The Offshoring Return Premium

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ABSTRACT

We use 10-K filings to construct novel text-based measures of the extent to which U.S. firms are exposed to three offshore activities: the sale of output, purchase of input, and ownership of producing assets. Our main result is that selling output abroad is associated with higher stock returns, especially when output is sold to more central nations in the real trade network. In contrast, offshore input serves as a hedge. Our findings are consistent with the conclusion that aggregate quantity shocks are the primary source of the return premium we document in the global trade network.

1 Introduction

In recent years, an increasing number of U.S. firms sell their products and services to foreign nations. Yet, we know little about what implications these activities have on U.S. stock returns. This is mainly due to data limitations as it is difficult to measure the existence of these activities and their intensities in each nation. We use text analytics of U.S. firm 10-Ks to measure offshore activities across all nations for all publicly traded U.S. firms in a dynamic fashion by regenerating the network annually. Central to our analysis is that nations have heterogeneous loadings on candidate risks. This allows us to examine possible channels that might drive the premium in expected returns we find.

Our central contribution is new evidence of an offshoring return premium and its probable channels as tested through a dynamic text-based offshoring network. U.S. firms that sell their goods abroad have higher expected returns than firms with purely domestic sales. This return premium is larger when output is particularly sold to foreign nations that have more central locations in the trade network and to nations with high exposures to consumption risk. These results are consistent with a risk-based interpretation. Although we discuss the related literature later in detail, we note briefly here that our findings do not square well with predictions in the earlier literature. For example, results in Lucas (1977) suggest that offshore operations might reduce risk as diversification benefits accrue to firms operating in many nations. More recently, the network theory of Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) reverses this early prediction when nations are interconnected in a network setting.

Our findings support the predictions of this recent network view, as we find that firms offshoring to more central nations in the trade network have higher expected returns. Intuitively, this theory predicts that risks can become amplified when nations are strongly interconnected in a network setting, leading to the prediction that offshoring can be more risky than domestic-only operations. This view also accords well with the text-book or practitioner's view that foreign operations entail more risk and require higher discount rates. A key follow-on question is then: which specific risks are prone to propagate through the network, thus creating the offshoring return premium? We find that our results are stronger for nations that are not only central in the trade network but also more exposed to consumption risk. In contrast, we find that other risks such as exchange rate risk, market risk, political risk, and carry trade strategies cannot explain our results. Overall, our findings suggest that the offshoring return premium is most likely explained by quantity risks such as consumption risk that can become amplified in the international trade network.

The intuition regarding why networks matter is best illustrated using two examples noted in Kireyev and Leonidov (2015), who study how demand shocks propagate to shock-amplifying, absorbing, and blocking nations. The first is a significant slowdown of growth originating in China. Beyond the direct impact on China's trading partners (Hong Kong, Singapore, Malaysia, Mongolia, and the Solomon Islands), the shock propagated further to indirect trading partners including Sweden, Brunei, Qatar, United Arab Emirates, Malta, Dominica, and Slovak Republic. In some affected nations, the relative loss of GDP was even greater than in China itself. In the second example, geopolitical tensions in Ukraine led to significant trade deterioration, which then affected Belarus, Lithuania, Singapore, Hong Kong, Sweden and small oil producers including the Republic of Congo and Libya. A key finding, as in the first example, is that some nations such as Belarus and Lithuania had even greater GDP loss than Ukraine. These examples illustrate that network effects can be substantial and can amplify materially as they propagate.

Our empirical tests are based on the simple idea that when a U.S. firm sells output to a given nation, the firm's sales growth becomes more correlated with economic conditions in that nation. Economic conditions in some nations can be more volatile or highly correlated with worldwide aggregate shocks than others, and hence the risk profiles of U.S. multinationals will depend on where they operate overseas. Examining the offshoring policies of U.S. multinationals, and observing which firms offshore to different sets of nations with heterogeneous risk traits, provides a unique laboratory to examine risk premia. Because U.S. firms sell an economically large fraction of their goods abroad (30% on average in our sample), we expect this approach will have both power and economic relevance.

To identify firm-specific offshoring policies, we examine statements in each firm's 10-K from 1997 to 2013 where firms mention any nation by name alongside a keyword that associates the discussion with the sale of output. In all, we create a complete time-varying network identifying all of the nations to which each publicly traded U.S. firm sells its output. We then separately score each nation based on its economic exposure to candidate risks including consumption risk, market risk, exchange rate risk, political risk, and nation size. This allows us to compute firm-level measures of ex-ante exposure to each candidate risk.

We extend this simple framework to include not only the sale of offshore output, but also offshore input (purchasing key input to production from offshore sources). The central idea is that offshore input from high risk nations can serve as a hedge against aggregate shocks. This hedging relationship is predicted by the production-based equilibrium in Tuzel and Zhang (2017)[1] and empirically supported by results in Hoberg and Moon (2017). Intuitively, buying input in high risk nations is likely to be counter-cyclical as citizens face higher marginal utility in bad times. In such times, employees should be willing to work for lower wages, and also the cost of raw materials needed for input should be lower due to reduced demand. This prediction is most direct when a firm buys input without owning assets in the given nation (we label this form of offshoring "offshore external input") than when a firm does own offshore assets used to produce input (we refer to this activity as "offshore internal input"). This dichotomy arises because the efficacy of the aforementioned hedge might be reduced due to the pro-cyclical value of the assets themselves, offsetting the counter-cyclical benefits noted above. Tuzel and Zhang (2017) in the related context of real estate and Hoberg and Moon (2017) in the international hedging context support this prediction. With this extended hypothesis in mind, we identify all statements in each firm's 10-Ks in which firms mention a nation alongside a keyword identifying offshore input, and in particular, whether the input is internal input or external input.

[1]Tuzel and Zhang (2017) focus on operations in multiple U.S. locations, but the predictions can be generalized in an international setting.

We find broad support for the conclusion that the sale of offshore output is associated with higher excess returns among U.S. equities. Returns attributable to offshore output are economically large, commensurate with or larger than the value premium in our sample. A one standard deviation shift in offshore output is associated with a nearly 3% higher annualized excess return. The risk-adjusted excess return (*alpha*) on a high-minus-low offshore output portfolio is also significantly positive and results in a Sharpe ratio of roughly 0.9 and 0.5 when the portfolio is equally and value weighted, respectively. We also find support for our extended prediction that offshore external input is negatively priced, although this input effect is not as strong as the output effect. These results are consistent with the conclusion that offshore output generates risk exposures, and offshore input can serve as a hedge.

Next, we examine whether offshore output to different counter-party nations generates different return premia. We consider a network analysis that compares the intensity of each nation's trade flows as in the international trade literature.[2] We measure trade network centrality based on bilateral trade intensities (exports and imports) for all pairs of all nations in the world with available data. We find that both the offshoring return premium and the negative premium of offshore input are stronger in more central nations in the network. Finally, our results are also stronger when offshoring involves nations with high consumption risk exposure, whereas other sources of risk cannot explain our results.

Our findings regarding network centrality and quantity risks, along with the above intuitive examples, are consistent with the network theory of risk propagation in Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012). However, we also note the following limitation. Our objective is to empirically document the offshoring return premium and its unique properties related to the trade network and quantity risks. Because we report associations and not direct causal relationships, our findings should be viewed as suggestive. Further research, especially natural experiments or instrumental variable tests, should be fruitful to establish causality.

[2] See for example Anderson and Van Wincoop (2003), Helpman, Melitz, and Rubinstein (2008), and Chaney (2014) among others. Also see Jackson (2008) and Goyal (2012) for an excellent review on networks and centrality in economics.

2 Related Literature

Existing studies provide strong motivation for our focus on network models of risk exposure to offshoring risk. Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) show in their model that when the input-output network is asymmetric, idiosyncratic sectoral shocks do not cancel and instead they can create economy-wide aggregate volatility cascades (aggregate fluctuations). Their model is particularly relevant in our context because it challenges the standard diversification argument in the early literature. In particular, when nations are interconnected in a network setting, risk can propagate and offshoring to more central nations can expose firms to elevated systematic risks.

Ahern (2013) examines the network of supply chain linkages and stock returns among U.S. firms based on the Input-Output tables of the Bureau of Economic Analysis (BEA). Although his setting is domestic and thus distinct from ours, the paper shows that supply chain network centrality is associated with exposure to U.S. market risk and thus a return premium. We document an analogous network-based return premium in the global trade network. Richmond (2016) also examines risk exposures related to the global trade network. However, that study examines currency returns, while our focus is on stock returns. We show that our results are distinct as they cannot be explained by an array of alternative risks including exchange rate risk. Ultimately our findings are complementary to Richmond (2016), as currency returns are most directly related to price risks, whereas we find evidence that distinct quantity risks influence equity returns.

Fillat and Garetto (2015) find that multinational firms have higher stock returns and develop a real options model of the decision to initiate offshoring to explain this finding. Their model examines endogenous selection into becoming an offshoring firm assuming heterogeneous productivity among firms, exogenous disaster risk among nations, and large sunk costs of entry. In their model, firms are reluctant to exit a foreign nation following a negative shock in the nation due to the large fixed and sunk costs of entry. The inflexibility related to entry costs makes offshoring firms more exposed to aggregate risk, which they show empirically is consistent with disaster risk as in Rietz (1988). Our analysis extends this line of inquiry by examining which firm and national characteristics associate with offshoring activities using a unique text-based dynamic network that identifies specific counter-party nations. This granularity also allows us to explore an array of candidate risk-based explanations for our return predictability by sorting counter-party nations based on their risk attributes.

Existing studies that consider quantity risk are also relevant. One key finding is that quantity risk is difficult to diversify using financial derivatives (see Brown and Toft (2002) and Hoberg and Moon (2017)). Hence, it is not surprising that we might observe that heterogeneity in firm exposures to quantity risk are indeed priced in the cross-section of stock returns. Studies that consider common consumption growth shocks that might propagate as aggregate shocks include Lustig and Verdelhan (2007), Lustig, Roussanov, and Verdelhan (2011), and Richmond (2016). Richmond (2016) considers a general equilibrium model where countries that are central in the global trade network have consumption growth that is more exposed to global consumption shocks. These studies primarily focus on currency returns, whereas our study uniquely considers corporate equity returns using a novel dynamic text-based offshore network. We furthermore control for currency risk and the carry-trade based risk factors introduced by these existing studies and find that our results are distinct.

