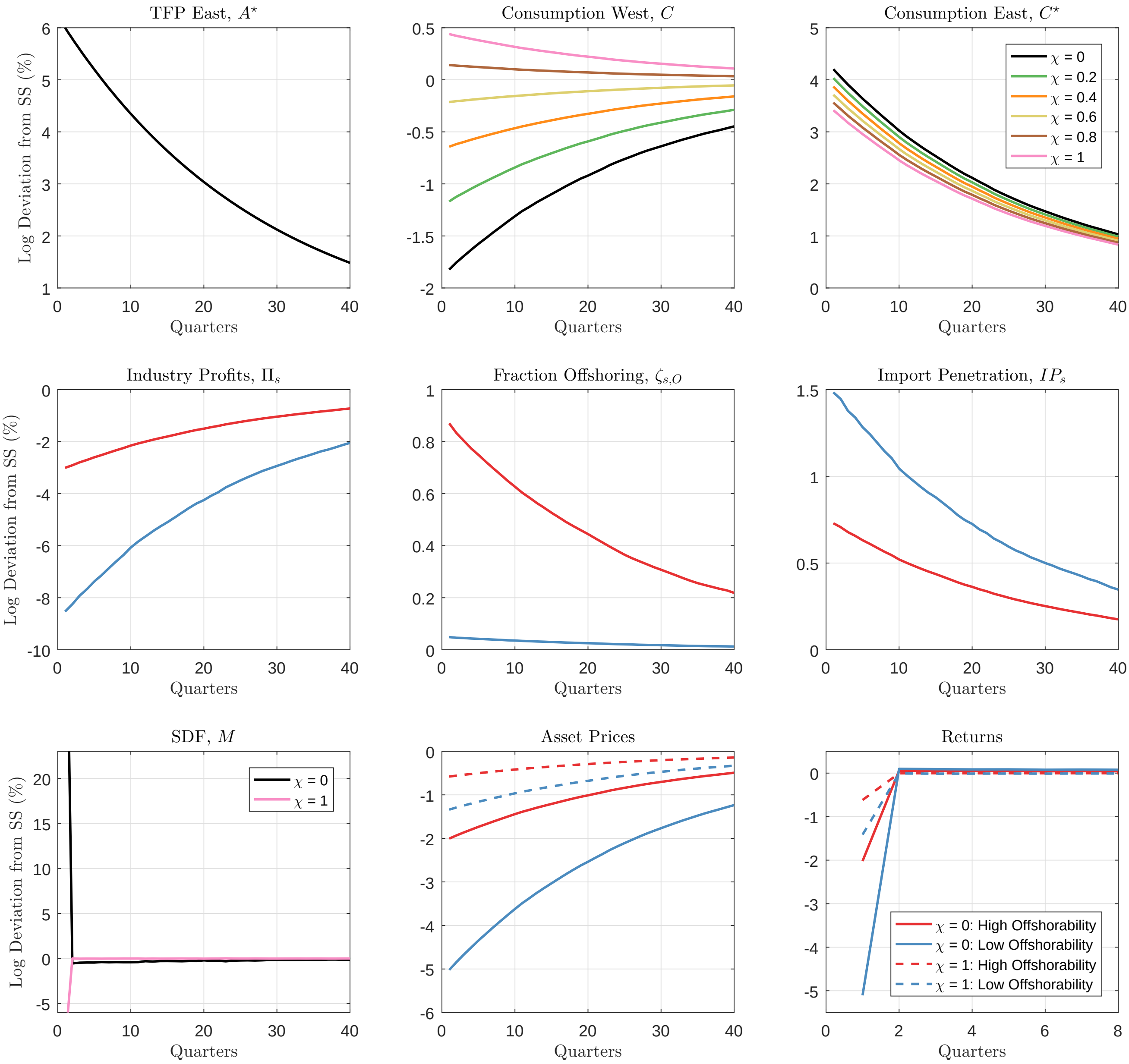

Figure 4: **Mechanism: Positive Shock to $A^\star$**

This figure plots various impulse response functions to a one standard deviation shock to aggregate productivity in the East, $A^\star$. The first row shows how the response of aggregate consumption in both countries changes with risk sharing (exogenously determined by χ). The second row contains the responses of industry profits (Π_s), the fraction of firms that offshore ($\zeta_{s,O}$) and import penetration in the West, IP_s with no risk sharing ($\chi = 0$). The three last plots show how the stochastic discount factor (SDF, M), asset prices and excess returns respond under no and full risk sharing.

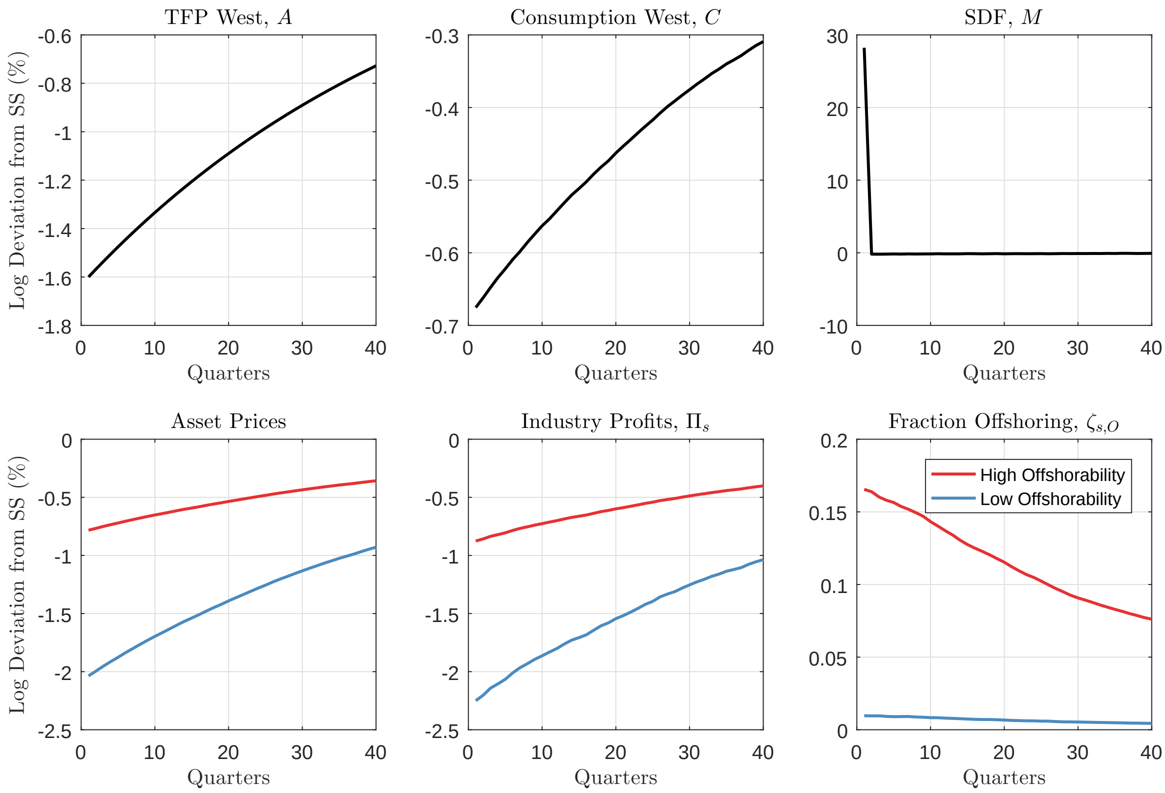

Figure 5: **Mechanism: Negative Shock to A**

This figure plots the impulse response functions of aggregate productivity in the West (A), consumption (C), the stochastic discount factor (SDF, M), asset prices, industry profits (Π_s) and fraction of firms that offshore ($\zeta_{s,O}$) to a negative one standard deviation shock to aggregate productivity in the West, A.

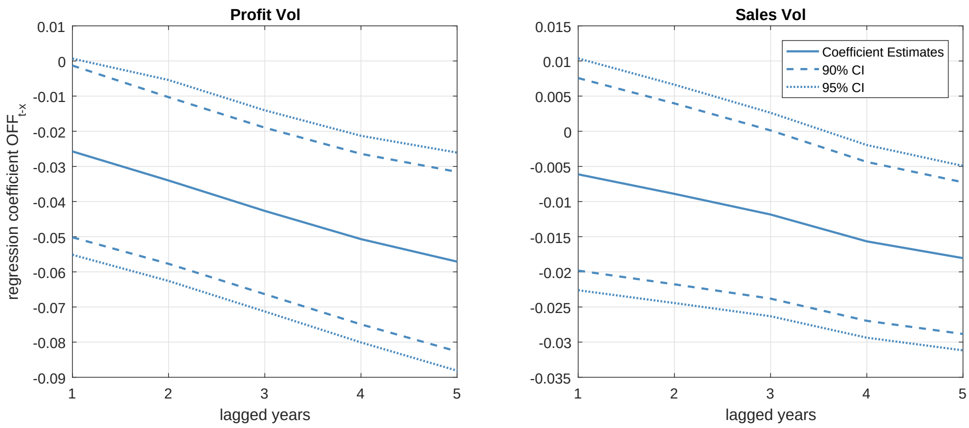

Figure 6: **Panel Regression Coefficients on OFF_{t-x}**

This figure plots the regression coefficients of OFF_{t-x} for different lags x. The regressions are identical to Panel C of table 15. Solid lines indicate the regression coefficient point estimates, dashed lines correspond to the 90% confidence bands and dotted lines correspond to the 95% confidence bands. The regressions control for firm characteristics (size, Tobin's Q, leverage, and investment) and include year fixed effects. The standard errors are clustered at the firm and year level.

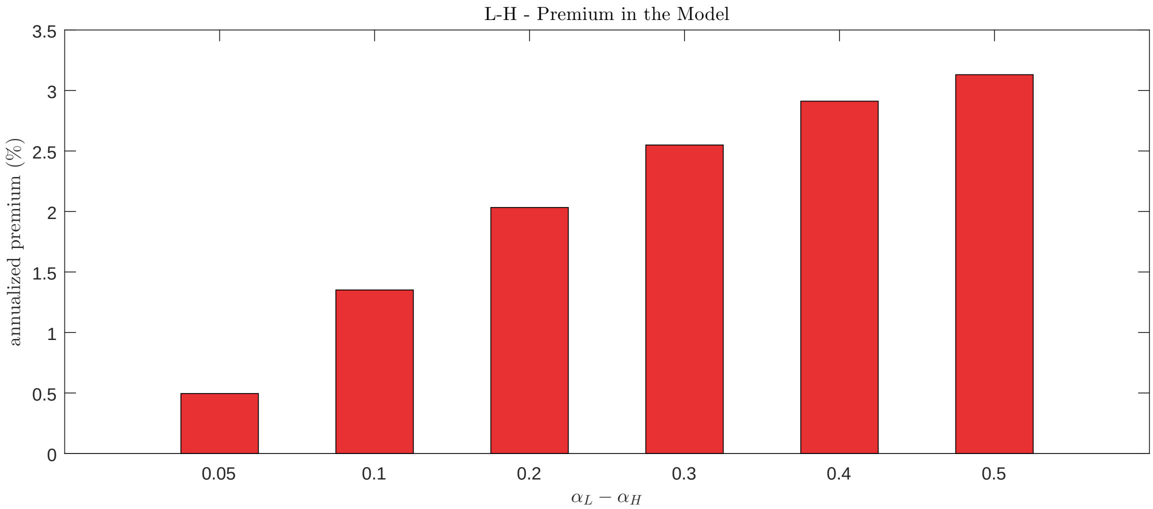

Figure 7: **L-H Premium in the Model**

This figure plots the model-implied L-H premium as a function of the difference in headquarter intensity across the two model industries. Differences in headquarter intensity across industries directly map into differences in offshoring potential across industries. In other words, $\alpha_L - \alpha_H = (1 - \alpha_H) - (1 - \alpha_L)$.

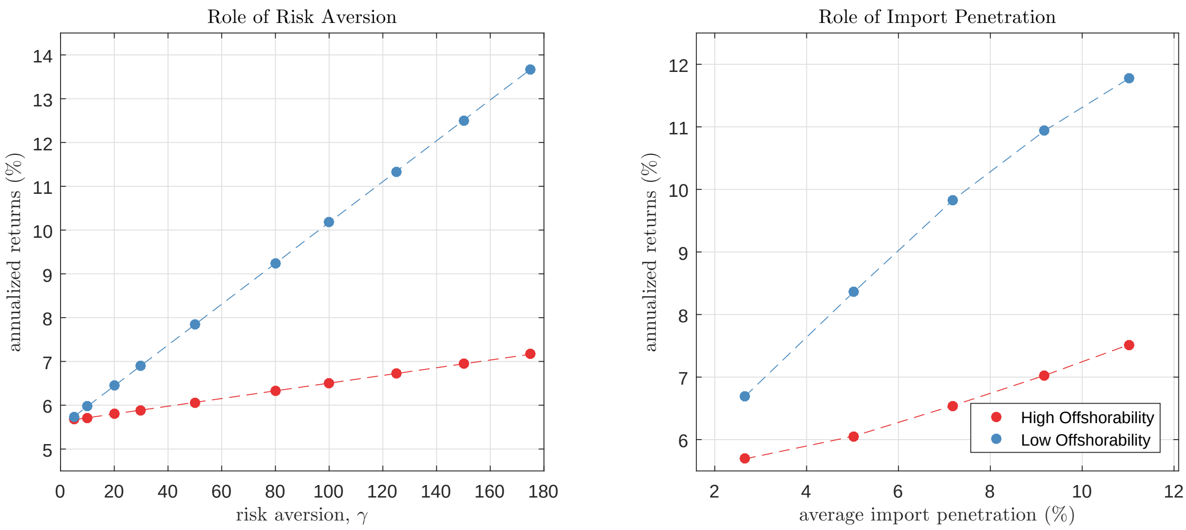

Figure 8: **Role of Risk Aversion and Import Penetration**

The figures plot averages of simulated model returns for the high and low offshorability industries. The left panel plots mean returns for different coefficients of risk aversion. The right panel plots returns for different levels of average import penetration. Average import penetration is calculated as $IP = \left[\sum_s \eta_s IP_s^{1-\theta}\right]^{\frac{1}{1-\theta}}$, where IP_s is the import penetration of a single industry.