Studies of international price risk are also relevant to our study. International finance theories predict that currency and exchange rate risk might be priced (Solnik (1974), Solnik (1977), Stulz (1981), Adler and Dumas (1983), and Dumas and Solnik (1995)).[3] We consider controls for each stock's exposure to the exchange rate risk of 40 large nations using the approach indicated in the model of Dumas and Solnik (1995). We do not find any evidence that our results can be explained by price risk including exchange rate risk.

[3]In a study of four global markets, Dumas and Solnik (1995) find evidence supporting this hypothesis. Jorion (1990), Amihud (1994), and Bartov and Bodnar (1994) do not find a link between exchange rate risk and U.S. multinational stock returns, and Vassalou (2000) finds that exchange rate risk is priced in some markets but can be positive or negative. Perold and Schulman (1988) further argue that hedging activities can reduce exchange rate risk at little cost, potentially eliminating any observable exchange rate risk premium. More recently, Brusa, Ramadorai, and Verdelhan (2015) use an international equity and currency factor model and find that investors are compensated for bearing currency risk when investing in foreign local stock markets.

We also consider stock market risk and other risks such as political risk and nation size. Our consideration of stock market risk relates in part to the theoretical predictions of the Capital Asset Pricing Model (CAPM). Because our framework is international, we also consider political instability risk and nation size. See for example Bailey and Chung (1995) for a discussion on political risk and stock returns, and Bekaert, Harvey, Lundblad, and Siegel (2014) for a link to foreign investment. We find that our results cannot be explained by stock market risk, political risk, or nation size (GDP).

Our study also relates to the trade and corporate finance literatures (see for example Grossman and Rossi-Hansberg (2008) and Moon and Phillips (2013)). Barrot, Loualiche, and Sauvagnat (2016) find that a portfolio of low minus high shipping cost industries carry a return premium that is likely driven by exposure to import competition. Other studies examine U.S. exporters and multinationals through plant-level or aggregate-level data from the Census Bureau and the BEA (see Bernard, Jensen, Redding, and Schott (2007) and Bernard, Jensen, and Schott (2009)). These studies are relevant to understanding offshoring activity, but they do not address our hypotheses. Our paper also adds to a growing literature that considers text-based analysis in financial markets. Early studies include Antweiler and Frank (2004) and Tetlock (2007). More recent work includes Hanley and Hoberg (2010), Hoberg and Phillips (2016), Loughran and McDonald (2011), and Garcia and Norli (2012). See Sebastiani (2002) for a review of text analytic methods.

3 Data and Variables

We collect and process offshoring data from the SEC's Edgar 10-K filings. We utilize software provided by metaHeuristica LLC for high speed searching of the 10-K filings. We then merge the textual offshoring data with the CRSP/Compustat merged database using the SEC Analytics table for CIK to gvkey links. For monthly stock returns, we use the CRSP database. Our sample period covers from 1997 to 2013, as 1997 is the first year of full electronic coverage of 10-K filings in the SEC Edgar database. We require that each firm has a valid link from its 10-K CIK to the Compustat database and that adequate CRSP and

Compustat data are available to compute the log book to market ratio and the log of firm market capitalization following Davis, Fama, and French (2000). Additionally, we require one year of past monthly stock returns from CRSP in order to compute a momentum control following Jegadeesh and Titman (1993). We discard firms with a missing SIC code, a SIC code in the range of 6000 to 6999 to exclude financial firms, or a SIC code in the range 4900 to 4949 to exclude regulated utilities. We lag all Compustat variables, and all 10-K variables, for at least 6 months following the lag structure in Davis, Fama, and French (2000). Hence, although our 10-K sample begins in 1997, our monthly database used to predict returns begins in July of 1998 and ends in June of 2015. Also, following standard procedure in the literature, our momentum control variable is based on the 11-month window from month $t-12$ to $t-2$. This leaves us with 102,615 firm-year observations and 793,293 firm-month stock return observations.

3.1 Offshoring Data

We first compile a complete list of *nation words* for 236 nations and 25 regions, considering variations that include official and non-official nation names and their adjective forms. Then, we create another extensive list of the nearest neighbor words that coexist with nation words from 10-K filings in the base-year 1997. Nearest neighbor words are those that occur within a 25-word window of any of the nation words. We then manually inspect all roughly 5,000 nearest neighbor words that are mentioned more than 100 times, in order to determine whether the word refers to any of the following offshoring activities: (a) output, (b) external input, and (c) internal input. For example,"Sell", "Sales", "Revenues", "Markets", "Consumers", "Store", "Export", and "Distribute" are regarded as (a) output. "Supplier", "Vendor", "Subcontract", "Import", and "Purchase & From" are regarded as (b) external input. (c) internal input includes "Subsidiary", "Facility", "Plant", "Venture", "Factory", and "Warehouse" for example.[4] We refer to the resulting list of words as *offshore words*

[4]Some input words that are not explicitly identified as either external input or internal input such as "Manufacture" and "Produce" are regarded as (d) indeterminate input, as the subject of the sentence is not clear in these cases.

throughout the paper. In Appendix A, we report the complete list of words for each activity.

The following examples extracted from three different 10-K filings show how the coexistence of nation words and neighboring offshore words determines offshore output, external input, and internal input activities, respectively.

> (a) Output: The NCP system is currently **sold** by a direct **sales** force in **Germany, France, Austria, Switzerland, and the United Kingdom.**
>
> —*Cyberonics Inc., 10-K, 2000*

> (b) External input: The company **purchases** its components **from** a variety of manufacturers, most of which are located in **China, South Korea, Mexico**, and the United States.
>
> —*Allied Digital Technologies Corp, 10-K, 1997*

> (c) Internal input: Wood coatings are manufactured at six U.S. locations, as well as five foreign **facilities** located in **Canada, China, Ireland, Malaysia, and Taiwan**.
>
> —*Lilly Industries Inc., 10-K, 1997*

We then reexamine all 10-K filings in the base-year 1997 and extract all paragraphs that contain words from both lists of nation words and offshore words. Our approach to extract paragraphs instead of sentences intends to reduce false negatives. This choice is due to the fact that many firms discuss their offshoring activities over several sentences, and hence just one sentence often misses related nation words and offshore words as required. Our paragraph approach may generate false positives. To address this issue, we set a maximum distance between nation words and offshore words at 25 words, and drop hits when the two words are more than 25 words apart even if they are in the same paragraph.[5]

We then estimate success rates based on whether each hit correctly identifies one of the offshoring activities, using ten separate random samples of 1% of all observations in our 1997 database of hits. Manual validation reveals that our success rate ranges from 75% to 90%. As an additional quality check, we additionally examine paragraphs that contain nation words but no offshore words, and confirm that nearest neighbor words associated with nation words in these cases are not related to offshoring. For example, such unrelated discussions might

[5] We conclude that the distance of 25 words is robust and quite accurate after manually inspecting alternatives such as 5, 15, 30 or 50 words.

mention neighboring words such as “University”, “Patent”, “Carry-forwards”, “Airlines” and “Court”.

Our final step is to run our final queries based on nation words and offshore words for all 10K filings from 1997 to 2013. This generates a full panel of offshoring data with the raw counts of how many times a given firm mentions each of the offshoring activities in each nation. Our final sample has 102,615 firm-year observations, and 65,755 firm-years have at least one offshoring activity mentioned. We discuss details regarding these offshoring statistics in the next section.

3.2 Offshoring Variables

In our asset pricing tests, we consider the following three variables: *Offshore Output*, *Abnormal Offshore Input*, and *Abnormal Offshore External Input.* First, we construct Offshore Output by taking the natural log of one plus the raw count of how many times a firm mentions offshoring output words.[6] This variable is zero if a firm has no such mentions. Second, in each year, we regress the natural log of one plus the raw count of input words (Offshore Input) on the aforementioned Offshore Output variable and define the residual as Abnormal Offshore Input. We take this additional step to reduce the correlation between measured output and input, as more than 80% of offshoring firms in our sample do both output and input in the same nation. This normalization is based on the fact that many firms localize input operations when they sell output in a foreign nation. Third, following a similar procedure, we regress the log of one plus the raw count of external input words (Offshore External Input) on both Offshore Output and Offshore Input, and we define the residual from this regression as Abnormal Offshore External Input. We use the above stepwise regression procedure to ensure that any findings are not driven by multicollinearity concerns. After the stepwise procedure, all offshoring variables by construction are uncorrelated, and this approach thus allows us to assess the impact of all offshoring activities by the given firms.

[6] We note that our results are very similar if we instead use the number of mentions divided by the number of words in the document. We also note that all of our results are robust to including a control for document length.

We further note following motivations as to why we order the stepwise decomposition as output, input, and then external input. The first two motivations are from our own empirical evidence. First, our data consists of a total of 649,257 firm-nation-year offshoring observations. Of these, 516,691 entail offshoring output (80%), 417,810 entail offshoring input (64%), and 78,152 entail offshoring external input (12%).[7] This confirms that offshoring output is indeed the most dominant offshoring activity in our data. Second, assessment of our aggregated asset pricing tests later in Section 5 illustrates that our results are in fact not sensitive to the use of the stepwise residuals. In unreported tests, regardless of whether we use the raw values of our three offshoring variables or the stepwise residual values described here, our results change little. In both cases, offshore output is strongly priced with 1% significance, and offshore input is not priced.

4 Summary of Offshoring Input and Output

4.1 Descriptive Statistics

In this section, we present descriptive figures and statistics to summarize our key offshoring variables.