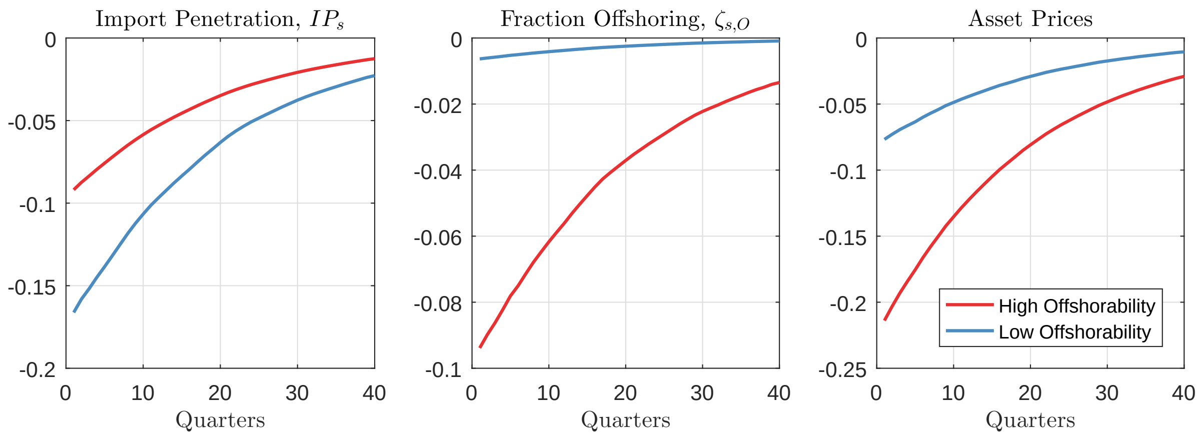

Figure 9: **Model Counterfactual: Shock to Variable Trade Costs $\tau^{\star}$**

This figure plots the impulse response functions import penetration (IP_s), fraction of firms that offshore ($\zeta_{s,O}$) and asset prices to a positive one percent shock to variable trade costs ($\tau^{\star}$).

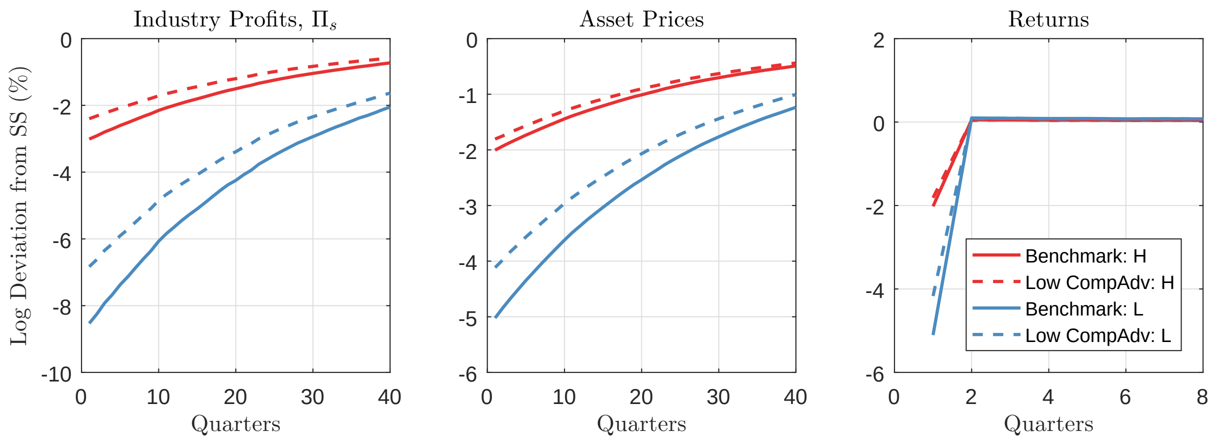

Figure 10: **Model Counterfactual: Benchmark vs Low Comparative Advantage**

This figure plots the impulse response functions of industry profits (Π_s), asset prices and industry excess returns to a positive one standard deviation shock to aggregate productivity in the East, $A^{\star}$. The solid lines are the impulse responses in the benchmark economy, while the dashed lines correspond to impulse responses in an economy in which the comparative cost advantage in offshorable labor of the East is lower compared to the benchmark calibration.

Tables

Table 1: **Occupation Tasks that define Offshorability**

Panel A tabulates the tasks used to calculate occupation offshorability by Acemoglu and Autor (2011). The acronyms *WA* and *WC* in the third column stand for work activity and work context. Panels B and C report the top and bottom ten occupations by offshorability, off_j.

Panel A: Acemoglu and Autor (2011)

4.C.1.a.2.l	Face-to-Face Discussions	WC
4.A.4.a.5	Assisting and Caring for Others	WA
4.A.4.a.8	Performing for or Working Directly with the Public	WA
4.A.1.b.2	Inspecting Equipment, Structures, or Material	WA
4.A.3.a.2	Handling and Moving Objects	WA
4.A.3.b.4	Repairing and Maintaining Mechanical Equipment (*0.5)	WA
4.A.3.b.5	Repairing and Maintaining Electronic Equipment (*0.5)	WA

Panel B: Top Ten Occupations by Offshorability

SOC	Occupation Title	off_j
31-9094	Medical Transcriptionists	0.50
41-9041	Telemarketers	0.48
43-4011	Brokerage Clerks	0.47
51-6021	Pressers, Textile, Garment, and Related Materials	0.46
15-2041	Statisticians	0.45
43-3031	Bookkeeping, Accounting, and Auditing Clerks	0.45
43-9022	Word Processors and Typists	0.45
51-6031	Sewing Machine Operators	0.44
15-2099	Legal Support Workers	0.44
15-1131	Computer Programmers	0.44

Panel C: Bottom Ten Occupations by Offshorability

SOC	Occupation Title	off_j
37-3013	Tree Trimmers and Pruners	0.26
47-4021	Elevator Installers and Repairers	0.26
29-1151	Nurse Anesthetists	0.26
29-1021	Dentists	0.26
47-5013	Service Unit Operators, Oil, Gas, and Mining	0.26
29-1024	Prosthodontists	0.25
29-2041	Emergency Medical Technicians and Paramedics	0.25
33-1021	Firefighters	0.25
49-9051	Electrical Power-Line Installers and Repairers	0.25
49-9095	Manufactured Building and Mobile Home Installers	0.24

Table 2: **Most Offshorable and Non-Offshorable Manufacturing Industries**

Panels A and B tabulate the top and bottom ten manufacturing industries in terms of their offshoring potential, $OFF_{i,t}$. Industries are defined at the three-digit SIC level until 2001 and at the four-digit NAICS level thereafter. Manufacturing encompasses industries with SIC codes between 2011 and 3999 and NAICS codes between 311111 and 339999. Panel C reports industry transition probabilities (in percent), e.g., the probabilities that an industry in the highest offshorability quintile in year t will be in the second highest offshorability quintile in years $t+1$ and $t+5$.

Panel A: 1992 - Top and Bottom Ten Manufacturing Industries by Offshorability

SIC	Industry Title	$OFF_{i,t}$	SIC	Industry Title	$OFF_{i,t}$
2310	Men's and Boys' Suits, Coats, and Overcoats	2.85	3730	Ship and Boat Building and Repairing	-1.43
2320	Men's and Boys' Furnishings, Work Clothing	2.58	2450	Wood Buildings and Mobile Homes	-1.51
2360	Girls', Children's, and Infants' Outerwear	2.56	2110	Cigarettes	-1.52
2330	Women's, Misses', and Juniors' Outerwear	2.35	2430	Millwork, Veneer, Plywood, and Structural Wood	-1.63
2340	Women's, Misses', and Children's Undergarments	2.17	3530	Construction, Mining, and Materials Handling	-1.88
2350	Hats, Caps, and Millinery	2.05	3860	Photographic Equipment and Supplies	-2.09
3150	Leather Gloves and Mittens	1.94	2530	Public Buildings and Related Furniture	-2.13
2370	Fur Goods	1.77	3820	Analytical, Optical, Measuring, and Controlling	-2.32
2380	Miscellaneous Apparel and Accessories	1.75	3760	Guided Missiles and Space Vehicles and Parts	-2.50
3010	Tires and Inner Tubes	1.39	3810	Navigation, Aeronautical, and Nautical Systems	-2.95

Panel B: 2015 - Top and Bottom Ten Manufacturing Industries by Offshorability

NAICS	Industry Title	$OFF_{i,t}$	NAICS	Industry Title	$OFF_{i,t}$
334100	Computer and Peripheral Equipment Manufacturing	2.59	311400	Fruits and Vegetables and Specialty Food	-0.84
334200	Communications Equipment Manufacturing	2.46	331300	Alumina and Aluminum Production	-0.85
334600	Manufacturing Magnetic and Optical Media	2.28	336600	Ship and Boat Building	-0.88
334400	Semiconductors and Other Electronic Components	2.16	321200	Veneer, Plywood, and Engineered Wood Products	-1.12
333300	Commercial and Service Industry Machinery	1.50	321100	Sawmills and Wood Preservation	-1.23
315200	Cut and Sew Apparel Manufacturing	1.47	336100	Motor Vehicle Manufacturing	-1.28
315900	Apparel Accessories and Other Apparel	1.32	327300	Cement and Concrete Product Manufacturing	-1.33
316900	Other Leather and Allied Products	1.24	331100	Iron and Steel Mills and Ferroalloy Manufacturing	-1.38
314900	Other Textile Product Mills	1.10	322100	Pulp, Paper, and Paperboard Mills	-1.38
316200	Footwear Manufacturing	1.01	327400	Lime and Gypsum Product Manufacturing	-1.43

Panel C: Manufacturing Transition Probabilities

	year t+1				
year t	Q1(t+1)	Q2(t+1)	Q3(t+1)	Q4(t+1)	Q5(t+1)
Q1(t)	86%	11%	2%	1%	0%
Q2(t)	13%	73%	12%	3%	1%
Q3(t)	2%	12%	72%	12%	1%
Q4(t)	1%	3%	13%	78%	6%
Q5(t)	1%	1%	1%	7%	90%

	year t+5				
year t+5	Q1(t+5)	Q2(t+5)	Q3(t+5)	Q4(t+5)	Q5(t+5)
Q1(t)	76%	17%	3%	3%	1%
Q2(t)	17%	61%	17%	5%	1%
Q3(t)	2%	19%	59%	18%	2%
Q4(t)	2%	5%	20%	65%	7%
Q5(t)	3%	1%	2%	9%	85%

Table 3: **Most Offshorable and Non-Offshorable Services Industries**

Panels A and B tabulate the top and bottom ten service industries in terms of their offshoring potential, $OFF_{i,t}$. Industries are defined at the three-digit SIC level until 2001 and at the four-digit NAICS level thereafter. Services encompasses industries with SIC codes below 2011 and above 3999 and NAICS codes below 311111 and above 339999, respectively. Panel C reports industry transition probabilities (in percent), e.g., the probability that an industry in the highest offshorability quintile in year t will be in the second highest offshorability quintile in year $t+1$ and $t+5$.

Panel A: 1992 - Top and Bottom Ten Services Industries by Offshorability

SIC	Industry Title	$OFF_{i,t}$	SIC	Industry Title	$OFF_{i,t}$
8110	Legal Services	3.47	4740	Rental of Railroad Cars	-2.29
6220	Commodity Contracts Brokers and Dealers	2.65	8650	Political Organizations	-2.43
8720	Accounting, Auditing, and Bookkeeping Services	2.38	1010	Iron Ores	-2.49
6210	Security Brokers, Dealers, and Flotation Companies	2.23	1230	Anthracite Mining	-2.52
5120	Drugs, Drug Proprietaries, and Druggists' Sundries	2.09	8730	Research, Development, and Testing Services	-2.53
6060	Credit Unions	1.60	4970	Irrigation Systems	-2.56
6140	Personal Credit Institutions	1.46	8230	Libraries	-2.78
6030	Savings Institutions	1.41	8620	Professional Membership Organizations	-2.78
7290	Miscellaneous Personal Services	1.40	8610	Business Associations	-3.30
7370	Computer Programming and Data Processing	1.37	8630	Labor Unions and Similar Labor Organizations	-3.32

Panel B: 2015 - Top and Bottom Ten Services Industries by Offshorability

NAICS	Industry Title	$OFF_{i,t}$	NAICS	Industry Title	$OFF_{i,t}$
511200	Software Publishers	3.18	622100	General Medical and Surgical Hospitals	-1.23
541200	Accounting, Bookkeeping, and Payroll Services	2.85	623100	Nursing Care Facilities (Skilled Nursing Facilities)	-1.25
519100	Other Information Services	2.85	483200	Inland Water Transportation	-1.25
541500	Computer Systems Design and Related Services	2.49	212100	Coal Mining	-1.29
523100	Commodity Contracts Intermediation and Brokerage	2.41	481200	Nonscheduled Air Transportation	-1.31
525900	Other Investment Pools and Funds	2.39	485100	Urban Transit Systems	-1.38
541100	Legal Services	2.12	485200	Interurban and Rural Bus Transportation	-1.43
523900	Other Financial Investment Activities	2.05	621900	Other Ambulatory Health Care Services	-1.43
518200	Data Processing, Hosting, and Related Services	2.04	487900	Scenic and Sightseeing Transportation, Other	-1.54
525100	Insurance and Employee Benefit Funds	1.93	621200	Offices of Dentists	-1.93

Panel C: Transition Probabilities Services

	year t+1				
year t	Q1(t+1)	Q2(t+1)	Q3(t+1)	Q4(t+1)	Q5(t+1)
Q1(t)	90%	6%	1%	1%	1%
Q2(t)	7%	83%	7%	1%	1%
Q3(t)	2%	8%	83%	6%	1%
Q4(t)	1%	1%	6%	86%	5%
Q5(t)	0%	1%	2%	6%	91%

	year t+5				
year t+5	Q1(t+5)	Q2(t+5)	Q3(t+5)	Q4(t+5)	Q5(t+5)
Q1(t)	79%	11%	3%	3%	3%
Q2(t)	14%	63%	15%	6%	2%
Q3(t)	3%	18%	61%	16%	2%
Q4(t)	4%	4%	18%	64%	10%
Q5(t)	1%	2%	4%	11%	82%

Table 4: **Correlations**

This table reports correlation coefficients of offshorability with various labor-related variables. Panel A reports the coefficients for correlations at the occupation level. *off* is occupation-level offshorability; $\mathbb{1}_{\{off_j > off_{p66}\}}$ is a variable that is equal to *off* if an occupation ranks in the top tercile in terms of offshorability and zero otherwise; *skill* is the job zone measure from O*NET; and *routine* equals the routine-task content score of an occupation calculated with O*NET task-level data, as in Acemoglu and Autor (2011). Panel B reports the percentage overlap in occupations within the top tercile for the different measures. For example, an overlap of 50% means that half of the top tercile tasks are identical for two variables. Finally, Panel C reports the time-series averages of annual Spearman rank sum correlations of different variables at the industry level, both for manufacturing and services. The sample period is 1990-2016. The aggregation to the industry level for *Skill* and *Routine* is discussed in detail in the appendix. *Mobility* is the industry-level labor mobility measure from Donangelo (2014), which is available between 1990 and 2011. *SC* is shipping costs paid by importers. Shipping costs are obtained at the product-level for all U.S. manufacturing imports and then aggregated at the 3-digit SIC and 4-digit NAICS industry levels, as in Barrot, Loualiche, and Sauvagnat (2017). U.S. trade data are only available for manufacturing industries. *Tradability* is final product tradability per industry from Jensen (2011), which is available at the 4-digit NAICS level. This restricts the sample period to 2002 to 2016. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%.