[Insert Figure 1 Here]

Figure 1 presents U.S. firm offshoring activities both in time series and across offshoring activity types. The figure shows that, overall in our sample from 1997 to 2013, roughly 60 to 70% of U.S. firms participate in offshoring activities, and they do so in 7 to 9 different countries on average. Overall offshore activity slightly decreases over our sample period. Although U.S. firms do more offshore output (roughly 95% of firms among the offshoring firms) than they do offshore input (90% of firms on average), the offshore input activities are increasing over time. This increasing trend is especially pronounced for offshore external input (when input is obtained from a foreign source without ownership of assets). However, offshore internal input is overall one and a half times as common as offshore external input.

[7]We have 65,755 firm-year observations with offshoring activity, and the mean and median number of counter-party nations in the sample are 8.14 and 6, respectively. See Section 4 for more details on these statistics.

The number of offshoring nations also steadily increases over time for both offshore output and input activities. This indicates that U.S. firms globally expanded their operations geographically, and both in terms of selling output and in terms of securing input.

[Insert Figure 2 Here]

Figure 2 shows the international breadth of these offshoring activities. The figure displays maps of the counter-party nations for offshoring (a) output, (b) input, (c) internal input, and (d) external input activities during the sample period from 1997 to 2013. The shading indicates the offshoring intensity with darker shades for greater intensity. We construct an intensity measure for each offshoring activity using the number of textual mentions of the activity in the given nation adjusted for the total number of U.S. firms.[8] In figure (a), we observe that U.S. firms' outputs were primarily sold to Canada and China over the sample period. In unreported results, we note that at the beginning of our sample period, outputs were primarily sold to Canada, England, and Japan. Those activities significantly expanded to the Southeast Asian region with a focus on China toward the end of the sample period.

Figure (b) shows that locations for offshore total input are more spread out over the world as compared to output locations. Figures (c) and (d) take a closer look at offshore input operations. The external input figure shows that U.S. firms significantly rely on sources in Southeast Asia to obtain external input. This is likely because they purchase inputs that are labor intensive from these sources. The internal input figure shows that U.S. firms do more internal input operations than external input operations in Canada, Latin America and Europe. These figures thus suggest that U.S. firms own input-producing assets in nations that are relatively close to U.S., whereas they purchase external input (without owning assets) mainly from Asia.[9]

Table 1 presents summary statistics for our offshoring variables in Panel A. 64% of U.S.

[8]For offshore output intensity, we use Offshore Output divided by the total number of firms. For offshore input, we use Abnormal Offshore Input variables, including total, internal and external inputs, divided by the total number of firms. We use these relative measures for input activities because raw offshore output and raw offshore input are correlated, as we discussed in the previous section.

[9]In online appendix Table OA.1, we display lists of the top 10 nations in which U.S. firms offshore their output and input. We provide comparisons between our rankings and the rankings based on the U.S. Census Bureau's historical trade data.

firms do at least one kind of offshoring activity over the sample period. 60% of U.S. firms participate in offshoring output, and most of these offshoring firms (about 89%) actually do both offshore output and offshore input at the same time. 57% of the U.S. firms in our sample participate in offshoring input.[10] Among these, 47% and 88% entail offshore external and internal input, respectively.

[Insert Table 1 Here]

The table also presents summary statistics for our three variables for analysis: *Offshore Output*, *Abnormal Offshore Input*, and *Abnormal Offshore External Input*, which are used in our asset pricing tests. We also report a variable (Offshore) based on raw counts of all offshoring words. The mean and median number of nations or regions where U.S. firms offshore is eight and six, respectively. The number of offshore output nations is slightly greater than the number of the offshore input nations. The number of offshore external input nations is smaller and is equal to one on average. The number of offshore internal input nations is four.

Panels B and C summarize the financial characteristics and asset pricing control variables associated with the firms in our sample, respectively. These control variables include firm size, the book-to-market ratio and the past 11-month return.

4.2 Firm and Nation Characteristics for Offshoring Activities

In this section, we examine potential determinants of offshore activities both at the firm and nation levels. This analysis can help in understanding how observable characteristics are related to the decision to offshore. To do so, we run regressions of our offshoring variables including *Offshore Output*, *Abnormal Offshore Input*, *Abnormal Offshore Internal Input*, and *Abnormal Offshore External Input* on firm and nation characteristics separately.

[Insert Table 2 Here]

Panel A of Table 2 displays the regression results for firm characteristics. The sample consists of all firms with any type of offshore activity for the period from 1997 to 2013 that

[10]this includes indeterminate input, which cannot be easily coded as internal input or external input.

have non-missing firm characteristics variables. All regressions include year and industry fixed effects using 3-digit SIC codes. All characteristics variables are lagged one year.

We find a positive relation between our overall offshoring variable and firm size in columns (1) to (3), indicating that larger firms are more likely to participate in offshoring. This relationship is reversed for abnormal offshore external input in column (4), indicating that smaller firms tend to purchase more input from foreign nations without owning assets in those nations. We also note that profitability-related measures such as Tobin's Q and operating margin are positively related to offshore external input, while these variables are negatively related to other types of offshore activities.

We expect that offshoring activities are associated with lower fixed asset ratios, as such firms are more likely to use outside supply or production contracts or operating leases in foreign nations. Results in column (1) and (4) support this prediction as we find negative links between offshoring variables and book leverage, PPE/Assets, and CAPX/Sales. It is worth noting that offshore input and abnormal internal input in columns (2) and (3) show opposite relations for these ratios. This is likely because offshoring firms that own input-producing assets in offshore nations should have higher fixed asset ratios. This suggests that these firms own non-trivial assets abroad, which are also potentially exposed to foreign risks, as suggested by our extended hypothesis regarding internal vs. external inputs.

Also, offshoring firms overall have lower R&D, indicating that their businesses are more capital-intensive than R&D-intensive. We also consider variables related to intangible capital as in Eisfeldt and Papanikolaou (2013). Firms with offshore output are more likely to have skilled labor given the positive coefficient for Organization Capital, whereas firms with offshore input are less likely to use skilled labor. As previously noted, firms that use abnormal offshore external input have lower capital to labor ratios, because that type of offshore activity is more likely to involve labor outsourcing through outside supply or production contracts.

Panel B examines counter-party nation characteristics and offshoring decisions. The sample consists of nation-year observations from 1997 to 2013 that have non-missing national characteristics data from the World Bank. Offshore output is more prevalent in nations with greater GDP and lower tariffs. GNP per capita (*i.e.,* lower price of labor) is an important determinant for offshore external input, while the geographical distance between the U.S. and the given nation is important for offshore internal input decisions. It is also worth noting that nation governance, measured by rule of law, is positively related to offshore internal input decisions.[11] We conclude that the results in Panel B are intuitive and further serve to validate our measures of offshoring activity.

In our online appendix Table OA.2, we further validate the information content in our offshoring data. We predict that firms with more offshore output in a given nation will experience greater stock return comovement with the nation's economic conditions. This for example could relate to exchange rate changes or foreign stock market index returns. We examine both, and the results strongly validate our dynamic firm-nation-year offshoring network.

5 Offshoring and Stock Returns

5.1 Cross-sectional Stock Returns

We next examine the extent to which foreign country exposures are related to ex-post stock returns. If foreign operations on average provide diversification that can reduce domestic risks, we would expect offshoring output to generate a negative premium in the cross section of stock returns. In contrast, if overseas output on average is riskier than domestic output, we would expect a positive premium in the cross section of stock returns for overseas output. Moreover, if offshore input is a hedge to this risk (see the model in Tuzel and Zhang (2017) for example), we would also expect offshore input, especially external input, to be associated with a negative risk premium.[12]

[11] In unreported results, we consider all available nation governance measures including political stability, corruption control, rule of law, media accountability, government effectiveness, and regulatory quality. However, these variables are correlated with coefficients ranging from 70 to 90%, and hence we only include one of these variables in our regression analysis. Our results are qualitatively similar if we use any of these variables.

[12] See Harvey (2001) for a detailed discussion on domestic versus international costs of capital.

We test these competing arguments using Fama-MacBeth regressions based on stock return data from July 1998 to June 2015. The dependent variable is the excess monthly stock return. As right-hand-side variables, we consider our three offshoring variables: Offshore Output, Abnormal Offshore Input, and Abnormal Offshore External Input. We also include a standard slate of control variables from Fama and French (1992) and Jegadeesh and Titman (1993): the natural log of the book to market ratio, the natural log of firm market capitalization, and the past 11-month stock return from month $t-12$ to month $t-2$.[13] We follow the lagging convention identified in Fama and French (1992) not only to compute the book to market ratio and firm size, but also to compute our own 10-K based variables. In particular, to predict returns for an interval July of year t to June of year $t+1$, we consider 10-K data on offshoring activities measured from the fiscal year that ended in calendar year $t-1$. This ensures that all data used to predict ex-post returns is at least six months lagged and thus there is no look-ahead bias.

[**Insert Table 3 Here**]

The results of this test are presented in Table 3. We standardize all right-hand-side variables to have a standard deviation of one prior to running the regression, which allows all coefficients to be interpreted as the economic impact of a one standard deviation shift in the given variable on the ex-post stock return. Rows (1) to (3) in Panel A of Table 3 show that offshore output is a strong positive predictor of ex-post monthly excess stock returns. Regardless of whether measures of offshoring input or external input are included, this result is significant at the 1% level with a t-statistic of 4.24. The coefficient magnitude of 0.241 indicates that a one standard deviation increase in offshoring output textual mentions implies a 2.892% ($= 12*0.241$) higher annualized stock return. This figure is roughly as large as the value premium in the same period (coefficient of 0.222), although it is smaller than the small firm premium in this sample (coefficient of -0.363). These results are consistent with an interpretation that overseas sales entail additional risks to offshoring firms and the

[13] We also include a dummy indicating when the book to market ratio is negative, and in these cases we then set the log book to market ratio to be zero. We also include a control for document length in all of our asset pricing regressions. We do not display the negative book to market dummy or the document size control to conserve space.

standard diversification argument may not empirically apply to offshoring activities.[14]

Next, we examine whether these results are driven primarily by small-cap stocks. In rows (4) and (5) of Panel A, we exclude small-cap stocks, and both small- and medium-cap stocks from our sample, respectively. We continue to find that offshore output strongly predicts ex-post stock returns at the 1% significance level and one standard deviation generates a 2.004% ($= 12 * 0.167$) higher annualized stock return even within the large-cap stocks.[15] Our strong results for larger firms are also consistent with our findings in Table 2 regarding the characteristics of offshoring firms.