Panel A: Correlation at the Occupation Level

	off_j	$\mathbb{1}_{\{off_j > off_{p66}\}}$	Skill	Routine
off_j	1			
$\mathbb{1}_{\{off_j > off_{p66}\}}$	0.79***	1		
Skill	0.31***	0.33***	1	
Routine	0.04	-0.02	-0.67***	1

Panel B: Overlap in Top 33% Occupations per Measure

	# Occ	# Top 33%	# Overlap	%-Overlap
off vs skill	772	259	113	43.63%
off vs routine	772	257	86	33.46%

Panel C: Correlation at Industry Level

	Skill	Routine	Mobility	SC	Tradability
Manufacturing:					
Corr($OFF_{i,t}$,)	0.29**	0.10	-0.22*	-0.16*	0.13
Services:					
Corr($OFF_{i,t}$,)	0.44***	0.14	0.11	NaN	0.23***

Table 5: **All Industries: Univariate Sorts and Four- and Five-Factor Models**

Panel A reports mean excess monthly levered and unlevered returns and corresponding Sharpe Ratios. L-H stands for an investment strategy that is long the portfolio of firms with low offshorability (L) and short the portfolio of firms with high offshorability (H). Values in parentheses next to the L-H mean excess returns correspond to the p-values of the "monotonic relationship (MR)" test by Patton and Timmermann (2010). Panel B (C) reports Carhart (1997) four- (Fama and French (2015) five-) factor model regression results both for equal-weighted (columns 2-8) and value-weighted (columns 10-16) portfolio returns. Monthly α estimates are expressed in percent. $Offshorability$ is lagged by 18 months. Returns are at a monthly frequency. Standard errors reported in parentheses are adjusted for heteroscedasticity and autocorrelation (Newey-West). R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. The sample covers returns from July 1991 to June 2016.

	Equal-Weighted Returns						Value-Weighted Returns					
	L	2	3	4	H	L-H	L	2	3	4	H	L-H
Panel A: Portfolio Sorts												
Levered Ret.	1.061***	0.893***	0.712***	0.398	0.452	0.609** (0.07)	1.059***	0.814***	0.586***	0.434	0.255	0.804* (0.00)
Sharpe Ratio	0.69	0.60	0.51	0.27	0.35	0.48	0.73	0.64	0.49	0.30	0.18	0.47
Unlevered Ret.	0.824***	0.655***	0.573***	0.297	0.318	0.506* (0.04)	0.895***	0.628***	0.463**	0.341	0.165	0.730** (0.01)
Sharpe Ratio	0.69	0.57	0.52	0.24	0.29	0.46	0.71	0.60	0.47	0.26	0.13	0.43
Panel B: Carhart (1997) Four-Factor												
Alpha (%)	0.261**	0.093	0.068	-0.263**	-0.057	0.318	0.372***	0.212	0.102	0.054	-0.062	0.434*
	(0.12)	(0.11)	(0.12)	(0.12)	(0.15)	(0.21)	(0.15)	(0.13)	(0.13)	(0.16)	(0.16)	(0.26)
MKT Beta	1.010***	1.015***	0.951***	0.989***	0.846***	0.163**	0.929***	0.938***	0.874***	0.852***	0.901***	0.028
	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)	(0.08)	(0.08)	(0.06)	(0.04)	(0.06)	(0.06)	(0.13)
SMB Beta	0.624***	0.470***	0.272***	0.406***	0.227***	0.397***	0.283***	-0.072	-0.200***	0.091*	-0.071	0.354***
	(0.04)	(0.08)	(0.07)	(0.09)	(0.10)	(0.10)	(0.06)	(0.04)	(0.06)	(0.05)	(0.08)	(0.12)
HML Beta	0.239***	0.365***	0.227***	0.185***	-0.032	0.271***	-0.038	0.113*	0.081	-0.166*	-0.328***	0.291*
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.10)	(0.09)	(0.07)	(0.05)	(0.09)	(0.08)	(0.16)
UMD Beta	-0.048	-0.064	-0.123***	-0.173***	-0.133***	0.085	0.117***	0.000	-0.082*	-0.226***	-0.265***	0.382***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.10)
R^2 (%)	89.22	87.44	85.70	86.71	75.48	22.09	70.23	76.54	77.98	73.89	77.25	19.41
Panel C: Fama and French (2015) Five-Factor												
Alpha (%)	0.081	-0.193**	-0.206	-0.466***	-0.269*	0.350*	0.370**	0.046	-0.061	-0.031	-0.171	0.541*
	(0.12)	(0.09)	(0.13)	(0.14)	(0.15)	(0.21)	(0.17)	(0.13)	(0.12)	(0.17)	(0.18)	(0.31)
MKT Beta	1.108***	1.172***	1.098***	1.094***	0.958***	0.150**	0.937***	1.031***	0.960***	0.885***	0.947***	-0.010
	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.05)	(0.07)	(0.08)	(0.12)
SMB Beta	0.706***	0.613***	0.345***	0.450***	0.285***	0.421***	0.370***	0.036	-0.204***	-0.062	-0.152*	0.522***
	(0.04)	(0.05)	(0.06)	(0.07)	(0.08)	(0.10)	(0.07)	(0.04)	(0.06)	(0.08)	(0.09)	(0.15)
HML Beta	0.163***	0.237***	0.142**	0.250***	-0.031	0.195*	-0.150*	-0.001	-0.004	-0.054	-0.107	-0.043
	(0.06)	(0.05)	(0.06)	(0.08)	(0.07)	0.100	(0.08)	(0.06)	(0.08)	(0.08)	(0.10)	0.148
RMW Beta	0.272***	0.464***	0.293***	0.177*	0.221*	0.051	0.212	0.329***	0.074	-0.326***	-0.167	0.379
	(0.06)	(0.06)	(0.07)	(0.10)	(0.11)	0.151	(0.13)	(0.08)	(0.08)	(0.13)	(0.14)	0.231
CMA Beta	0.035	0.042	0.104	-0.129	-0.041	0.076	0.026	0.047	0.216	0.139	-0.190	0.216
	(0.07)	(0.06)	(0.10)	(0.13)	(0.12)	(0.16)	(0.15)	(0.11)	(0.11)	(0.17)	(0.18)	(0.30)
R^2 (%)	90.13	90.54	85.83	84.95	74.56	20.64	69.69	78.84	77.70	71.56	71.80	8.07

Table 6: **Manufacturing vs Services Industries**

Panel A (B) reports mean excess monthly levered and unlevered returns as well as CAPM regression results for the sample of manufacturing (services) industries. L-H stands for an investment strategy that is long the portfolio of firms with low offshorability (L) and short the portfolio of firms with high offshorability (H). Values in parentheses next to the L-H mean that excess returns correspond to the p-values of the "monotonic relationship (MR)" test by Patton and Timmermann (2010). Monthly α estimates are expressed in percent. $Offshorability$ is lagged by 18 months. Returns are at a monthly frequency. Standard errors reported in parentheses are adjusted for heteroscedasticity and autocorrelation (Newey-West). R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. Panel C reports portfolio characteristics for manufacturing and services industries separately. *Size* is the time-series average of annual portfolio means of the market capitalization (logarithm); *# Employees* is the number of employees as reported in Compustat; *Book to Market* is defined as the book value (item CEQ) of equity divided by the market value of equity (item CSHO $\times$ item PRCC_F); *Leverage* is total debt (item DLC + item DLTT) divided by the sum of total debt and market value of equity; *Labor Intensity* is a firm's labor intensity defined as the logarithm of the ratio of the number of employees divided by gross property, plant and investment (PPEGT). The sample covers returns from July 1991 to June 2016.

	Equal-Weighted Returns						Value-Weighted Returns					
	L	2	3	4	H	L-H	L	2	3	4	H	L-H
Panel A: Manufacturing - Portfolio Sorts & CAPM Regressions												
Levered Ret.	1.134***	0.949***	0.945***	0.387	0.103	1.031*** (0.01)	1.257***	0.614***	0.737***	0.466	0.045	1.212*** (0.16)
	(0.34)	(0.31)	(0.29)	(0.33)	(0.27)	(0.44)	(0.32)	(0.26)	(0.22)	(0.34)	(0.29)	(0.43)
Unlevered Ret.	0.905***	0.719***	0.776***	0.276	-0.131	1.036*** (0.06)	1.117***	0.441**	0.620***	0.378	-0.003	1.120*** (0.22)
	(0.27)	(0.24)	(0.24)	(0.30)	(0.24)	(0.36)	(0.28)	(0.21)	(0.19)	(0.31)	(0.27)	(0.39)
Alpha (%)	0.420**	0.293*	0.355**	-0.306*	-0.424***	0.844***	0.649***	0.112	0.341**	-0.256	-0.503***	1.152***
	(0.19)	(0.18)	(0.16)	(0.18)	(0.16)	(0.23)	(0.21)	(0.17)	(0.16)	(0.19)	(0.19)	(0.34)
MKT Beta	1.119***	1.026***	0.924***	1.085***	0.826***	0.293***	0.953***	0.787***	0.619***	1.130***	0.858***	0.095
	(0.06)	(0.06)	(0.04)	(0.05)	(0.03)	(0.06)	(0.06)	(0.05)	(0.04)	(0.07)	(0.07)	(0.10)
R^2 (%)	71.02	70.61	68.83	71.52	62.20	10.03	55.50	61.84	48.72	65.16	59.45	0.22
Panel B: Services - Portfolio Sorts & CAPM Regressions												
Levered Ret.	1.010***	0.818***	0.468	0.640*	0.455	0.555* (0.27)	0.991***	0.577**	0.538*	0.444	0.513*	0.478* (0.06)
	(0.35)	(0.33)	(0.34)	(0.33)	(0.28)	(0.33)	(0.33)	(0.30)	(0.32)	(0.33)	(0.28)	(0.30)
Unlevered Ret.	0.751***	0.568**	0.309	0.462*	0.405	0.346 (0.37)	0.746***	0.437*	0.366	0.298	0.412	0.334 (0.15)
	(0.28)	(0.25)	(0.25)	(0.27)	(0.26)	(0.38)	(0.28)	(0.23)	(0.24)	(0.29)	(0.26)	(0.38)
Alpha (%)	0.305	0.146	-0.259*	-0.010	-0.058	0.363	0.324*	-0.028	-0.096	-0.256	0.014	0.310
	(0.20)	(0.19)	(0.16)	(0.20)	(0.19)	(0.25)	(0.20)	(0.16)	(0.20)	(0.18)	(0.19)	(0.27)
MKT Beta	1.105***	1.053***	1.139***	1.018***	0.803***	0.301***	1.046***	0.947***	0.993***	1.095***	0.781***	0.264***
	(0.06)	(0.06)	(0.04)	(0.05)	(0.05)	(0.05)	(0.07)	(0.05)	(0.05)	(0.07)	(0.05)	(0.07)
R^2 (%)	68.65	67.53	77.55	65.35	55.98	9.30	64.39	66.42	61.44	70.30	50.80	5.61

Panel C: Portfolio Characteristics

	Manufacturing					Services				
Size	12.80	12.70	12.48	12.66	12.58	12.69	13.04	12.63	12.56	12.67
# Employees	9756	10091	6947	6866	6775	9741	12996	5745	6125	9365
Book to Market	0.66	0.76	0.86	0.92	0.93	0.80	0.85	0.85	0.82	0.81
Leverage	0.23	0.23	0.24	0.25	0.28	0.26	0.28	0.29	0.23	0.25
Labor Intensity	2.67	3.20	3.56	3.31	3.32	3.18	3.29	3.11	3.54	4.07

Table 7: **Manufacturing - Four- and Five-Factor Models**

Panel A reports the Carhart (1997) four-factor model regression results both for equal-weighted (columns 2-8) and value-weighted (columns 10-16) portfolio returns. Panel B tabulates similar regression results for the five-factor model of Fama and French (2015). Monthly α estimates are expressed in percent. $Offshorability$ is lagged by 18 months. Returns are at a monthly frequency. Standard errors reported in parentheses are adjusted for heteroscedasticity and autocorrelation (Newey-West). R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. The sample covers returns of manufacturing industries from July 1991 to June 2016.