In Panels B and C, we examine the offshoring premium separately for developed and developing nations.[16] We find that the offshoring premium is robust and statistically significant in both subsamples. The coefficients are larger in Panel B for developed nations (0.223) versus Panel C for developing nations (0.083). This supports the intuition that potential underlying risks are likely higher in more developed nations, which motivates our tests later regarding global trade centrality. More developed nations contribute more to potential aggregate worldwide shocks, as their local shocks are more correlated with aggregate shocks.

5.2 Foreign vs Domestic: Trade Network Centrality

Why should stocks with foreign output exposures earn higher return premia than those only exposed to domestic markets? According to the early-literature's diversification argument, foreign activities diversify the total risks that U.S. investors face. Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) challenge this diversification argument and show that

[14] We also note that, consistent with theoretical predictions, offshoring intensity has impact over and above a simple dummy indicating whether a firm engages in offshoring activity or not. Although we do not report the results to conserve space, our main results are robust to additionally including dummy variables indicating whether a firm engages in each type of offshoring activity or not in these regressions. In particular, in such specifications, the dummy variable is not significant and the existing intensity based variables remain little changed. We also note that our results are additionally robust to including a control for profitability (operating income/sales), and hence our results are not due to the fact that offshoring firms tend to be more profitable.

[15] We further illustrate this result by double-sorting our sample by offshore output and market capitalization variables, and examining calendar time average portfolio returns. Results are available in online appendix Table OA.3 and the results further support our conclusion.

[16] We obtain developing versus developed nation status as of 1996 from the World Bank.

sectoral shocks (*e.g.,* U.S. systematic risks) can generate volatility cascades throughout a network and can create even larger shocks in more central sectors of the network. We thus first examine whether foreign nations that are more central than U.S. in the world trade network indeed have greater aggregate shocks.

We separately score each nation based on its trade network centrality. This captures the degree of concentration (or importance) of a given nation in the network of global bilateral trade flows, and therefore can proxy the level of risk that a given nation bears in the global network. Many recent studies use network centrality as a measure of risk exposure of a given entity in a network (*e.g.,* Ahern (2013) and Richmond (2016) among others). We use eigenvector centrality with both directed and undirected bilateral trades to measure the degree of aggregate risk for each nation. Our bilateral trade data come from the National Bureau of Economic Research (NBER) and the United Nations (UN) International Trade Data.[17]

For each year, we then run a cross-sectional regression of each nation's directed or undirected trade with each other nation on the two nations' log GDP and/or their log distance from each other. We take the residuals of this regression and use them as adjacency edge weights (value-weights) for bilateral trade pairs. This approach is based on the gravity model of international trade and generates each nation's time-varying centrality adjusted for the size of the nation and/or geographical distance to each counter-party nation. We consider both directed and undirected networks. The directed networks use imports and exports separately, and the undirected network uses the average of imports and exports, as the dependent variable in the gravity regression.[18]

[Insert Figure 3 Here]

Figure 3 displays distributions of our trade network centrality measures using (a) directed and (b) undirected trade data, respectively. Below each figure, we present summary statistics

[17]See Feenstra, Lipsey, Deng, Ma, and Mo (2005) for the detailed description about the NBER-UN trade data for 1962-2000. The data are available at http://cid.econ.ucdavis.edu/nberus.html.

[18]For robustness, we also consider geometric means of imports and exports instead of arithmetic means in the undirected network. We also consider a regression that excludes the geographical distance between a pair of nations. Our results are robust to these variations.

for the eigenvector centrality in the complete trade network in 1997 across all nations in our sample that have available NBER-UN trade data. From the figures and statistics, we find that our global centrality measures have a bimodal distribution and are skewed negatively. The kurtosis of the distributions is also high. In Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012), the asymmetric nature of a network is the key feature that makes idiosyncratic sectoral shocks difficult to diversify as they do not cancel out. We confirm that the global trade network thus has a high degree of asymmetry as is required for network-transmission of aggregate shocks.

In our list of most to least central nations in 1997 (adjusted for the nation size), we note that U.S. is not at the top of the list. Ahead of the U.S. are a number of nations in Europe (*e.g.,* Belgium and Netherlands) and a few nations in Southeast Asia (*e.g.,* South Korea and China). This suggests that selling output to these more central nations can entail greater risks than U.S. only operations.[19]

To examine our predictions regarding centrality risk and expected returns, we run Fama-MacBeth regressions using the same sample and controls as in Table 3, but we separately tabulate offshore activities over nations with high, low and medium centrality measures. In particular, we consider the following monthly Fama-MacBeth regression (we omit the time subscript for parsimony):

$$R_i \; = \; a + b \; Output_{i,high} + c \; Output_{i,medium} + d \; Output_{i,low} + e \; X_i + \epsilon_i \qquad (1)$$

The dependent variable is firm i's monthly return, and the vector X_i is the standard set of controls. $Output_{i,high}$ is the natural logarithm of one plus the number times firm i mentions offshoring output words specifically to nations that are in the highest tercile of trade network centrality. $Output_{i,medium}$ and $Output_{i,low}$ are analogous tabulations of offshore output to medium and low centrality nations. These regressions thus echo our baseline model in Table 3, except that we replace the total offshore output with the three subcomponents relating to nations in different centrality groups. We analogously divide the offshore input and offshore

[19]We list the top 50 central nations in the world trade network for 1997 in online appendix Table OA.4.

external input into three parts based on the same centrality groups. Our central prediction is that investors should earn a higher offshoring premium when they hold stocks specifically having high offshore output exposure to more central nations, as such nations are more likely to be exposed to aggregate shocks.

[**Insert Table 4 Here**]

Table 4 presents the results. Panels A and B are different due to their use of directed vs. undirected trade data, and excluding vs. including a geographical distance control, respectively. Results in both panels are qualitatively similar, and thus the following discussions apply to both panels. Row (1) displays a specification that only includes the three offshore output variables from high, medium, and low centrality nations. The table shows that offshoring output to high centrality nations entails a significant premium. Offshoring output to medium and low centrality nations entails no premium. The high centrality offshore output coefficient is statistically different both from zero, and also from the low centrality offshore output coefficient. It also remains significant in rows (2) and (3) as the additional variables are added. This indicates that offshoring in itself does not necessarily generate a significant risk premium. Rather, offshoring to nations that are more central is critical.

In row (4), motivated by the model in Dumas and Solnik (1995), we consider additionally controlling for the exchange rate risks of 40 large nations that pass basic data screens.[20] We separately compute and include in our regression each asset's exposure to exchange rate changes to control for exchange rate risk. We hypothesize that if our results can be explained by exchange rate risk, then controls for the firm-specific exchange rate exposures will subsume our offshoring variables. Row (4) shows that although including the additional 40 right-hand-side variables in the regression reduces explanatory power some, our main result that offshore output to high centrality nations entails a risk premium remains statistically significant at the 5% level. We thus conclude that exchange rate exposures cannot explain our findings

[20]We start with the universe of nations having valid World Bank data identifying their GDP in 1996. Among all nations that adopted the Euro, we only include Germany in order to avoid collinearity of exposures. We also exclude nations that pegged their currency strictly to the dollar including Ecuador and Argentina. We then sort the remaining nations by 1996 GDP and retain only the fifty largest. Finally, we additionally require that Datastream has adequate monthly exchange rate data starting in 1997, which leaves us with 40 nations for which we can estimate exchange rate exposures in our Panel.

regarding global risk exposures through trade network centrality. We note that this test, which includes 40 control variables and thus reduces available degrees of freedom, imposes a high bar.

Overall, we find strong support for the prediction that the global trade network is important in understanding systematic risk as shown in the model of Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012). This indeed challenges the standard diversification argument in the early international trade literature and provides a basis for understanding why foreign operations can be risker than pure domestic operations.

Row (4) shows that offshore input is negatively priced for high centrality nations. This result supports the second key prediction of our study: the purchase of input from high risk nations can serve as a hedge to global risk, and thus demands a negative risk premium. However, we also find a significant negative risk premium for the overall offshore input variable that does not distinguish between external and internal input. Therefore, we draw a conclusion that offshore input in high risk nations either in the form of internal or external input can serve as a hedge.

6 Potential Risk-Based Explanations

In this section, we examine specific types of risk that might explain the offshoring return premium. In particular, we consider consumption risk, stock market risk, political risk, and GDP (nation size). In all tests, we use the same tercile-based approach as in Table 4, except that we separately tabulate offshore activities for low, medium, and high risk nations based on each risk metric.

6.1 Consumption Risk

We first consider consumption risk, which relates to international consumption risk sharing (for example, Lewis (1996) and Lewis and Liu (2015)). Our broader prediction is that U.S. investors will require higher risk premia when they hold equities of firms that have greater offshore output exposures to high consumption risk nations compared to low consumption risk nations. We define a nation as a high consumption risk nation when its consumption growth comoves more with worldwide or U.S. consumption growth. To score each nation with respect to consumption risk, we compute the covariance between a given nation's consumption growth and global or U.S. consumption growth using yearly observations from 1960 to 1995.[21] We use real consumption data for each nation in 2005 U.S. dollars recognizing that the marginal investor of a U.S. traded stock lives in the United States and consumes in real terms using U.S. dollars. Each nation's consumption growth is the logarithmic growth of this time series for each nation.[22]

For each nation, we thus regress its consumption growth in time series on our aggregate measure of global consumption growth using yearly observations from 1960 to 1995 to obtain each nation's overall global consumption exposure. We compute global consumption growth as the GDP weighted average consumption growth across all nations as in Sarkissian (2003). We analogously regress each nation's consumption growth on U.S. consumption growth to obtain each nation's U.S. consumption exposure. We then sort nations into terciles based on their exposure to global or U.S. consumption growth, and define the highest covariance tercile as the high risk nations, the middle tercile as the medium risk nations, and the lowest tercile as the low risk nations. As in Table 4 for trade network centrality, we use the regression specification in equation (1), except this time the high, medium, and low groups are based on the consumption risk terciles.

[**Insert Table 5 Here**]

The results for global consumption risk are displayed in Panel A of Table 5. Row (1) shows that only offshoring output to high consumption risk nations entails a significant risk

[21] The consumption data used are available from the World Bank website at http://data.worldbank.org/indicator/NE.CON.PRVT.KD

[22] Our approach, which focuses on a U.S. investor as the marginal investor, may differ from the existing literature. Many prior studies, which do not focus on the U.S. investor as the marginal investor, compute consumption growth based on real per capita consumption in each nation's local currency (without any conversion to dollars). See Breeden, Gibbons, and Litzenberger (1989), Epstein and Zin (1989), and Yogo (2006) among others for details. As our data entails predicting the stock returns of U.S. assets, which are primarily owned by U.S. investors who consume in dollars, we focus on real consumption growth in U.S. dollars as this better matches the inputs to the utility function of the marginal investor in our sample.

premium. The high risk nation offshore output coefficient is also significantly different from the low risk coefficient at the 5% level. In rows (2) and (3), after additional variables related to offshore input are added, the result remains significant. This result is consistent with our hypothesis that the offshoring return premium is likely related to quantity risk and not price risk. Underscoring this conclusion, in row (4) we additionally control for the exchange rate risks of 40 large nations. Our result that only offshore output to high consumption risk nations entails a risk premium remains statistically significant at the 1% level after including the additional exchange rate controls. Because exchange rate controls account for price risk, we thus conclude that exchange rate exposures and price risk likely cannot explain our findings.

In Panel B of Table 5, we consider analogous tests for U.S. consumption risk. Theoretically, if markets are segmented across nations, then U.S. consumption risk should matter more for our sample of U.S. traded assets. In contrast, if markets are not segmented, then global consumption risk should matter more. We view this as an empirical question, especially given the significant effects for the global trade network. As was the case for global consumption risk, rows (1) to (4) of Panel B show that offshore output to high risk nations entails a significant risk premium for U.S. consumption risk.

Row (4) of Panel B also shows that both offshore internal and external input are negatively priced in high U.S. consumption risk nations, different from the insignificant results in Panel A for global consumption risk. This result is consistent with the previous results for trade network centrality and support for the conclusion that offshore input in high risk nations either in the form of internal or external input can serve as a hedge.

6.2 Stock Market Risk and Other Risk

We also consider stock market risk. In particular, Ahern (2013) shows that the U.S. vertical industry network centrality is strongly related to exposure to U.S. market risk. Moreover, consumption risk, which we consider in the previous section, might be correlated with stock market risk. We therefore consider stock market risk as a potential candidate by examining the covariance between each nation's stock market returns and either worldwide stock market returns or U.S. stock market returns. We use Datastream nation-by-nation stock market index return data and compute the global stock market index returns as the market capitalization weighted average stock returns of the indices of all nations in the Datastream sample. The five year window from 1992 to 1996 is used to compute these covariances using monthly stock index returns.[23] As in Table 4 for trade network centrality, we use the regression specification in equation (1), except this time the high, medium, and low groups are based on market risk terciles.

[Insert Table 6 Here]

The results for both Panel A (global stock market risk) and Panel B (U.S. stock market risk) of Table 6 do not support for the conclusion that stock market risk can explain our results. In particular, in both panels we do not observe a monotonic pattern of high expected stock returns for firms that offshore to high risk nations compared to middle or low risk nations. In fact, in both panels, offshoring output to middle risk nations is associated with the highest expected return. We also observe that offshore external input demands a negative risk premium in the middle risk nations. We thus conclude that our offshoring premium is likely more related to consumption risk than it is to stock market risk. We also note that this test is quite discriminating as nation-by-nation consumption risk and stock market risk exposures are just 9% correlated, allowing us to separate their effects.

We consider analogous tests for political instability risk and GDP in online appendix Table OA.5 and find that our results are not explained by either political risk or GDP. In a final test, we also examine if our results can be explained by nations that simply had high stock returns in our sample period. In order for this to be the case, we would expect that nation-by-nation consumption covariances would be strongly positively correlated with the nation-by-nation stock returns in our ex-post sample. We note that this is not the case, as these quantities are in fact -22% correlated.

[23] The availability of stock market index data reduces our sample of nations to just 51 instead of the 130 for which we have consumption data. However, this likely has little impact on power due to the fact that the 51 nations that are covered have the lion's share of offshoring activities.

In conclusion, we explored potential candidates of aggregate risk identified in the literature: global and U.S. consumption risk, stock market risk, political risk, GDP, and possible abnormal nation stock returns during the sample period. Overall, we find that our results are only consistent with a consumption risk explanation. This supports our hypothesis that the offshoring return premium is likely driven by quantity risk exposures and not price risk exposures. This finding is also consistent with our trade network centrality interpretation, as shocks to consumption should specifically interact with this network.

7 Calendar Time Portfolios

Previous results are based on cross-sectional Fama-MacBeth regressions and show that consumption risk through the global trade network mechanism best explains our findings. In this section, we examine robustness of our results to calendar time portfolio tests.

In particular, we construct calendar time zero-investment portfolios investing long in high offshore output firms and short in low or zero offshore output firms. We consider both equal and value weighted portfolios. We form these zero-cost portfolios using the optimized method of Fama (1976), Hoberg and Welch (2009), and Back, Kapadia, and Ostdiek (2015). These studies show that the time series of Fama-MacBeth regression coefficients are tradable portfolio returns that have unique properties making them ideally suited for testing more sophisticated trading strategies where strict controls are needed. We thus start by running Fama-MacBeth monthly return regressions based on the models in Table 3, and we extract the time series of coefficients on the offshore output variable. As indicated in the above studies, these coefficients are the monthly returns of a calendar time portfolio that loads one standard deviation long on offshore output, and that has exactly zero exposure to size, book to market, momentum, document size, and the other two offshoring variables.[24] We also construct analogous portfolios using offshore output to high, medium, and low tercile centrality nations as discussed earlier.

[24] As the above studies note, such a portfolio is not feasible to construct using sort-based methods, particularly given the number of controls we include.

We then regress the time-series returns of this zero-cost portfolio on the three Fama-French factors plus the momentum factor.[25] In unreported results, we also consider a model that additionally includes the currency related risk factors as in Lustig, Roussanov, and Verdelhan (2011) and Lustig, Roussanov, and Verdelhan (2014).[26] Our results are robust to including the currency related risk factors, further illustrating that our results are likely due to quantity risk and not price risk.

[Insert Table 7 Here]

Table 7 presents the results of these calendar time regressions. In Panel A, we use the models in Table 3 to create a calendar time portfolio that only loads one standard deviation long on offshore output with all other control variables held to zero. In Panels B and C, we extract the coefficients of offshoring output for high, medium, and low centrality nations using the models in Table 4 based on directed and undirected trades, respectively. We thus create calendar time portfolios with one standard deviation higher offshoring output to high centrality nations, etc., with all controls held to zero.

We first find in rows (1) and (2) that the risk-adjusted excess return (alpha) on the high-minus-low offshore output portfolio is positive and statistically significant at the 1% level. The intercept is 20.6 basis points for equally-weighted portfolios, which translates into a 2.5% annualized return. The intercept for value-weighted portfolios is slightly smaller as 12.9 basis points (a 1.5% annualized return) but significant at the 1% level as well. We further examine whether our results are driven by small-cap stocks by excluding small and both small and medium cap stocks in rows (3) and (4), respectively. Results remain strong with the 1% significance after the exclusion of small-cap stocks from our sample.

We find in rows (5) to (7) for directed centrality, or rows (13) to (15) for undirected centrality, that equally-weighted portfolios have alphas that are positive and statistically significant only for the most risky portfolios. The intercepts of the most minus the least (henceforth "most-least") centrality portfolios in rows (8) and (16) imply a roughly 2.0% annualized return. We obtain annualized Sharpe ratios of approximately 0.6 for the equal-

[25]We thank Ken French for providing factor data on his website.

[26]We thank Adrien Verdelhan for providing factor data on his website.

weighted most-least centrality portfolios for both directed and undirected centrality. These figures are substantial and a bit larger than the long run Sharpe ratio of the U.S. stock market.

We find even stronger centrality results for value-weighted portfolios. The alphas for value-weighted most-least centrality portfolios in rows (12) and (20) imply an approximately 2.8% annualized return. The Sharpe ratios for value-weighted portfolios are approximately 0.6. Overall, these results strongly suggest that a portfolio with greater exposure to the nations with greater centrality earns higher risk-adjusted excess returns.

Table 8 presents analogous calendar time portfolio tests for global or U.S. consumption risk. In particular, we extract the coefficients of offshoring output for high, medium, and low consumption risk nations using the models in Table 5.

[Insert Table 8 Here]

We find in rows (5) to (7) for global consumption risk, or rows (13) to (15) for U.S. consumption risk, that equally-weighted portfolios have alphas that are positive and statistically significant only for the most risky portfolios. The intercepts of the most minus the least consumption risk portfolios in rows (8) and (16) imply a 2.5% annualized return. We obtain annualized Sharpe ratios of approximately 0.9 for equal-weighted most-least consumption risk portfolios for both global and U.S. consumption risk. We also find similar results for value-weighted portfolios although moderate in magnitude (the most-least portfolios imply an approximately 1.4% annualized return). Overall, these figures are substantial, and echo our results for trade network centrality. Our results are thus consistent with more central nations being more risky, and that consumption risk likely plays an amplified role in impacting these nations.

We also note that our results are robust in the subsample of larger firms. In particular, we consider a subsample of firms with market capitalizations in the highest tercile in the given month. The coefficient magnitudes are somewhat smaller, but because there is less volatility in this sample, the results maintain their overall significance levels. This finding is particularly consistent with a risk-based explanation as we would predict that globally exposed firms should have higher returns even if they are larger and more easily arbitraged.