	Equal-Weighted Returns						Value-Weighted Returns					
	L	2	3	4	H	L-H	L	2	3	4	H	L-H
Panel A: Manufacturing - Carhart (1997) Four-Factor												
Alpha (%)	0.272*	0.163	0.355***	-0.258*	-0.399***	0.671***	0.556***	0.054	0.335**	-0.002	-0.225	0.782***
	(0.15)	(0.14)	(0.14)	(0.15)	(0.15)	(0.22)	(0.19)	(0.16)	(0.16)	(0.18)	(0.17)	(0.29)
MKT Beta	1.071***	1.001***	0.878***	1.011***	0.766***	0.306***	0.940***	0.821***	0.654***	1.019***	0.761***	0.180**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)	(0.06)	(0.05)	(0.04)	(0.07)	(0.05)	(0.08)
SMB Beta	0.583***	0.411***	0.250***	0.308***	0.284***	0.299***	0.285***	-0.081*	-0.193***	0.097	-0.034	0.319***
	(0.06)	(0.08)	(0.09)	(0.07)	(0.08)	(0.11)	(0.09)	(0.05)	(0.07)	(0.07)	(0.07)	(0.13)
HML Beta	0.301***	0.390***	0.232***	0.238***	0.182***	0.119	-0.134	0.222***	0.089	-0.179**	-0.214**	0.081
	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.09)	(0.10)	(0.08)	(0.06)	(0.08)	(0.10)	(0.18)
UMD Beta	-0.021	-0.059	-0.140***	-0.216***	-0.157***	0.136*	0.145***	-0.013	-0.005	-0.274***	-0.272***	0.417***
	(0.07)	(0.05)	(0.04)	(0.03)	(0.03)	(0.08)	(0.05)	(0.06)	(0.05)	(0.07)	(0.07)	(0.11)
R^2 (%)	82.26	80.74	75.39	79.64	69.85	17.98	61.02	64.63	51.48	69.70	66.83	16.70
Panel B: Manufacturing - Fama and French (2015) Five-Factor												
Alpha (%)	0.092	-0.196	0.077	-0.617***	-0.594***	0.687***	0.571***	-0.145	0.167	-0.144	-0.257	0.828***
	(0.14)	(0.12)	(0.15)	(0.16)	(0.16)	(0.24)	(0.22)	(0.16)	(0.16)	(0.20)	(0.19)	(0.35)
MKT Beta	1.159***	1.175***	1.005***	1.173***	0.848***	0.311***	0.945***	0.919***	0.739***	1.070***	0.754***	0.191**
	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)	(0.05)	(0.09)
SMB Beta	0.679***	0.599***	0.343***	0.331***	0.342***	0.337***	0.372***	0.012	-0.132**	-0.105	-0.195**	0.567***
	(0.06)	(0.05)	(0.07)	(0.08)	(0.07)	(0.10)	(0.09)	(0.06)	(0.06)	(0.08)	(0.09)	(0.16)
HML Beta	0.185***	0.185***	0.180***	0.129	0.236***	-0.051	-0.270***	0.063	-0.074	-0.122	0.034	-0.304*
	(0.08)	(0.06)	(0.07)	(0.10)	(0.09)	0.131	(0.11)	(0.08)	(0.08)	(0.10)	(0.10)	0.170
RMW Beta	0.302***	0.591***	0.324***	0.207**	0.196*	0.106	0.210	0.312***	0.227***	-0.409***	-0.390***	0.600**
	(0.08)	(0.05)	(0.10)	(0.10)	(0.11)	0.168	(0.17)	(0.10)	(0.09)	(0.13)	(0.15)	0.278
CMA Beta	0.097	0.154**	0.039	0.313*	-0.112	0.209	0.055	0.182	0.240***	0.370**	-0.091	0.146
	(0.11)	(0.07)	(0.12)	(0.17)	(0.13)	(0.20)	(0.19)	(0.12)	(0.10)	(0.19)	(0.17)	(0.32)
R^2 (%)	83.39	85.92	75.39	77.33	68.11	15.86	59.98	66.96	53.46	68.19	62.42	8.80

Table 8: **Subsample Analysis**

The table reports univariate portfolio sorts for manufacturing industries for different time subsamples. Panel A tabulates results for equal-weighted returns and Panel B for value-weighted returns. L-H is an investment strategy that is long the portfolio of firms with low offshorability (L) and short the portfolio of firms with high offshorability (H). Column *MR* reports the p-values of the "monotonic relationship (MR)" test by Patton and Timmermann (2010). Standard errors are adjusted for heteroscedasticity and autocorrelation (Newey-West). Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. The sample includes manufacturing firms and covers the period July 1991 to June 2016.

Panel A: Equal-weighted Returns

	Offshorability						
	L	2	3	4	H	L-H	MR
1991:07 - 2016:06	1.134***	0.949***	0.945***	0.387	0.103	1.031***	0.005***
	(0.34)	(0.31)	(0.29)	(0.33)	(0.27)	(0.44)	
1991:07 - 1999:12	1.484***	1.123***	0.888**	0.660	0.446	1.038*	0.000***
	(0.50)	(0.47)	(0.44)	(0.44)	(0.41)	(0.62)	
2000:01 - 2009:12	0.813	0.630	0.712	-0.019	-0.086	0.899	0.017**
	(0.65)	(0.57)	(0.51)	(0.65)	(0.50)	(0.65)	
2010:01 - 2016:06	1.171**	1.211**	1.376***	0.653	-0.054	1.225*	0.332
	(0.57)	(0.54)	(0.52)	(0.56)	(0.49)	(0.72)	
2000:01 - 2008:08	0.906*	0.705*	0.834*	-0.134	-0.057	0.963	0.068*
	(0.48)	(0.40)	(0.47)	(0.56)	(0.47)	(0.62)	

Panel B: Value-weighted Returns

	Offshorability						
	L	2	3	4	H	L-H	MR
1991:07 - 2016:06	1.257***	0.614***	0.737***	0.466	0.045	1.212***	0.162
	(0.32)	(0.26)	(0.22)	(0.34)	(0.29)	(0.43)	
1991:07 - 1999:12	1.956***	0.970**	0.917***	0.805**	0.619**	1.336***	0.003***
	(0.65)	(0.46)	(0.36)	(0.39)	(0.30)	(0.71)	
2000:01 - 2009:12	0.733	0.063	0.186	-0.038	-0.582	1.315*	0.016**
	(0.49)	(0.45)	(0.35)	(0.72)	(0.63)	(0.70)	
2010:01 - 2016:06	1.150***	0.996***	1.348***	0.797	0.258	0.892*	0.946
	(0.44)	(0.39)	(0.41)	(0.53)	(0.30)	(0.54)	
2000:01 - 2008:08	0.887*	0.094	0.184	-0.061	-0.681	1.568*	0.067*
	(0.48)	(0.36)	(0.34)	(0.72)	(0.68)	(0.83)	

Table 9: **Panel OLS Regressions - Annual Regressions**

This table reports panel regression results. Panel A tabulates results for the sample of manufacturing firms and Panel B for services firms. The regression design is as follows:

$$r_{i,t} = a + b_{j,t} + c * OFF_{i,t-1} + d * controls_{i,t-1} + \epsilon_{i,t}$$

where the subscripts i stand for firm i = 1, ..N, and t stands for time t = 1, .., T . The explained variable is $r_{i,t}$, the firm's i future annual excess stock return. Realized annual stock returns are aggregated from July of year t to June of year $t+1$ and are expressed in percentages. Control variables are the following: a is a constant term; $b_{j,t}$ is an industry×year fixed effect, where industries represent the Fama-French 17 industries; OFF is the offshorability score lagged by 18 months; Size is the firm's lagged market capitalization; BM is the firm's lagged log book-to-market ratio; *R&D* is the firm's lagged R&D investment scaled by assets; *Leverage* is the firm's lagged leverage ratio; HN is the firm's lagged hiring rate; IK is the firm's lagged physical investment rate; *StockReturn* is the lagged stock return; *CashFlow* is the firm's lagged cash flow according to Zhang (2016); *Op.Lev* is the firm's lagged operational leverage, as in Donangelo (2014); *LaborInt* is the lagged labor intensity following Donangelo (2014); *Profitability* is a firm's gross profitability, as defined in Novy-Marx (2011). See appendix for definitions of firm characteristics. All variables are standardized. Standard errors are clustered at the firm and year level and reported in parentheses. R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. The sample covers stock returns from July 1991 to June 2016.

Panel A: Manufacturing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
OFF_{t-1}	-4.64*	-4.74*	-5.06**	-4.52*	-5.00*	-5.04*	-4.84*	-4.84*	-4.72*	-5.73**
	(2.57)	(2.56)	(2.56)	(2.64)	(2.72)	(2.79)	(2.61)	(2.56)	(2.53)	(2.88)
$Size_{t-1}$		-4.69***								-2.33
		(1.79)								(1.89)
BM_{t-1}			6.16***							4.36***
			(1.30)							(1.28)
$Mkt.Leverage_{t-1}$				3.42**						1.39
				(1.58)						(1.22)
HN_{t-1}					-3.63***					-2.63***
					(0.58)					(1.03)
IK_{t-1}						-2.22*				-1.37
						(1.18)				(1.15)
$StockReturn_{t-1}$							-2.75***			-2.97**
							(1.16)			(1.28)
$Op.Lev_{t-1}$								3.48***		0.28
								(0.88)		(0.83)
$Profitability_{t-1}$									2.55*	5.75***
									(1.54)	(1.62)
Fixed Effects	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind
Clustered by	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID
N	39,387	39,336	37,552	32,481	34,743	34,899	38,369	36,103	39,387	25,194
R^2 (%)	10.26	10.55	11.01	10.03	10.63	10.23	10.54	9.78	10.34	11.23

Panel B: Services

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
OFF_{t-1}	-1.98*	-2.02	-1.50	-1.74	-1.71	-1.46	-1.90	-1.75	-2.11*	-0.96
	(1.21)	(1.29)	(1.34)	(1.41)	(1.24)	(1.29)	(1.33)	(1.23)	(1.22)	(1.31)
Fixed Effects	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind
Clustered	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID
N	33,824	33,729	31,701	28,090	28,742	28,976	32,837	30,703	33,824	19,912
R^2 (%)	8.69	9.21	9.39	9.41	9.28	8.95	8.92	9.02	8.86	11.51

Table 10: **Offshorability and Low Wage Countries' Import Penetration**

Panel A reports equal- and value-weighted excess returns conditionally double-sorted on import penetration from low wage countries and offshorability. In any given month, stocks are first sorted into three portfolios based on their industry import penetration from low wage countries and then into five portfolios based on industry offshorability. Import penetration from low wage countries is calculated as in Bernard, Jensen, and Schott (2006a). Due to data availability, import penetration can only be calculated until 2011. See appendix for more details on the calculation of import penetration. The split into low (1), medium (2) and high (3) import penetration industries is based on import penetration terciles calculated each year. Offshorability is lagged 18 months. Standard errors reported in parentheses are adjusted for heteroscedasticity and autocorrelation (Newey-West). Panel B tabulates conditional panel regression results, as in table 9. Low IP (High IP) refers to regressions based on firms that belong to industries with import penetration below (above) the median. For each group, the results for regression specifications 1 and 10 are reported. All variables are standardized. Standard errors are clustered at the firm and year level and reported in parentheses. R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. The sample includes manufacturing firms from 1991 to 2011.

Panel A: Return Double Sorts

		Equal-weighted Returns					
		Offshorability					
		L	2	3	4	H	L-H
Imp Penetration	1	1.015***	1.007***	0.798***	0.275	0.429	0.585
		(0.34)	(0.36)	(0.30)	(0.44)	(0.28)	(0.44)
	2	1.067***	0.709	0.764**	0.356	0.282	0.785
		(0.42)	(0.46)	(0.38)	(0.41)	(0.41)	(0.59)
	3	1.515***	1.172***	1.009	0.085	-0.128	1.643***
		(0.47)	(0.44)	(0.65)	(0.40)	(0.47)	(0.66)
		Value-weighted Returns					
		Offshorability					
		L	2	3	4	H	L-H
Imp Penetration	1	0.789***	0.716***	0.629***	0.401	0.570**	0.219
		(0.29)	(0.30)	(0.26)	(0.38)	(0.29)	(0.41)
	2	0.858***	0.949**	0.730**	0.198	-0.063	0.921
		(0.36)	(0.48)	(0.32)	(0.38)	(0.46)	(0.58)
	3	1.533***	0.873	1.253*	-0.180	-0.004	1.537***
		(0.42)	(0.56)	(0.66)	(0.39)	(0.46)	(0.62)

Panel B: Conditional Panel Regressions

	Low IP	Low IP	High IP	High IP
OFF_{t-1}	-1.78	-2.85	-4.80*	-5.90*
	(2.60)	(199)	(2.53)	(3.15)
Firm Control	N	Y	N	Y
Fixed Effects	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind
Clustered by	Yr & ID	Yr & ID	Yr & ID	Yr & ID
N	18,676	11,477	16,866	11,100
R^2 (%)	10.66	12.39	11.87	12.71

Table 11: **Offshorability and Shipping Costs**

Panel A reports equal- and value-weighted excess returns sorted on offshorability and shipping costs. In any given month, stocks are sorted into three portfolios based on their industry shipping costs and five portfolios on industry offshorability. Shipping costs are calculated as in Barrot, Loualiche, and Sauvagnat (2017). The split into low (1), medium (2) and high (3) shipping cost industries is based on shipping cost terciles calculated each year. Offshorability is lagged 18 months. Standard errors reported in parentheses are adjusted for heteroscedasticity and autocorrelation (Newey-West). Panel B tabulates conditional panel regression results, as in table 9. Low SC (High SC) refers to regressions based on firms that belong to industries with shipping costs below (above) the median. For each group, the results for regression specifications 1 and 10 are reported. All variables are standardized. Standard errors are clustered at the firm and year level and reported in parentheses. R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. The sample includes manufacturing firms from July 1991 to June 2016.

Panel A: Return Double Sorts

Equal-weighted Returns

Shipping Costs	Offshorability: L	2	3	4	H	L-H
1	1.469***	0.838*	0.554*	0.218	0.129	1.340**
	(0.48)	(0.46)	(0.29)	(0.38)	(0.34)	(0.59)
2	0.940***	0.923***	0.867***	0.165	0.053	0.887
	(0.36)	(0.34)	(0.32)	(0.34)	(0.45)	(0.58)
3	0.962**	0.944***	0.670	-0.002	0.406	0.556
	(0.45)	(0.36)	(0.42)	(0.48)	(0.43)	(0.63)

Value-weighted Returns

Shipping Costs	Offshorability: L	2	3	4	H	L-H
1	1.504***	0.797*	0.657***	0.169	0.079	1.425***
	(0.51)	(0.45)	(0.26)	(0.41)	(0.33)	(0.61)
2	0.675**	0.678***	0.713**	0.543	-0.011	0.686
	(0.31)	(0.29)	(0.31)	(0.35)	(0.44)	(0.54)
3	0.625*	0.799***	0.683*	0.359	0.490	0.135
	(0.36)	(0.27)	(0.40)	(0.36)	(0.39)	(0.53)

Panel B: Conditional Panel Regressions

	Low SC	Low SC	High SC	High SC
OFF_{t-1}	-4.86*	-5.92*	-2.22	-1.66
	(2.94)	(3.43)	(1.52)	(1.13)
Firm Controls	N	Y	N	Y
Fixed Effects	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind
Clustered by	Yr & ID	Yr & ID	Yr & ID	Yr & ID
N	17,145	10,489	16,129	10,691
R^2 (%)	10.19	12.13	11.11	12.86

Table 12: **Offshorability and Multinational Companies**

Panel A reports the post-ranking mean of equal- and value-weighted excess returns of stocks sorted on offshorability for multinational manufacturing firms and domestic manufacturing firms. Excess Returns are calculated as realized monthly returns minus the one-month risk-free rate. *EW* refers to equal-weighted and *VW* to value-weighted portfolio returns. L-H stands for an investment strategy that is long the portfolio of firms with low offshorability (L) and short the portfolio of firms with high offshorability (H). The column *MR* reports the p-values of the "monotonic relationship (MR)" test by Patton and Timmermann (2010). Standard errors reported in parentheses are adjusted for heteroscedasticity and autocorrelation (Newey-West). The sample includes manufacturing firms from July 1991 to June 2016. Panel B tabulates conditional panel regression results, as in table 9. MNC (Domestic) refer to regressions based on multinational (domestic) manufacturing firms. For each group, the results for regression specifications 1 and 10 are reported. All variables are standardized. Standard errors are clustered at the firm and year level and reported in parentheses. R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%.