[Insert Figure 4 Here]

Finally, to better understand the offshoring return premium in time-series, we plot in Figure 4 the cumulative abnormal returns of our calendar time zero-cost portfolios for the period from 1998 to 2015. For both equally- and value-weighted portfolios in the figure, we observe that the accretions to portfolio returns are remarkably steady over the sample period. Although we find slight aberrations near the financial crisis, even these aberrations are small because zero-cost portfolios are by construction likely insulated from broad market changes. Our previous results show that the offshoring return premium is most likely explained by consumption risk exposure that is amplified for central nations in the global trade network. Therefore, without massive trade or tariff shocks (not observed during the sample period), financial crises having roots other than trade are not found to be necessarily important factors for the offshoring return premium.

8 Conclusions

We use novel text-based measures to examine global offshoring activities, stock returns, and risk exposures of U.S. firms when they participate in offshoring activities around the world. We first analyze the characteristics of firms that participate in offshoring, and the characteristics of the nations that they offshore to. Relevant characteristics include firm size, profitability, fixed asset ratio, R&D, and the capital to labor ratio at the firm level. At the nation level, size, relative price of local labor, geographical distance, tariffs, and rule of law are all relevant characteristics. These findings can inform practitioners and academics alike in understanding how those characteristics are related to decisions to offshore.

Our central finding is the offshoring return premium. U.S. firms selling their output abroad have higher expected returns, and these returns are economically large. A one standard deviation shift in offshore output is associated with 3% higher annual excess returns. This result is significant at the 1% level. This finding is inconsistent with the standard argument in the early literature that international operations diversify a firm's overall risk profile, thus reducing risk. Instead, our results are consistent with recent theory predicting that nation-specific shocks do not diversify, and instead can become amplified when nations are interconnected as is the case for the global trade network. Our results also support the textbook view that offshore projects are riskier and require a higher discount rate. Regarding empirical tests, we further show that the global trade network is key to our results, as firms specifically selling their output to nations with higher trade network centrality experience higher ex-post stock returns.

Our dynamic text-based network of offshoring activities of U.S. firms to all nations around the world provides us with flexibility to test an array of specific risk exposures that might be related to trade network centrality, and also a series of alternative explanations. We examine consumption risk, exchange rate risk, carry trades, stock market risk, political instability and nation size. Consistent with our network centrality hypothesis, we find that only quantity risk related to consumption risk can explain the offshoring return premium, whereas exchange rate risk and the other alternatives cannot explain our results. We conclude that because both trade and consumption are quantity measures of goods, that trade network centrality likely amplifies consumption risk, and nations that score highly on either experience the largest risk premia.

Appendix A Offshore Words

Offshoring output words: SALES, MARKETS, CUSTOMERS, DISTRIBUTION, MARKETING, REVENUES, DISTRIBUTORS, REVENUE, EXPORT, CUSTOMER, DISTRIBUTOR, DEMAND, STORES, CONSUMER, MARKETED, DISTRIBUTE, DISTRIBUTES, DISTRIBUTED, SHIPMENTS, DEALERS, CLIENTS, WHOLESALE, EXPORTS, STORE, MARKETPLACE, CONSUMERS, DEALER, EXPORTED, CLIENT, DISTRIBUTING, DISTRIBUTIONS, DEMANDS, DISTRIBUTORSHIP, EXPORTING, WHOLESALERS, RECEIVABLE, RECEIVABLES.

Offshoring external input words: SUPPLIERS, IMPORT, SUPPLIER, IMPORTS, IMPORTED, IMPORTATION, VENDORS, SUBCONTRACTORS, SUBCONTRACTOR, VENDOR, IMPORTING, SUBCONTRACT, PURCHASE & FROM, PURCHASED & FROM, PURCHASES & FROM.

Offshoring internal input words: SUBSIDIARIES, SUBSIDIARY, FACILITIES, FACILITY, VENTURE, PLANT, EXPLORATION, PLANTS, VENTURES, WAREHOUSE, STORAGE, FACTORY, SUBSIDIARIES, WAREHOUSES, WAREHOUSING, FACTORIES.

Offshoring indeterminate input words: MANUFACTURING, PRODUCTION, MANUFACTURED, MANUFACTURE, MANUFACTURES, PRODUCED, PRODUCING, PRODUCE, PRODUCES, PRODUCTIONS.

Appendix B. Variable Descriptions

Size	is the log of market value of total assets (market value of common equity plus book value of preferred stock, long-term and short-term debt, and minority interest).
Age	is the log of one plus firm age based on first appearance in Compustat.
Tobin's Q	is market value of assets divided by book value of assets.
Operating Margin	is operating income before depreciation, scaled by sales.
Book Leverage	is the ratio of total debt to the book value of assets.
Dividend Payer	is one if the firm paid dividends in the given year.
Cash/Assets	is cash and short-term investments divided by total assets.
PPE/Assets	is gross property, plant, and equipment divided by total assets in the prior year.
CAPX/Sales	is capital expenditures divided by sales.
R&D/Sales	is research and development expenditures divided by sales.
Organization Capital	is selling, general, and administrative (SG&A) expenses divided by total assets in the prior year, similar to the organization capital measure in Eisfeldt and Papanikolaou (2013).
Capital to Labor	is the log ratio of gross property, plant, and equipment to number of employees.
Log(GDP)	is a given nation's gross domestic product in 1996 available from the World Bank.
Log(GNPpc)	is a given nation's gross national product per capita in 1996 available from the World Bank.
Distance from US	is a given nation's distance from US, computed using the latitude and longitude information of the nation's capital city.
Tariffs	is a given nation's tariff rate, which is the unweighted average of effectively applied rates for all products subject to tariffs calculated for all traded goods. The rates are available from the World Bank website at http://data.worldbank.org/indicator/TM.TAX.MRCH.SM.AR.ZS.
Rule of law	is a measure of perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. The Worldwide Governance Indicators including political stability, corruption control, rule of law, voice/accountability, government effectiveness, and regulatory quality are available from the World Bank website at http://info.worldbank.org/governance/wgi/index.aspx#home.

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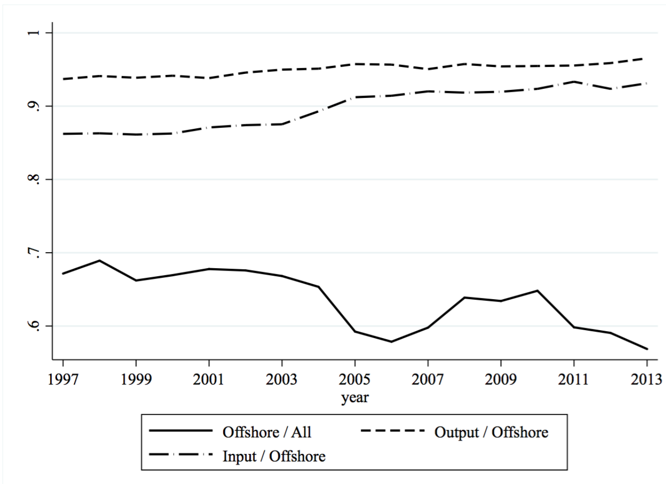
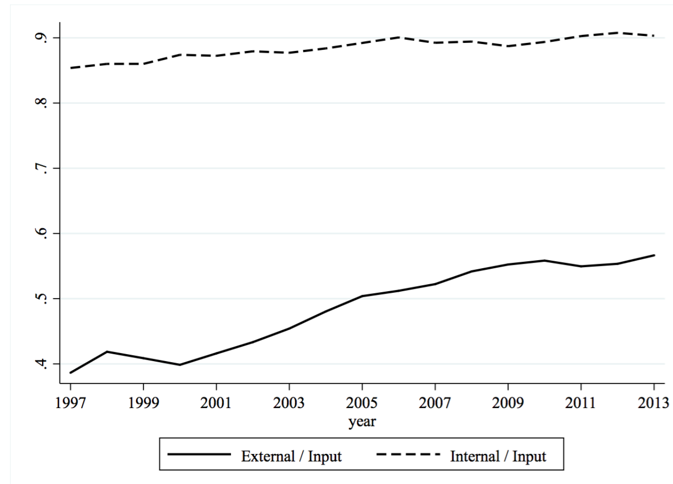
Figure 1: Offshore Activities over Time

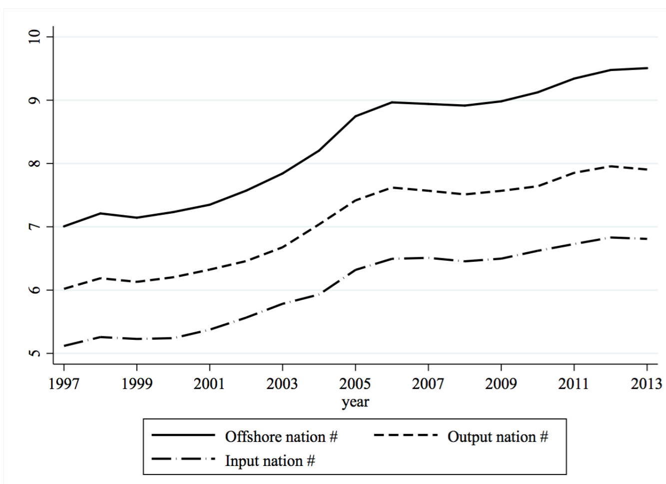
The figures display time-series trends of the U.S. firm offshoring activities. (a) and (b) show the percentage of the firms with each offshore activity among offshore, offshore output, offshore input, offshore external input and offshore internal input in a relevant sample in each year. In (a), the solid line is for the fraction of firms with any type of offshore activity in all firms in each year, and other two lines are for the fractions of firms with offshore output and input activities respectively in offshoring firms in each year. (c) and (b) show the average number of the counter-party nations for each offshore activity in each year.



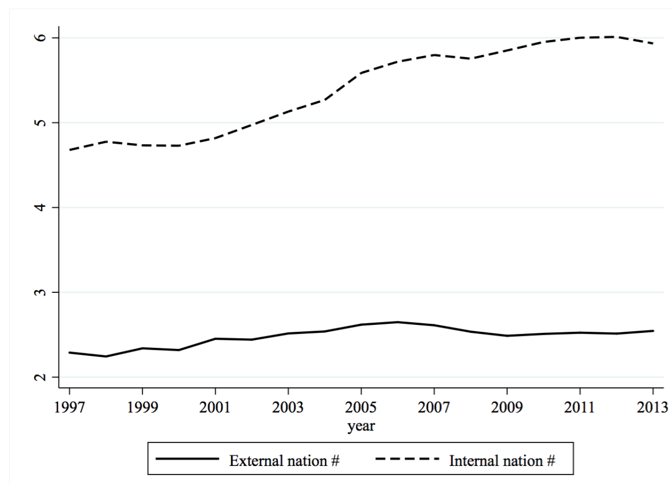
(a) Output offshore vs. Input offshore



(b) External input vs Internal input



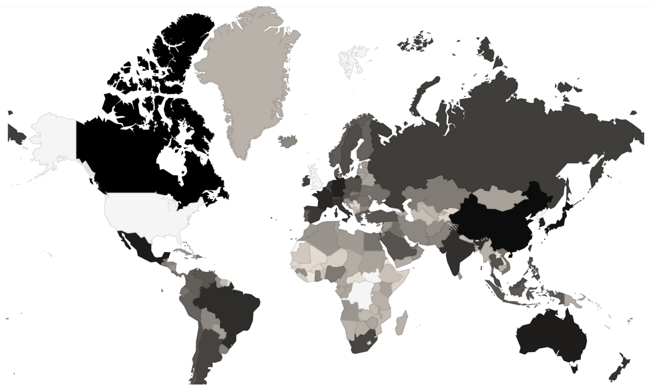
(c) Number of counter-party nations



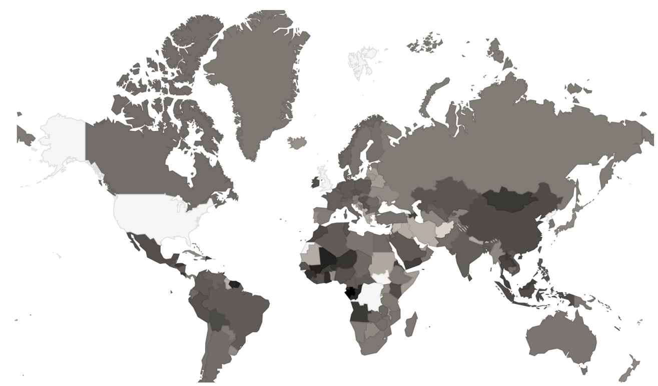
(d) Number of counter-party nations for input

Figure 2: Offshore Output and Input by Nation

The figures display counter-party nations where the U.S. firms in our sample offshore their (a) output, (b) input, (c) internal input, and (d) external input during the sample period from 1997 to 2013. The shading indicates the offshoring intensity with darker shades for greater intensity for each measure. For offshore output intensity, we use Offshore Output divided by the total number of firms. For offshore input intensities, we use Abnormal Offshore Input variables, including total, internal and external inputs, divided by the total number of firms. We use these relative measures for input activities because raw offshore output and raw offshore input are correlated.

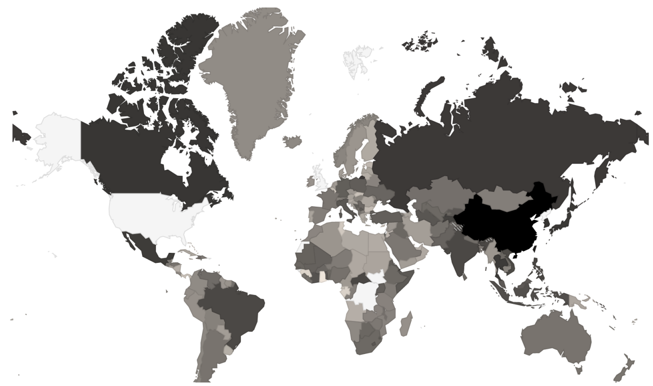


(a) Offshore output intensity



(b) Abnormal input intensity

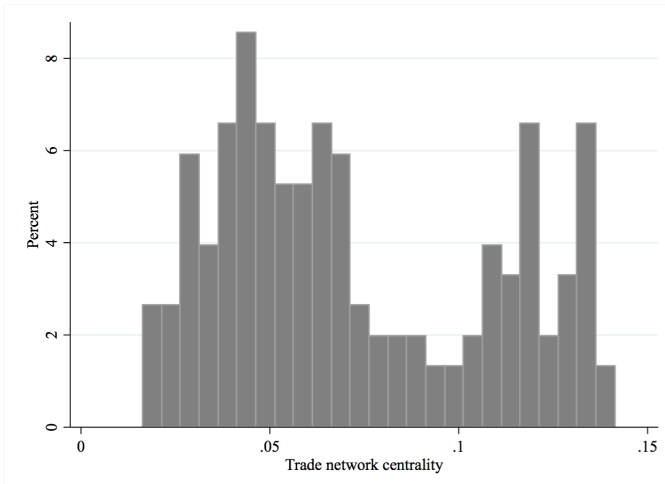
(c) Abnormal internal input intensity



(d) Abnormal external input intensity

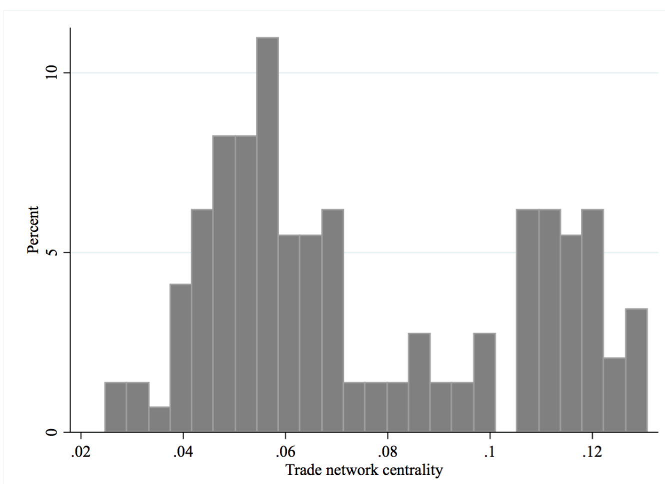
Figure 3: Distribution of Trade Network Centrality

The figures display distributions of our trade network centrality for 164 nations with available NBER-UN trade data in 1997. The trade network centrality is the eigenvector centrality constructed using (a) directed and (b) undirected bilateral trades. For each year, we run a cross-sectional regression of each nation's directed or undirected trade value with another nation on the two nations' log GDPs and/or the log distance, and take the residuals of the regression as the weights for bilateral trade pairs. The directed and undirected trade values are imports and exports separately, and the average of imports and exports, respectively. For this test, we use the centrality estimates for 1997, the year our sample period starts. The summary statistics of centrality across nations are present below each figure.



(a) Centrality from Directed Network

Min	25%	Median	75%	Max	Mean	Std. Dev	Skewness	Kurtosis
0.016	0.044	0.064	0.109	0.141	0.073	0.036	0.399	1.826



(b) Centrality from Undirected Network

Min	25%	Median	75%	Max	Mean	Std. Dev	Skewness	Kurtosis
0.025	0.051	0.066	0.108	0.131	0.076	0.030	0.382	1.685

Figure 4: Cumulative Abnormal Returns of Calendar Time Portfolios

Cumulative abnormal returns of calendar time zero investment portfolios investing long in various high offshore output firms and short in low or zero offshore output firms. The figure plots cumulative monthly returns for portfolios that are equal (EW) or value weighted (VW) as noted in the legend. We form zero-cost portfolios using the optimized method in Fama (1976), Hoberg and Welch (2009), and Back, Kapadia, and Ostdiek (2015). These studies show that Fama-MacBeth regression coefficients are tradable portfolio returns having unique properties making them ideally suited for testing more sophisticated trading strategies where rigorous controls are needed. In our setting, we run Fama-MacBeth monthly returns regressions based on the models in Table 3 and extract the time series of coefficients on the offshore output term. The coefficients on our offshore output variable is a calendar time portfolio that loads one standard deviation long on offshore output, and has exactly zero exposure to size, book to market, momentum, document size, and the other two offshoring variables. These portfolios are scalable and have Sharpe ratios of 1.088 (EW) and 0.696 (VW).