Panel A: Univariate Return Sorts

	Offshorability L	2	3	4	H	L-H	MR
Multinational Manufacturing Firms							
EW	1.146***	1.031***	0.872***	0.381	0.076	1.071***	0.001***
	(0.34)	(0.32)	(0.32)	(0.29)	(0.28)	(0.45)	
VW	1.209***	0.837***	0.687***	0.480	0.021	1.188***	0.004***
	(0.30)	(0.28)	(0.23)	(0.32)	(0.31)	(0.43)	
Domestic Manufacturing Firms							
EW	0.979***	0.694*	0.805*	0.120	-0.016	0.995*	0.127
	(0.41)	(0.41)	(0.46)	(0.46)	(0.32)	(0.52)	
VW	1.044***	0.522	1.064***	-0.082	0.132	0.912***	0.871
	(0.34)	(0.39)	(0.45)	(0.46)	(0.17)	(0.38)	

Panel B: Conditional Panel Regressions

	MNC		Domestic	
OFF_{t-1}	-4.16*	-4.56*	-5.11*	-6.06*
	(2.34)	(2.66)	(2.95)	(3.50)
Firm Controls	N	Y	N	Y
Fixed Effects	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind
Clustered by	Yr & ID	Yr & ID	Yr & ID	Yr & ID
N	21,769	16,195	17,509	10,376
R^2 (%)	12.51	14.15	9.62	11.19

Table 13: **Model Parameters**

This table reports the parameters used in the benchmark calibration of the model (see section 4.6 for a more detailed description).

Parameter		Value	Source
Industry Parameters:			
Expenditure share differentiated goods	$a_0, a_0^\star$	0.1, 0.9	Barrot, Loualiche, and Sauvagnat (2017)
Elasticity across industries	θ	1.2	Loualiche (2015)
Elasticity of industry demand	σ_s	3.8	Broda and Weinstein (2006)
Pareto tail parameter	κ_s	3.4	Ghironi and Melitz (2005)
Industry taste parameter	δ_s	0.5	
Production:			
Headquarter intensity	α_s	0.55, 0.95	OECD, Blinder (2009)
Wage costs	c, $c^\star$	0.32, 0	labor costs other than wages/salaries for time actually worked
Labor supply	$L, L^\star$	1.02, 5	match ratio of working age population in U.S. and China
Mass of firms	N_s, $N_s^\star$	30, 2.57	match ratio of market capitalization in U.S. and China
Trade:			
Iceberg costs	τ_s, $\tau_s^\star$	1.1	Ghironi and Melitz (2005)
Fixed exporting costs	f_X, $f_X^\star$	3, 0.01	Barrot, Loualiche, and Sauvagnat (2017) & match avg import penetration
Fixed offshoring costs	f_O	$5e^{-3}$	match avg import penetration
Aggregate Productivity			
West	ρ_a	0.98	U.S. GDP, Barrot, Loualiche, and Sauvagnat (2017)
	σ_a	1.6%	U.S. GDP, Barrot, Loualiche, and Sauvagnat (2017)
East	$\rho_a^\star$	0.96	Chinese imports to the U.S., Barrot, Loualiche, and Sauvagnat (2017)
	$\sigma_a^\star$	6%	Chinese imports to the U.S., Barrot, Loualiche, and Sauvagnat (2017)
Stochastic Discount Factor:			
Discount factor	β	0.99	Bansal and Yaron (2004)
Intertemporal Elasticity of Substitution	ψ	1.50	Bansal and Yaron (2004)
Risk aversion parameter	γ	80	match U.S. equity premium

Table 14: **Model Simulations: Targeted and Model-Implied Moments**

The table reports the main moments of the model-generated data. Panel A tabulates the targeted moments in the model and the data. The share of the market capitalization (MC) in China is calculated as $MC_{China}/(MC_{US} + MC_{China})$ and the share of the working age population (WP) in China as $WP_{China}/(WP_{US} + WP_{China})$. Panel B (C and D) focuses on moments of macroeconomic (industry and financial) quantities. Column titles "Low" and "High" refer to low and high offshorability industries. The model is solved using perturbation methods and is approximated to the 3rd-order around the deterministic steady state. Moments are calculated based on simulations over 10'000 periods (with a burn-in period of 1'000 periods).

Panel A: Targeted Moments

	model	data
Share Market Capitalization China	0.28	0.25
Share Working Age Population China	0.17	0.17
Avg Import Penetration China - Mean	6.26%	6.36%
Avg Import Penetration China - Std	4.08%	2.75%

Panel B: Macro Moments

	Agg. Consumption		Risk-free Rate		Labor Share	
	model	data	model	data	model	data
mean			2.80%	2.63%	60.54%	58.40%
std	9.44%	2.00%	0.27%	2.12%		

Panel C: Industry Quantities

	Import Penetration		Industry Profits	
	Low	High	Low	High
mean	7.39%	5.36%	0.28	0.32
std	5.91%	2.83%	8.14%	3.67%
cov($,A$)	-0.60	-0.30	0.24	0.12
cov($,A^\star$)	5.00	2.48	-1.75	-0.79
cov($,C$)	-0.51	-0.26	0.76	0.34

Panel D: Asset Prices and Excess Returns

	Valuations		Excess Returns		Export Excess Returns	
	Low	High	Low	High	Low	High
mean	10.31	19.96	6.44%	3.53%	8.04%	3.62%
std	2.14%	1.65%	16.33%	8.42%	19.07%	9.14%
cov($,A$)	0.09	0.06	0.07	0.02	0.13	0.03
cov($,A^\star$)	-0.43	-0.34	-0.90	-0.31	-1.28	-0.31
cov($,C$)	0.20	0.16	0.09	0.03	0.13	0.03

Table 15: **Variance Decomposition, Model Predictions and Counterfactuals**

The left (right) part of Panel A shows industry profits and excess returns for the model economy with shocks only to A ($A^{\star}$). Panel B reports panel regression results for profit and sales volatility. Firm-specific profit and sales volatility are calculated as in Minton and Schrand (1999). All regressions include year fixed effects. Firm control variables are size, Tobin's Q, leverage and investment. Standard errors are clustered at the firm and year level and reported in parentheses. The sample covers manufacturing firms from 1991 to 2016. R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. Panel C investigates the role of import penetration in the model by counterfactually equating import penetration across the two model industries. In addition, Panel C reports moments of industry valuations and excess returns, assuming that industries have zero offshorability, i.e., $\alpha_s = 1$ for any s. In other words, the firm's production function in both industries relies exclusively on headquarter tasks. Consequently, the two industries are no longer distinguishable and, hence, have identical excess returns and valuations. Throughout the table, column titles "Low" and "High" label low and high offshorability industries. The model is solved using perturbation methods and is approximated to the 3rd-order around the deterministic steady state. Moments are calculated based on simulations over 10'000 periods (with a burn-in period of 1'000 periods).

Panel A: Shock Decomposition

	Only Shocks to A				Only Shocks to A*			
	Profits		Excess Returns		Profits		Excess Returns	
	Low	High	Low	High	Low	High	Low	High
mean	0.29	0.32	1.10%	0.59%	0.28	0.32	5.33%	2.93%
std	3.03%	1.33%	4.34%	2.61%	7.59%	3.33%	14.67%	7.70%
cov(,A)	0.24	0.10	0.07	0.04				
cov(,$A^{\star}$)					-1.74	-0.77	-0.87	-0.32
cov(,C)	0.13	0.06	0.04	0.02	0.63	0.28	0.31	0.11

Panel B: Panel Regressions

	One-Year Lagged Offshorability ($x = 1$)				Five-Year Lagged Offshorability ($x = 5$)			
	Profit Vol		Sales Vol		Profit Vol		Sales Vol	
OFF_{t-x}	-0.03**	-0.03*	-0.01	-0.01	-0.06***	-0.06***	-0.02***	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Firm Control	N	Y	N	Y	N	Y	N	Y
Fixed Effects	Yr	Yr	Yr	Yr	Yr	Yr	Yr	Yr
Clustered by	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID
N	21,133	20,819	21,133	20,819	15,056	14,838	15,056	14,838
R^2 (%)	1.52	6.41	1.87	10.12	2.58	9.05	3.05	12.57

Panel C: Counterfactuals

	Role of Import Penetration				No Offshorability ($1 - \alpha_s = 0$)			
	Import Penetration		Excess Returns		Valuations		Excess Returns	
	Low	High	Low	High	Low	High	Low	High
mean	7.31%	7.31%	6.99%	4.37%	10.86	10.86	9.64%	9.64%
std	4.97%	3.53%	13.60%	8.36%	2.62%	2.62%	19.45%	19.45%
cov(,A)	-0.50	-0.38	0.08	0.05	0.11	0.11	0.02	0.02
cov(,$A^{\star}$)	4.15	3.10	-0.79	-0.49	-0.52	-0.52	-0.62	-0.62
cov(,C)	-0.47	-0.36	0.09	0.05	0.25	0.25	0.08	0.08

Table 16: **Double-Sorts: Offshorability and U.S. Trade Elasticities**

Panel A reports equal- and value-weighted excess returns conditionally double-sorted on U.S. trade elasticities and offshorability. In any given month, stocks are first sorted into three portfolios based on their industry trade elasticities and then further into five portfolios based on industry offshorability. U.S. trade elasticities are estimated by Broda and Weinstein (2006) from 1990 to 2001 at the commodity level and are aggregated at the industry level based on total imports over 1990-2001. The split into low (1), medium (2) and high (3) trade elasticity industries is based on trade elasticity terciles. Offshorability is lagged 18 months. Standard errors reported in parentheses are adjusted for heteroscedasticity and autocorrelation (Newey-West). Panel B tabulates conditional panel regression results as in table 9. Low TE (High TE) refers to regressions based on firms that belong to industries with U.S. trade elasticities below (above) the median. For each group, results for regression specifications 1 and 10 are reported. All variables are standardized. Standard errors are clustered at the firm and year level and reported in parentheses. R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. The sample includes manufacturing firms from July 1991 to June 2016.

Panel A: Return Double Sorts

Equal-weighted Returns

Trade Elasticities	Offshorability: L	2	3	4	H	L-H
L	0.918***	0.761**	0.785***	0.403	0.027	0.891
	(0.36)	(0.34)	(0.31)	(0.35)	(0.45)	(0.57)
2	1.406***	0.650*	0.109	0.507	0.109	1.2971**
	(0.35)	(0.34)	(0.46)	(0.42)	(0.43)	(0.56)
H	1.879***	0.996***	0.866**	0.535	-0.335	2.213***
	(0.48)	(0.39)	(0.39)	(0.52)	(0.67)	(0.82)

Value-weighted Returns

Trade Elasticities	Offshorability: L	2	3	4	H	L-H
L	0.941***	0.597**	0.750***	0.434	-0.116	1.057*
	(0.31)	(0.26)	(0.27)	(0.31)	(0.43)	(0.53)
2	1.217***	0.900***	0.380	0.566	0.006	1.211**
	(0.33)	(0.31)	(0.42)	(0.38)	(0.44)	(0.55)
H	1.532***	0.818***	0.424	0.601	-0.193	1.725**
	(0.42)	(0.35)	(0.42)	(0.50)	(0.66)	(0.78)

Panel B: Conditional Panel Regressions

	Low TE	Low TE	High TE	High TE
OFF_{t-1}	-2.74	-2.71	-10.36**	-12.14***
	(2.10)	(2.46)	(4.47)	(5.17)
Firm Controls	N	Y	N	Y
Fixed Effects	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind
Clustered by	Yr & ID	Yr & ID	Yr & ID	Yr & ID
N	19,427	13,672	19,667	11,307
R^2 (%)	8.33	10.33	12.86	13.49

Table 17: **Model Prediction: Consumption CAPM**

Panel A reports consumption CAPM (CCAPM) regressions on simulated model data both for return horizons of 4 and 8 quarters. The reported coefficients, standard errors and R^2 are averages over the regression results of 200 regressions of identical sample size as observed in the data. α estimates are expressed in percent. L and H stand for low and high offshorability industries in the model. Panel B then reports analogous CCAPM regression results for my sample of manufacturing industries. Results are tabulated both for equal-weighted (columns 2-6) and value-weighted (columns 8-12) portfolio returns. 4-quarter, 6-quarter and 8-quarter α estimates are expressed in percent. The portfolios L and H invest in industries with offshorability in the lowest and highest quintiles. $2-4$ is a portfolio that invests in the remaining industries. $Offshorability$ is lagged by 18 months. Returns on consumption are calculated based on U.S. real per capita non-durable consumption, as in Parker and Julliard (2005). Standard errors reported in parentheses are adjusted for heteroscedasticity and autocorrelation (Newey-West). R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. The sample covers returns from July 1991 to June 2016.

Panel A: Model Regressions

	4 Quarter Returns			8 Quarter Returns		
	L	H	L-H	L	H	L-H
Avg Alpha (%)	8.685***	4.745***	3.940***	17.088***	9.361***	7.727***
	(0.25)	(0.07)	(0.19)	(0.48)	(0.13)	(0.37)
Avg C Beta	3.679***	1.452***	2.227***	3.708***	1.461***	2.247***
	(0.06)	(0.02)	(0.04)	(0.08)	(0.02)	(0.06)
Avg R^2 (%)	97.79	98.73	96.62	96.02	98.00	93.80

Panel B: Empirical Evidence

	Equally Weighted Returns				Value-Weighted Returns			
	L	2 - 4	H	L-H	L	2 - 4	H	L-H
				4 Quarter Returns				
Alpha (%)	3.708	1.309	-5.346***	9.054***	5.888***	0.605	-5.714*	11.602***
	(3.23)	(2.62)	(2.02)	(2.23)	(2.46)	(2.22)	(3.00)	(3.08)
C Beta	6.318***	4.334***	3.513***	2.805***	6.346***	3.833***	3.755***	2.591**
	(1.61)	(1.47)	(1.07)	(1.16)	(1.45)	(0.96)	(1.10)	(1.32)
R^2 (%)	19.77	14.10	10.62	5.30	16.24	13.790	8.80	2.35
				6 Quarter Returns				
Alpha (%)	5.769	3.061	-7.606***	13.375***	8.227***	1.798	-7.339*	15.566***
	(3.65)	(3.50)	(2.45)	(2.88)	(2.60)	(2.93)	(3.75)	(4.19)
C Beta	6.646***	4.042***	3.451***	3.195***	7.352***	3.615***	3.348***	4.004**
	(1.43)	(1.41)	(1.04)	(1.20)	(1.77)	(0.90)	(0.96)	(1.86)
R^2 (%)	27.18	15.03	12.87	6.90	19.68	13.81	8.12	4.62
				8 Quarter Returns				
Alpha (%)	7.508*	4.273	-10.375***	17.882***	9.602***	2.957	-8.869**	18.471***
	(3.96)	(4.05)	(2.72)	(3.49)	(3.04)	(3.53)	(4.15)	(5.05)
C Beta	6.911***	3.956***	3.503***	3.408***	8.331***	3.568***	3.107***	5.225***
	(1.06)	(1.24)	(0.96)	(1.17)	(1.69)	(0.81)	(0.80)	(2.07)
R^2 (%)	33.95	15.94	15.11	7.91	27.21	13.66	7.73	6.86

Online Appendix to "From Local to Global: Offshoring and Asset Prices"

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This online appendix contains additional information on the sample and data construction (section 1), and on the OES data set and the industry offshorability index across sectors (section 2), further robustness tests of the empirical results of the paper (section 3) and details about the computational approach employed to solve the model (section 4).

1 Sample Construction and Variable Definition

Monthly common stock data is from the Center for Research in Security Prices (CRSP share code SHRCD = 10 or 11). The sample includes stocks listed on NYSE, AMEX, and NASDAQ (exchcd = 1 or 2 or 3). Accounting information is from Standard and Poor's Compustat annual industrial files. I follow the literature and exclude from my sample firms with primary standard industrial classifications between 4900 and 4999 (regulated firms) and between 6000 and 6999 (financial firms). Following Zhang (2016), the firm-level accounting variables and size measures are winsorized at the 1% level to reduce the influence of possible outliers.

I construct the following variables for every firm:

- $Assets$ is the logarithm of a firm's total book assets (AT).
- $Cash$ is a firm's cash holdings defined as cash and short-term investments (CHE) scaled by total book assets (AT).
- Q is a firm's Tobin's Q defined as total book assets (AT) minus common equity (CEQ) plus the market value of equity scaled by total assets (AT) following Dasgupta, Noe, and Wang (2011).
- $PP\&E$ is net property, plant and investment (PPENT) scaled by total book assets (AT).
- $Size$ and $BooktoMarket$ are calculated following Fama and French (1992).

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- $R\&D$ is defined as R&D expenses (XRD) scaled by total book assets (AT).

- $Mkt.Leverage$ is the firm's financial leverage and defined as the proportion of total debt of the market value of the firm defined following Fan, Titman, and Twite (2012). Total debt is the book value of short-term (DLC) and long-term interest bearing debt (DLTT). The market value of the firm is the market value of common equity defined as in Fama and French (1992).

- HN and IK are a firm's hiring and investment rate defined following Belo, Lin, and Bazdresch (2014).

- $CashFlow$ is the cash flow of a firm which is defined following Malmendier and Tate (2005): earnings before extraordinary items (IB) plus depreciation (DP) divided by capital stock (PPENT) at the beginning of the following year.

- $Op.Lev$ is a firm's operating leverage defined as in Novy-Marx (2011). It is calculated as cost of goods sold (COGS) plus selling, general, and administrative expenses (SGA) divided by total book assets (AT).

- $LaborInt.$ is a firm's labor intensity defined as the logarithm of the ratio of the number of employees divided by gross property, plant and investment (PPEGT) following Donangelo (2014).

- $Profitability$ is a firm's gross profitability defined as revenues (REVT) minus cost of goods sold (COGS) scaled by assets (AT) as defined by Novy-Marx (2011).

- I classify every sample firm in either a domestic, exporter or multinational firm as in Fillat and Garetto (2015). To do so I use information on geographical company segments from COMPUSTAT.

- I calculate a firm's profit and sales volatility following the methodology of Minton and Schrand (1999). In particular, I use Compustat quarterly for all manufacturing firms and download quarterly sales, revenues and costs of goods sold. Following Novy-Marx (2011), I define gross profits as revenues minus costs of goods sold.

I construct the following variables at the industry-level:

- $Offshorability$ is calculated as discussed in the main body of the paper.

- $Skill$ is calculated as in Ochoa (2013):

$$Skill_{i,t} = \sum_{j} \lambda_j \times \frac{emp_{i,j,t} \times wage_{i,j,t}}{\sum_j emp_{i,j,t} \times wage_{i,j,t}}, \tag{1}$$

where λ_j is the skill-level of occupation j. λ_j is the "job zone" of a given occupation which ranges between one and five.

- *Routine* is calculated as follows:

$$Routine_{i,t} = \sum_j \mathbb{1}_{\{routine_j > routine_{p66}\}} \times routine_j \times \frac{emp_{i,j,t} \times wage_{i,j,t}}{\sum_j emp_{i,j,t} \times wage_{i,j,t}}, \tag{2}$$

where $routine_j$ is the routine task score for occupation j which is calculated using task level content from O*NET as in Acemoglu and Autor (2011).

- *Shipping Costs* are calculated following Barrot, Loualiche, and Sauvagnat (2017).

- *Value Share of Imports* and *Import Penetration* are calculated following Bernard, Jensen, and Schott (2006). The value share of imports from low wage countries, for example, is calculated as the total imports from low wage countries in an industry divided by the total imports in the same industry. Import penetration by low wage countries of a given industry i at time t is calculated as follows:

$$LWPEN_{i,t} = \Big(\frac{V^L_{i,t}}{V_{i,t} + Q_{i,t} - X_{i,t}}\Big),$$

where $V^L_{i,t}$ and $V_{i,t}$ represent the value of imports from low wage countries and all countries, respectively, $Q_{i,t}$ is domestic production, and $X_{i,t}$ represents US exports.

2 OES Data and Industry Offshorability across Sectors

While the OES survey methodology is designed to create detailed cross-sectional employment and wage estimates for the U.S., States, metropolitan and nonmetropolitan areas, across industry and by industry, comparisons of two or more points in time might be difficult. The time-series interpretation of OES data might be misleading due to various changes in the construction of the data over time such as changes in the occupational and industrial classification. The nature of these changes are summarized on the webpage of the Bureau of Labor Statistics as follows:
(Excerpts were downloaded on October 10, 2017 from https://www.bls.gov/oes/oes_ques.htm)

Changes in occupational classification: The OES survey used its own occupational classification system through 1998. The 1999 OES survey data provide estimates for most of the nonresidual occupations in the 2000 Standard Occupational Classification (SOC) system. The 2004-2009 OES data provides estimates for all occupations in the 2000 SOC. The May 2010 data provides estimates for most occupations in the 2010 SOC (for more on the 2010 occupations, see below). Because of these changes, it may be difficult to compare some occupations even if they are found in both classification systems. For example, both the old OES system and the 2000 SOC include the occupation "computer programmers." However, estimates for this occupation may not be comparable over time because the 2000 SOC has several computer-related occupations that were not included in the older classification system. Workers in newly classified occupations, such as systems software engineers and applications software engineers, may have been reported as computer programmers in the past. Therefore, even occupations that appear the same in the two systems may show employment shifts due to the addition or deletion of related occupations.

Changes in industrial classification: In 2002, the OES survey switched from the Standard Industrial Classification (SIC) system to the North American Industry Classification System (NAICS). As a result, there were changes in many industry definitions. Even definitions that appear similar between the two industry classifications may have differences because of the way auxiliary establishments are treated. For example, under SIC the industry "grocery stores" included their retail establishments, warehouses, transportation facilities, and administrative headquarters. Under NAICS, the four establishment types would be reported in separate industries. Only the retail establishments would be included in the NAICS industry for "grocery stores." The change in industrial classification also resulted in changes to the occupations listed on the survey form for a given industry. In 2008, the OES survey switched to the 2007 NAICS classification system from the 2002 NAICS. The most significant revisions are in the Information Sector, particularly within the Telecommunications area. Beginning in 2010, Tennessee Valley Authority (TVA) data is included in the Federal Government estimates.

While the main paper shows rankings of industry offshorability for manufacturing and services separately, table A2 reports corresponding rankings across all industries. In 1992, the industries with the highest offshoring potential were almost exclusively manufacturing industries whereas the bottom industries feature mining industries. In 2015, the industry ranking looks very different. Industries among the top ten are by no means only related to manufacturing. The bottom industries, however, do not seem to have drastically changed in their nature compared to 1992. Interestingly, the top ten in 2015 are mostly service industries which is consistent with Jensen (2011), Blinder (2009) and Amiti and Wei (2009) who discuss that recent advances in communication technologies increasingly allow for offshoring of service industry jobs. Moreover, this change over time is in line with recent papers which document that offshoring and replacement of offshorable jobs with imports have led to a substantial decrease in manufacturing employment over the recent past.* This can be seen from figure A1 which plots a strongly negative relationship between U.S. imports as percentage of GDP and the manufacturing employment share. As a result of this, one would expect that the manufacturing sector becomes relatively less offshorable compared with services over time. Given that the rankings within manufacturing and services are very persistent over time, the drastic change in top ten industries in 1992 and 2015 is likely to be due to structural changes across sectors, i.e. services and manufacturing.

Yet another way to look at this sectoral change in offshorability over time is to plot cross-sectional correlations of industry offshorability and industry routine-task labor and skill at different points in time. The results are plotted in figure A2. While offshorability and routine are significantly and positively correlated at the beginning of the sample, the correlation coefficients decrease continuously from 1997 onwards. This pattern is not due to wage-weighting when constructing the offshorability index. The correlations look almost identical for the $OFF^{\star}_{i,t}$ measure that does not rely on wages (right panel in figure A2). The sudden drop in correlation in 2001 coincides with the sharp decrease in routine-labor in the U.S. documented by Zhang (2016) and the decrease in manufacturing employment which was fueled by China's admission to the World Trade Organization (WTO) in 2001 as discussed in Autor, Dorn, and Hanson (2016).

Finally, figure A3 reports additional evidence on the importance of China for the U.S. trade deficit in goods. The left panel plots the U.S. trade balance in goods when considering all countries (solid blue line) and China only (red solid line). The importance of trades with China for the overall trade balance are striking. In the year 2009, 44.5% of the U.S. trade deficit in goods was due to trades with China. Interestingly, the right panel of figure A3 shows the trade balance in goods for the U.S. and China, respectively. Consistent with the interpretation of comparative advantage, the U.S. and Chinese trade balances in goods look like a mirror image. Of course, this is at best suggestive evidence because the countries potentially trade with many other countries, i.e. have various and heterogenous trade partners.

3 Robustness: Asset Pricing Results

This section delivers further robustness tests for the asset pricing results in the main paper. Table A3 reports regression results across all industries for the unconditional (Panel A) and conditional CAPM (Panel B) as well as the Fama and French (1993) three factor model (Panel C).

Table A4 splits the sample into manufacturing and services industries and reports regression results

*See among others Autor, Dorn, and Hanson (2013), Acemoglu, Autor, Dorn, Hanson, and Price (2016) and Autor, Dorn, and Hanson (2016).

for the Fama and French (1993) three factor model.

Table A5 reports univariate returns both for the full as well as for various subsamples. In this robustness test I keep the ranking of industry offshorability fixed over time. In other words, for the period between 1991 and 2002, I keep the industry offshorability fixed at the values for 1990, and for the period from 2002 to 2016, I fix offshorability at the values from the year 2001. Hence, I simply fix offshorability at the first observation available for the two industry classification regimes in the OES data (as discussed above).

Table A6 shows robustness tests for the predictability regressions of the main paper. Panel A and B report regression results for manufacturing and services for different industry definitions. While the baseline specification uses industry×year fixed effects based on 17 industries as defined in Fama and French (1988), I assess the robustness of the results for 49 industries as defined in Fama and French (1997), industries defined by one and two digit SIC codes as well as with only year fixed effects.

Table A7 shows monthly excess return double sorts on import penetration from China and offshorability. The results are very similar to the double sorts on import penetration from low-wage countries and offshorability.

Finally, tables A8 and A9 report factor model regression results which control for the globalization risk premium as defined in Barrot, Loualiche, and Sauvagnat (2017) and factors based on foreign exchange exposure from Lustig, Roussanov, and Verdelhan (2011) and Verdelhan (2017).

4 Computational Approach

The model is solved using perturbation methods around the steady-state. In particular, I use third-order approximations of the policy function around the deterministic steady-state of the model. I then simulate the model for 11'000 periods. I disregard the first 1'000 periods as a so-called burn-in period. Based on the remaining 10'000 periods of simulated data, I calculate moments for different model quantities. Impulse response functions are calculated as the response of a model quantity with respect to a one standard deviation shocks of either A or $A^\star$ (or $\tau^\star$ for the counterfactual analysis on trade costs). The plotted IRFs are calculated as the mean over 500 simulated IRFs.

5 Figures

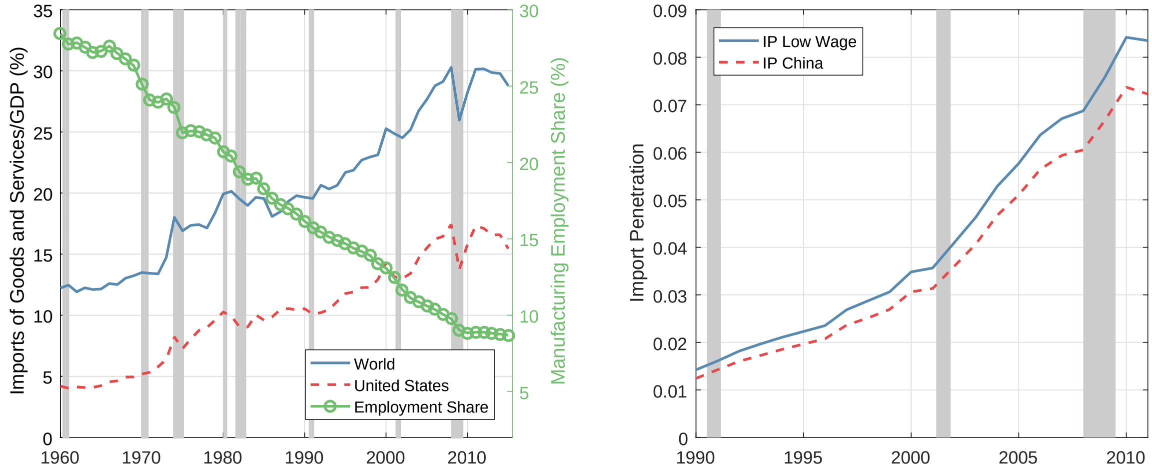

Figure A1: **Imports of Goods and Services as a Percentage of GDP**

The left figure plots the imports of goods and services as a percentage of GDP (left axis) as well as the manufacturing employment share (right axis). Data are obtained from the World Bank national accounts data and the OECD National Accounts data files. The sample period runs from 1960 to 2015. The right figure shows annual U.S. import penetration from low wage countries and China between 1990 and 2011.

Figure A2: **Correlation of Offshorability with Skill/Routine over time**

This figures plot the cross-sectional correlation coefficients (solid lines) along with 95% confidence intervals (dotted lines) of offshorability and skill and routine, respectively. The correlation coefficient in a given year is calculated as the Spearman rank correlation between quintiles of offshorability and skill or routine. The left panel plots the results for the wage-weighted industry offshorability measure and the right panel for industry offshorability without wage-weighting. The sample period runs from 1990 to 2016.

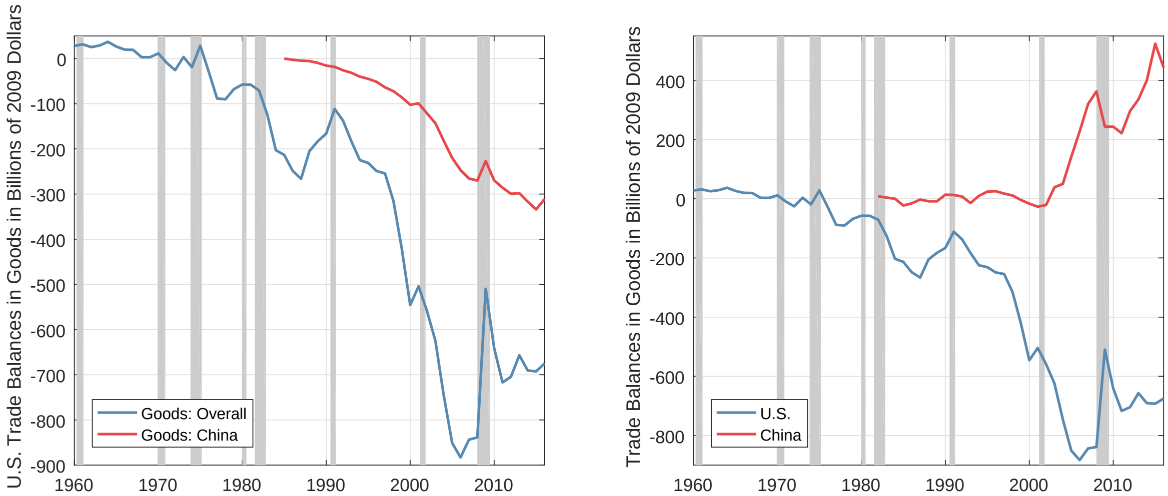

Figure A3: **Trade Balances in Goods**

The left panel plots the U.S. trade balances (i.e. exports minus imports) in goods in 2009 Dollars. The blue solid line refers to the overall trade balance in goods. In other words, trades between the U.S. and any other country are considered. On the other hand, the red solid line plots the U.S. trade balance in goods with China only. The right panel plots the overall trade balance in goods both for the U.S. and China. Data are obtained from the Bureau of Economic Analysis. The sample period runs from 1960 to 2016.

6 Tables

Table A1: **Occupation Tasks that define Offshorability**

This table tabulates the tasks used to calculate occupation offshorability by Firpo, Fortin, and Lemieux (2013). The acronyms *WA* and *WC* in the third column stand for work activity and work context.

	Firpo, Fortin and Lemieux (2013)	
Face-to-Face Contact		
4.C.1.a.2.l	Face-to-Face Discussions	WC
4.A.4.a.4	Establishing and Maintaining Interpersonal Relationships	WA
4.A.4.a.5	Assisting and Caring for Others	WA
4.A.4.a.8	Performing for or Working Directly with the Public	WA
4.A.4.b.5	Coaching and Developing Others	WA
On-site		
4.A.1.b.2	Inspecting Equipment, Structures, or Material	WA
4.A.3.a.2	Handling and Moving Objects	WA
4.A.3.a.3	Controlling Machines and Processes	WA
4.A.3.a.4	Operating Vehicles, Mechanized Devices, or Equipment	WA
4.A.3.b.4	Repairing and Maintaining Mechanical Equipment (*0.5)	WA
4.A.3.b.5	Repairing and Maintaining Electronic Equipment (*0.5)	WA
Decision-Making		
4.A.2.b.1	Making Decisions and Solving Problems	WA
4.A.2.b.2	Thinking Creatively	WA
4.A.2.b.4	Developing Objectives and Solving Problems	WC
4.C.1.c.2	Responsibility for Outcomes and Results	WC
4.C.3.a.2.b	Frequency of Decision Making	

Table A2: **Most Offshorable and Non-Offshorable Industries**

Panels A and B tabulate the top and bottom ten industries in terms of their offshoring potential, $OFF_{i,t}$, for the years 1992 and 2015, respectively. Industries are defined at the three-digit SIC level until 2001 and at the four-digit NAICS level thereafter.

Panel A: 1992 - Top and Bottom Ten Industries by Offshorability

SIC	Industry Title	$OFF_{i,t}$	SIC	Industry Title	$OFF_{i,t}$
8720	Accounting, Auditing, and Bookkeeping Services	2.419	8650	Political Organizations	-2.174
2310	Men's and Boys' Suits, Coats, and Overcoats	2.392	8620	Professional Membership Organizations	-2.213
7250	Shoe Repair Shops and Shoeshine Parlors	2.257	3760	Guided Missiles and Space Vehicles and Parts	-2.254
2320	Men's and Boys' Furnishings, Work Clothing, and Allied Garments	2.141	3660	Communications Equipment	-2.430
2360	Girls', Children's, and Infants' Outerwear	2.120	8730	Research, Development, and Testing Services	-2.438
2330	Women's, Misses', and Juniors' Outerwear	1.921	8630	Labor Unions and Similar Labor Organizations	-2.631
2340	Women's, Misses', Children's, and Infants' Undergarments	1.759	1060	Ferroalloy Ores, Except Vanadium	-2.715
2340	Hats, Caps, and Millinery	1.649	4820	Telegraph Communication	-2.827
3150	Leather Gloves and Mittens	1.543	3810	Aeronautical and Nautical Systems	-3.019
2380	Miscellaneous Apparel and Accessories	1.541	1230	Anthracite Mining	-3.843

Panel B: 2015 - Top and Bottom Ten Industries by Offshorability

NAICS	Industry Title	$OFF_{i,t}$	NAICS	Industry Title	$OFF_{i,t}$
511200	Software Publishers	3.240	237100	Nonscheduled Air Transportation	-1.307
541200	Acccounting, Tax Preparation, Bookkeeping, and Payroll Services	3.150	483200	Utility System Construction	-1.307
519100	Other Information Services	3.057	485500	Inland Water Transportation	-1.336
541500	Compuer Systems Design and Related Services	3.017	481100	Charter Bus Industry	-1.397
523900	Other Financial Activities	2.901	487900	Scenic and Sightseeing Transportation	-1.425
334100	Computer and Peripheral Equipment Manufacturing	2.521	212100	Coal Mining	-1.458
518200	Data Processing, Hosting, and Related Services	2.473	485200	Interurban and Rural Bus Transportation	-1.604
541100	Legal Services	2.470	485100	Urban Transport Sytems	-1.612
524100	Insurance Carriers	2.450	621200	Offices of Dentists	-1.706
511100	Newspaper, Periodical, Book, and Directory Publishers	2.346	621900	Other Ambulatory Health Care Services	-1.948

Table A3: CAPM and Three-Factor Model

Panel A reports unconditional CAPM regression results both for equal-weighted (columns 2-8) and value-weighted (columns 10-16) portfolio returns. Panel B tabulates results for conditional CAPM regressions and Panel C for the Fama and French (1992) three-factor model. Monthly α estimates are expressed in percent. $Offshorability$ is lagged by 18 months. Returns are at a monthly frequency. Standard errors reported in parentheses are adjusted for heteroscedasticity and autocorrelation (Newey-West). R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. The sample covers returns from July 1991 to June 2016.

	Equal-Weighted Returns						Value-Weighted Returns					
	L	2	3	4	H	L-H	L	2	3	4	H	L-H
Panel A: Unconditional CAPM												
Alpha (%)	0.313*	0.160	0.041	-0.335	-0.163	0.476**	0.468***	0.240*	0.049	-0.169	-0.367**	0.835***
	(0.17)	(0.16)	(0.15)	(0.15)	(0.15)	(0.24)	(0.18)	(0.13)	(0.13)	(0.17)	(0.18)	(0.31)
MKT Beta	1.176***	1.151***	1.065***	1.154***	0.955***	0.222***	0.949***	0.920***	0.859***	0.966***	0.993***	-0.044
	(0.07)	(0.07)	(0.05)	(0.05)	(0.05)	(0.09)	(0.07)	(0.06)	(0.04)	(0.07)	(0.07)	(0.13)
R^2 (%)	76.11	76.60	79.93	78.38	71.81	5.95	65.55	75.85	73.98	69.40	69.35	0.45
Panel B: Conditional CAPM												
Avg. Alpha (%)	0.239*	0.107	0.066	-0.233	-0.171	0.411	0.192	0.199	0.100	0.078	-0.215	0.406*
	(0.14)	(0.14)	(0.12)	(0.17)	(0.24)	(0.27)	(0.22)	(0.21)	(0.20)	(0.28)	(0.16)	(0.22)
Avg. MKT Beta	1.297***	1.230***	1.083***	1.215***	0.987***	0.310	1.093***	0.858***	0.774***	0.853*	0.986***	0.107
	(0.38)	(0.31)	(0.32)	(0.34)	(0.31)	(0.28)	(0.44)	(0.30)	(0.28)	(0.50)	(0.39)	(0.28)
Avg. R^2 (%)	76.32	77.91	78.78	73.35	68.93	11.51	71.92	74.24	72.95	71.42	71.27	3.62
Panel C: Fama and French (2015) Three-Factor												
Alpha (%)	0.218*	0.036	-0.042	-0.417***	-0.176	0.394*	0.476***	0.213*	0.029	-0.148	-0.298*	0.775***
	(0.12)	(0.10)	(0.13)	(0.13)	(0.16)	(0.20)	(0.16)	(0.13)	(0.13)	(0.16)	(0.16)	(0.28)
MKT Beta	1.031***	1.043***	1.006***	1.065***	0.906***	0.125	0.877***	0.938***	0.910***	0.952***	1.018***	-0.141
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.08)	(0.08)	(0.06)	(0.04)	(0.07)	(0.07)	(0.13)
SMB Beta	0.617***	0.460***	0.254***	0.380***	0.207*	0.410***	0.301***	-0.072*	-0.212***	0.058	-0.110	0.411***
	(0.04)	(0.09)	(0.08)	(0.10)	(0.11)	(0.10)	(0.07)	(0.04)	(0.06)	(0.06)	(0.10)	(0.15)
HML Beta	0.256***	0.387***	0.270***	0.245***	0.014	0.242**	-0.078	0.113*	0.110**	-0.087	-0.236**	0.158
	(0.06)	(0.06)	(0.06)	(0.08)	(0.08)	(0.11)	(0.10)	(0.06)	(0.05)	(0.11)	(0.10)	(0.19)
R^2	89.08	87.15	84.35	84.34	73.61	20.81	69.13	76.62	77.20	69.63	71.30	5.66

Table A4: Manufacturing vs. Services: Fama & French Three-Factor Model

Panel A (B) reports Fama and French (1992) three-factor model regression results for the sample of manufacturing (services) industries. Results are tabulated both for equal-weighted (columns 2-8) and value-weighted (columns 10-16) portfolio returns. Monthly α estimates are expressed in percent. $Offshorability$ is lagged by 18 months. Returns are at a monthly frequency. Standard errors reported in parentheses are adjusted for heteroscedasticity and autocorrelation (Newey-West). R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. The sample covers returns from July 1991 to June 2016.

	Equal-Weighted Returns						Value-Weighted Returns					
	L	2	3	4	H	L-H	L	2	3	4	H	L-H
Panel A: Manufacturing - Fama and French (2015) Three-Factor												
Alpha (%)	0.255*	0.112	0.234	-0.443***	-0.533***	0.788***	0.681***	0.044	0.331**	-0.237	-0.458***	1.139***
	(0.14)	(0.14)	(0.15)	(0.16)	(0.16)	(0.22)	(0.20)	(0.16)	(0.15)	(0.19)	(0.17)	(0.32)
MKT Beta	1.079***	1.021***	0.927***	1.085***	0.819***	0.259***	0.890***	0.825***	0.656***	1.113***	0.854***	0.036
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.06)	(0.05)	(0.05)	(0.04)	(0.07)	(0.06)	(0.09)
SMB Beta	0.581***	0.404***	0.233**	0.282***	0.265***	0.315***	0.303***	-0.083*	-0.194***	0.064	-0.066	0.369**
	(0.06)	(0.08)	(0.10)	(0.09)	(0.10)	(0.12)	(0.10)	(0.05)	(0.07)	(0.07)	(0.09)	(0.17)
HML Beta	0.309***	0.412***	0.285***	0.320***	0.241***	0.068	-0.189*	0.226***	0.090	-0.076	-0.111	-0.077
	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.11)	(0.11)	(0.07)	(0.06)	(0.10)	(0.12)	(0.22)
R^2 (%)	82.29	80.52	73.57	76.33	67.27	15.60	59.61	64.73	51.64	65.21	59.80	4.25
Panel B: Services - Fama and French (2015) Three-Factor												
Alpha (%)	0.190	-0.012	-0.363***	-0.087	-0.103	0.293	0.316*	-0.067	-0.173	-0.154	-0.022	0.338
	(0.15)	(0.15)	(0.14)	(0.18)	(0.18)	(0.22)	(0.19)	(0.17)	(0.20)	(0.18)	(0.19)	(0.26)
MKT Beta	1.037***	1.009***	1.103***	0.970***	0.798***	0.239***	1.006***	0.964***	1.006***	1.060***	0.798***	0.208***
	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.07)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)
SMB Beta	0.637***	0.586***	0.430***	0.442***	0.124	0.512***	0.248***	-0.018	0.082	-0.004	-0.020	0.268***
	(0.06)	(0.07)	(0.07)	(0.12)	(0.10)	(0.09)	(0.06)	(0.07)	(0.11)	(0.12)	(0.09)	(0.11)
HML Beta	0.144**	0.289***	0.177***	0.093	0.094	0.051	-0.054	0.121*	0.203**	-0.299***	0.113	-0.167
	(0.07)	(0.08)	(0.06)	(0.10)	(0.09)	(0.09)	(0.10)	(0.07)	(0.09)	(0.11)	(0.08)	(0.12)
R^2 (%)	80.27	79.54	83.54	71.49	56.65	22.92	66.21	66.77	62.58	72.73	51.05	9.77

Table A5: **Subsample Analysis - Fixed Quintiles**

The table reports univariate portfolio sorts for manufacturing industries for different time subsamples. Panel A tabulates results for equal-weighted returns and Panel B for value-weighted returns. L-H is an investment strategy that is long the portfolio of firms with low offshorability (L) and short the portfolio of firms with high offshorability (H). The column *MR* reports the p-values of the "monotonic relationship (MR)" test by Patton and Timmermann (2010). Standard errors are adjusted for heteroscedasticity and autocorrelation (Newey-West). Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. The sample includes manufacturing firms and covers the period from July 1991 to June 2016.

Panel A: Equal-weighted Returns

	Offshorability						
	L	2	3	4	H	L-H	MR
1991:07 - 2016:06	1.029***	0.854***	0.892***	0.287	0.173	0.856*	0.058*
	(0.35)	(0.32)	(0.33)	(0.29)	(0.27)	(0.45)	
1991:07 - 1999:12	1.466***	0.830**	0.906*	0.723*	0.462	1.004	0.085*
	(0.51)	(0.38)	(0.47)	(0.42)	(0.41)	(0.65)	
2000:01 - 2009:12	0.556	0.642	0.641	-0.178	-0.015	0.571	0.181
	(0.68)	(0.62)	(0.65)	(0.56)	(0.49)	(0.84)	
2010:01 - 2016:06	1.184**	1.211**	1.260**	0.431	0.085	1.099	0.055*
	(0.57)	(0.56)	(0.54)	(0.48)	(0.50)	(0.75)	
2000:01 - 2008:08	0.601	0.737	0.591	-0.203	0.025	0.576	0.261
	(0.54)	(0.47)	(0.54)	(0.49)	(0.46)	(0.71)	

Panel B: Value-weighted Returns

	Offshorability						
	L	2	3	4	H	L-H	MR
1991:07 - 2016:06	1.105***	0.817***	0.652***	0.452	0.207	0.898**	0.000***
	(0.38)	(0.25)	(0.23)	(0.29)	(0.23)	(0.44)	
1991:07 - 1999:12	2.173***	1.065***	0.793**	0.809**	0.615**	1.557**	0.021**
	(0.65)	(0.41)	(0.40)	(0.39)	(0.30)	(0.71)	
2000:01 - 2009:12	0.235	0.420	0.092	-0.033	-0.128	0.363	0.037**
	(0.70)	(0.45)	(0.38)	(0.58)	(0.47)	(0.85)	
2010:01 - 2016:06	1.047***	1.101***	1.330***	0.730	0.187	0.859*	0.955
	(0.43)	(0.40)	(0.40)	(0.47)	(0.30)	(0.52)	
2000:01 - 2008:08	0.313	0.502	0.077	-0.055	-0.157	0.470	0.018**
	(0.76)	(0.35)	(0.37)	(0.53)	(0.49)	(0.90)	

Table A6: Robustness: Industry Specification

This table reports robustness checks for the panel regression results in the main body of the paper. In particular, the table reports the two main regression specifications (regression specifications 1 and 14 in the main table) for different industry classifications both for manufacturing (Panel A) and services (Panel B). All variables are standardized. Standard errors are clustered at the firm and year level and reported in parentheses. R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. The sample covers stock returns from July 1991 to June 2016.

Panel A: Manufacturing - Alternative Industry Classifications

	Baseline		FF49		SIC1		SIC2		No Ind.	
OFF_{t-1}	-4.64*	-5.73**	-2.60**	-3.79***	-5.68**	-6.77**	-3.72*	-4.29*	-5.61**	-7.46**
	(2.57)	(2.88)	(1.30)	(1.40)	(2.92)	(3.06)	(2.13)	(2.27)	(2.54)	(3.32)
Firm Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Fixed Effects	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr	Yr
Clustered by	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID
N	39,387	25,194	39,387	25,194	39,387	25,194	39,387	25,194	39,387	25,194
R^2	10.26	11.23	12.44	14.07	6.79	8.75	10.16	11.80	6.46	8.10

Panel B: Services - Alternative Industry Classifications

	Baseline		FF49		SIC1		SIC2		No Ind.	
OFF_{t-1}	-1.98*	-0.96	-0.90	-0.25	-1.91	-0.49	-1.34	-0.25	-2.64*	-1.74
	(1.21)	(1.31)	(1.04)	(1.14)	(1.25)	(1.26)	(1.33)	(1.46)	(1.46)	(1.44)
Firm Controls	N	Y	N	Y	N	Y	N	Y	N	Y
Fixed Effects	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind	Yr	Yr
Clustered by	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID	Yr & ID
N	33,824	19,912	33,824	19,912	33,824	19,912	33,824	19,912	33,824	19,912
R^2	8.69	11.51	10.41	13.54	8.44	11.16	10.65	13.72	5.28	7.51

Table A7: Double-Sorts: Offshorability and China's Import Penetration

Panel A reports equal- and value-weighted excess returns conditionally double-sorted on import penetration from China and offshorability. In any given month, stocks are first sorted into three portfolios based on their industry import penetration from China and then into five portfolios based on industry offshorability. Import penetration from China is calculated as in Bernard, Jensen, and Schott (2006). Due to data availability import penetration can only be calculated until 2011. See appendix for more details on the calculation of import penetration. The split into low (1), medium (2) and high (3) import penetration industries is based on import penetration terciles calculated each year. Offshorability is lagged 18 months. Standard errors reported in parentheses are adjusted for heteroscedasticity and autocorrelation (Newey-West). The sample includes manufacturing firms from 1991 to 2011. Panel B tabulates conditional panel regression results identical to the ones in table 9 of the main paper. Low IP (High IP) refers to regressions based on firms that belong to industries with import penetration below (above) the median. For each group, results for regression specifications 1 and 10 are reported. All variables are standardized. Standard errors are clustered at the firm and year level and reported in parentheses. R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%.

Panel A: Return Double Sorts

Equal-weighted Returns

		Offshorability L	2	3	4	H	L-H
Imp Penetration	1	1.010***	0.914***	0.752***	0.445	0.408	0.602
		(0.33)	(0.39)	(0.30)	(0.46)	(0.27)	(0.43)
	2	1.134***	0.896**	0.778**	0.436	0.188	0.945
		(0.41)	(0.45)	(0.37)	(0.39)	(0.44)	(0.60)
	3	1.475***	1.184***	0.975	0.036	-0.135	1.610***
		(0.47)	(0.46)	(0.73)	(0.39)	(0.47)	(0.66)

Value-weighted Returns

		Offshorability L	2	3	4	H	L-H
Imp Penetration	1	0.805***	0.662**	0.621***	0.461	0.581**	0.224
		(0.28)	(0.30)	(0.26)	(0.43)	(0.28)	(0.39)
	2	0.925***	1.111**	0.812***	0.264	-0.168	1.093*
		(0.35)	(0.48)	(0.32)	(0.36)	(0.48)	(0.59)
	3	1.481***	0.875	1.319*	-0.175	0.021	1.460**
		(0.42)	(0.56)	(0.74)	(0.39)	(0.46)	(0.62)

Panel B: Conditional Panel Regressions

	Low IP	Low IP	High IP	High IP
OFF_{t-1}	-1.84	-2.95	-4.77*	-5.82*
	(2.58)	(1.96)	(2.57)	(3.18)
Firm Control	N	Y	N	Y
Fixed Effects	Yr x Ind	Yr x Ind	Yr x Ind	Yr x Ind
Clustered by	Yr & ID	Yr & ID	Yr & ID	Yr & ID
N	18,661	11,476	16,881	11,100
R^2 (%)	10.74	12.55	10.75	12.62

Table A8: Manufacturing - Offshorability and SC Betas

This table replicates the findings of Barrot, Loualiche, and Sauvagnat (2017). Panel A reports mean excess returns and Sharpe ratios for portfolios sorted on shipping costs. The remaining table reports time-series regression results with equal-weighted (Panel B) and value-weighted (Panel C) portfolios returns as dependent variables. The portfolios are sorted on $Offshorability$ which is lagged by 18 months. The long-short shipping costs portfolio (L-H from Panel A), SC, is the only independent variable in all regressions. Returns are at a monthly frequency. Standard errors reported in parentheses are adjusted for heteroscedasticity and autocorrelation (Newey-West). R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. The sample covers returns of manufacturing industries from July 1991 to June 2016.

Panel A: Portfolio Sorts						
	Shipping Cost Portfolios					
	L	2	3	4	H	L-H
Mean Excess Retrun (%)	1.517***	1.209***	1.144***	1.100**	0.878*	0.639**
Sharpe Ratio	0.62	0.58	0.59	0.59	0.57	0.48
Panel B: Equal-Weighted Returns						
	Offshorability					
	L	2	3	4	H	L-H
Alpha (%)	1.009***	0.919***	0.888***	0.327	0.055	0.954***
	(0.35)	(0.32)	(0.29)	(0.34)	(0.28)	(0.23)
SC Beta	0.189***	0.044	0.085	0.091	0.073	0.116
	(0.06)	(0.06)	(0.08)	(0.08)	(0.07)	(0.08)
R^2 (%)	4.22	0.04	0.98	0.79	0.75	3.32
Panel C: Value-Weighted Returns						
	Offshorability					
	L	2	3	4	H	L-H
Alpha (%)	1.047***	0.600**	0.681***	0.295	-0.078	1.125***
	(0.29)	(0.26)	(0.21)	(0.34)	(0.29)	(0.32)
SC Beta	0.317***	0.021	0.085	0.258***	0.185*	0.132
	(0.05)	(0.05)	(0.08)	(0.10)	(0.10)	(0.13)
R^2 (%)	13.58	0.24	1.72	7.35	5.94	2.07

Table A9: Manufacturing - Offshorability and FX Betas

This table reports regression results of two factor models based on the US market excess return and three different currency factors, respectively. I use the currency factor (excess return of high interest rate currencies minus low interest rate currencies) from Lustig, Roussanov, and Verdelhan (2011) in Panel A, the carry factor from Verdelhan (2017) in Panel B and the dollar factor from Verdelhan (2017) in Panel C. Each model is estimated for equal-weighted (columns 2-7) and value-weighted (columns 8-13) portfolio returns. Monthly α estimates are expressed in percent. $Offshorability$ is lagged by 18 months. Returns are at a monthly frequency. Standard errors reported in parentheses are adjusted for heteroscedasticity and autocorrelation (Newey-West). R^2 is adjusted for degrees of freedom. Significance levels are denoted by * = 10%, ** = 5%, and *** = 1%. The sample covers returns of manufacturing industries from July 1991 to June 2016.

	Equal-Weighted Returns						Value-Weighted Returns					
	L	2	3	4	H	L-H	L	2	3	4	H	L-H
Panel A: Currency Factor - Lustig, Roussanov and Verdelhan (2011)												
Alpha (%)	0.406**	0.330*	0.338**	-0.321*	-0.345**	0.751***	0.623***	0.101	0.418***	-0.323*	-0.532***	1.155***
	(0.19)	(0.19)	(0.17)	(0.18)	(0.17)	(0.23)	(0.22)	(0.18)	(0.15)	(0.19)	(0.19)	(0.35)
MKT Beta	1.109***	1.029***	0.907***	1.102***	0.811***	0.298***	0.937***	0.787***	0.612***	1.118***	0.868***	0.070
	(0.07)	(0.07)	(0.05)	(0.06)	(0.04)	(0.07)	(0.06)	(0.05)	(0.05)	(0.08)	(0.08)	(0.12)
FX Beta	0.050	-0.031	0.059	-0.036	-0.031	0.081	0.062	0.000	-0.068	0.088	0.019	0.043
	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)	(0.09)	(0.09)	(0.07)	(0.06)	(0.08)	(0.08)	(0.13)
R^2 (%)	70.63	70.00	68.11	71.72	61.87	11.45	54.56	60.95	47.61	65.12	59.48	0.53
Panel B: Carry Factor - Verdelhan (2017)												
Alpha (%)	0.592***	0.401**	0.427	-0.210	-0.251	0.843***	0.785***	0.140	0.184	-0.182	-0.469*	1.255***
	(0.23)	(0.21)	(0.20)	(0.21)	(0.18)	(0.28)	(0.26)	(0.20)	(0.19)	(0.23)	(0.25)	(0.43)
MKT Beta	1.093***	0.988***	0.868***	1.092***	0.799***	0.294***	0.953***	0.761***	0.593***	1.119***	0.888***	0.064
	(0.07)	(0.07)	(0.05)	(0.07)	(0.04)	(0.07)	(0.07)	(0.06)	(0.05)	(0.09)	(0.09)	(0.13)
Carry Beta	-0.014	0.008	-0.119	0.018	-0.033	0.019	0.017	-0.004	0.068	-0.106	-0.072	0.089
	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.09)	(0.11)	(0.08)	(0.06)	(0.09)	(0.09)	(0.15)
R^2 (%)	68.61	67.67	67.57	71.50	62.02	9.29	51.87	58.07	46.25	63.64	59.09	0.44
Panel C: Dollar Factor - Verdelhan (2017)												
Alpha (%)	0.602***	0.416**	0.386**	-0.200	-0.269	0.871***	0.795***	0.147	0.208	-0.230	-0.501**	1.296***
	(0.22)	(0.21)	(0.20)	(0.21)	(0.18)	(0.27)	(0.26)	(0.21)	(0.18)	(0.23)	(0.24)	(0.42)
MKT Beta	1.059***	0.957***	0.875***	1.082***	0.818***	0.241***	0.941***	0.740***	0.588***	1.152***	0.910***	0.031
	(0.07)	(0.07)	(0.05)	(0.06)	(0.04)	(0.07)	(0.07)	(0.06)	(0.05)	(0.09)	(0.08)	(0.13)
USD Beta	-0.287***	-0.230	-0.129	-0.051	0.098	-0.385***	-0.065	-0.167	0.062	0.099	0.062	-0.127
	(0.11)	(0.15)	(0.09)	(0.12)	(0.11)	(0.13)	(0.16)	(0.10)	(0.10)	(0.12)	(0.11)	(0.21)
R^2 (%)	69.30	68.21	67.40	71.52	62.12	11.85	51.90	58.48	46.14	63.53	59.01	0.41

Table A10: Low-wage Countries

This table lists the low-wage countries. I follow Bernard, Jensen, and Schott (2006) and define a country as low-wage in year t if its per capita GDP is less than 5% of U.S. per capita GDP.

Afghanistan	China	India	Pakistan
Albania	Comoros	Kenya	Rwanda
Angola	Congo	Lao PDR	Samoa
Armenia	Equitorial Guinea	Lesotho	Sao Tome
Azerbaijan	Eritrea	Madagascar	Sierra Leone
Bangladesh	Ethiopia	Malawi	Somalia
Benin	Gambia	Maldives	Sri Lanka
Bhutan	Georgia	Mali	St. Vincent
Burkina Faso	Ghana	Mauritania	Sudan
Burundi	Guinea	Moldova	Togo
Cambodia	Guinea-Bissau	Mozambique	Uganda
Central African Rep	Guyana	Nepal	Vietnam
Chad	Haiti	Niger	Yemen

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