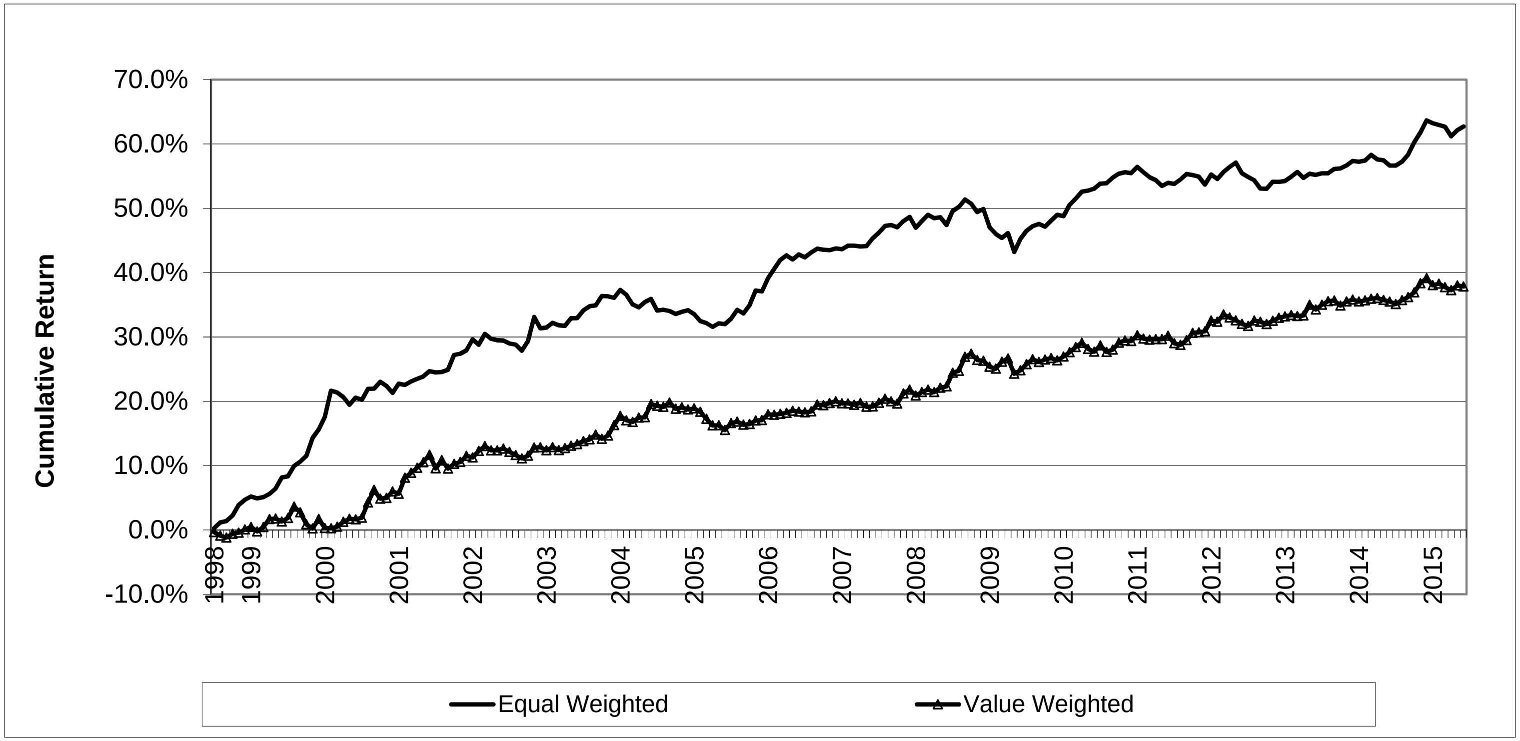


Table 1: Summary Statistics

Summary statistics are reported for our sample of 102,615 annual firm observations from 1997 to 2013. Our sample is all firms with machine readable 10-Ks, and having both Compustat and CRSP data. Offshore 'activity' dummy is one, if the firm discusses its offshore 'activity' with relevant vocabulary in our offshore words list along with nation words. *Offshore* and *Offshore Output* are the natural logs of the raw count (plus one) of offshore and offshore output words, respectively. *Abnormal Offshore Input* is the regression residual of the raw count of offshore input words on the raw count of offshore output words. *Abnormal Offshore External Input* is the regression residual of the raw count of offshore external input words on both the raw counts of offshore output words and offshore input words. The definitions of other financial variables are given in Appendix B. All non-binary variables are winsorized at the top and bottom 1% of the distribution.

Variable	Mean	Std. Dev.	Minimum	Median	Maximum	# Obs.
Panel A: Data on Offshore Activities						
Offshore Dummy	0.641	0.480	0.000	1.000	1.000	102,615
Offshore Output Dummy	0.608	0.488	0.000	1.000	1.000	102,615
Offshore Input Dummy	0.572	0.495	0.000	1.000	1.000	102,615
Offshore Output & Input Dummy	0.539	0.499	0.000	1.000	1.000	102,615
Offshore External Input Dummy	0.271	0.445	0.000	0.000	1.000	102,615
Offshore Internal Input Dummy	0.504	0.500	0.000	1.000	1.000	102,615
Offshore External & Internal Input Dummy	0.237	0.425	0.000	0.000	1.000	102,615
Offshore	2.117	1.901	0.000	2.197	7.039	102,615
Offshore Output	1.749	1.677	0.000	1.609	6.387	102,615
Abnormal Offshore Input	0.000	0.841	-4.000	-0.092	4.552	102,615
Abnormal Offshore Internal Input	0.000	0.435	-3.612	0.081	0.942	102,615
Abnormal Offshore External Input	0.000	0.580	-1.745	0.040	3.275	102,615
# of Offshore Countries	8.141	7.120	1.000	6.000	73.000	65,755
# of Offshore Output Countries	6.569	6.174	0.000	5.000	65.000	65,755
# of Offshore Input Countries	5.294	5.618	0.000	3.000	61.000	65,755
# of Offshore External Input Countries	1.048	1.922	0.000	0.000	30.000	65,755
# of Offshore Internal Input Countries	4.179	5.126	0.000	2.000	55.000	65,755
Panel B: Data on Financial Characteristics						
Log(Size)	6.306	2.162	-0.026	6.210	13.872	73,902
Log(Age)	2.179	0.996	0.000	2.303	3.951	74,048
Tobin Q	2.074	1.693	0.557	1.514	10.889	73,902
Operating Margin	-0.091	0.947	-6.718	0.100	0.671	74,122
Book Leverage	0.219	0.219	0.000	0.173	0.983	73,843
Dividend Payer	0.516	0.500	0.000	1.000	1.000	102,615
Cash/Assets	0.204	0.224	0.000	0.114	1.000	74,119
PPE/Assets	0.505	0.396	0.019	0.396	1.867	73,841
CAPX/Sales	0.126	0.297	0.000	0.040	2.168	63,391
R&D/Sales	0.150	0.531	0.000	0.002	4.137	63,391
Organization Capital	0.307	0.282	0.000	0.238	1.416	63,395
Capital to Labor	-2.416	1.436	-9.190	-2.590	8.535	71,386
Panel C: Data for Asset Pricing Tests						
Monthly Return	0.012	0.205	-0.981	0.000	15.774	793,293
Log B/M Ratio	-7.167	1.841	-15.772	-7.461	2.720	793,293
Log Size	12.626	2.132	2.894	12.604	20.137	793,293
Past 11 Mon. Return	0.141	1.047	-0.999	0.017	436.684	793,293

Table 2: Offshoring and Firm or Nation Characteristics

The table presents the propensity to offshore across offshoring activity types. Panels A and B analyze firm and nation characteristics associated with each offshoring activity, respectively. Panel A is for the sample of 45,797 annual firm observations from 1997 to 2013 that have any type of offshoring activities and non-missing firm characteristics variables. Panel B is for the sample of 2,189 annual nation observations from 1997 to 2013. The dependent variables include four types of offshoring activities: (1) Offshore Output, (2) Abnormal Offshore Input, (3) Abnormal Offshore Internal Input, and (4) Abnormal Offshore External Input. Offshore Output is the natural logs of the raw count (plus one) of offshore output words, respectively. Abnormal Offshore Input is the regression residual of the raw count of offshore input words on the raw count of offshore output words. Abnormal Offshore Internal (External) Input is the regression residual of the raw count of offshore (internal) external input words on both the raw counts of offshore output words and offshore input words. The definitions of other variables are given in Appendix B. All control variables are one year lagged and year fixed effects are included. *t*-statistics (in parentheses) in Panels A and B are robust and adjusted for firm and nation clustering, respectively. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

	Offshore Output (1)	Abnormal Offshore Input (2)	Abnormal Offshore Internal Input (3)	Abnormal Offshore External Input (4)
Panel A: Regressions on Firm Characteristics				
Log(Size)	0.209***	0.0969***	0.0620***	-0.0375***
	(24.94)	(14.30)	(17.21)	(-7.24)
Log(Age)	-0.0210	-0.0123	-0.0169**	-0.0223**
	(-1.36)	(-0.98)	(-2.52)	(-2.20)
Tobin Q	-0.0500***	-0.0462***	-0.0227***	0.00351
	(-6.93)	(-8.04)	(-7.63)	(0.88)
Operating Margin	-0.000585	-0.0297***	-0.00488	0.0115**
	(-0.05)	(-3.17)	(-0.89)	(2.16)
Book Leverage	-0.318***	0.222***	0.0397*	-0.0147
	(-5.40)	(4.82)	(1.71)	(-0.43)
Dividend Payer	-0.122***	-0.0337	0.00778	-0.0232
	(-4.33)	(-1.50)	(0.66)	(-1.28)
Cash/Assets	0.141**	-0.265***	-0.0573**	0.0363
	(2.09)	(-4.79)	(-2.03)	(0.90)
PPE/Assets	-0.164***	0.225***	0.100***	-0.156***
	(-3.05)	(5.09)	(4.54)	(-4.73)
CAPX/Sales	-0.186***	0.0760***	0.0227*	-0.0187
	(-5.51)	(3.06)	(1.76)	(-1.10)
R&D/Sales	-0.0871***	-0.0696***	-0.0579***	-0.0145
	(-4.40)	(-4.37)	(-6.27)	(-1.43)
Organization Capital	0.442***	-0.247***	0.0231	0.0273
	(8.53)	(-6.30)	(1.05)	(0.95)
Capital to Labor	-0.00586	-0.0759***	-0.0530***	0.0463***
	(-0.31)	(-5.19)	(-7.47)	(4.19)
Observations	45,797	45,797	45,797	45,797
Adjusted R^2	0.335	0.254	0.241	0.184
Panel B: Regressions on Nation Characteristics				
Log(GDP)	0.0471***	0.00927	-0.0118***	0.00845***
	(4.69)	(0.68)	(-2.73)	(3.13)
Log(GNPpc)	-0.00554	0.00119	0.00722	-0.0214***
	(-0.23)	(0.03)	(0.83)	(-3.30)
Distance from US	-0.00925	-0.0160	-0.00581**	0.0000513
	(-1.08)	(-1.50)	(-2.03)	(0.03)
Tariffs	-0.00481***	0.00736**	-0.0000591	-0.000857
	(-2.66)	(2.47)	(-0.07)	(-1.46)
Rule of Law	0.0276	0.00772	0.0310***	-0.000754
	(0.88)	(0.17)	(2.62)	(-0.08)
Observations	2,189	2,189	2,189	2,189
Adjusted R^2	0.181	0.019	0.082	0.080

Table 3: Offshore Activities and Stock Returns

Fama-MacBeth regressions with own-firm monthly stock return as the dependent variable. One observation is one firm month from July 1998 to June 2015. The independent variables include three types of offshoring activities: (1) the sale of output in foreign nations (Offshore Output), (2) the procurement of input in foreign nations (Offshore Input), and (3) the extent to which foreign input is bought directly from an external party rather than produced by own-firm foreign assets (Offshore External Input). The latter two measures are constructed in a fashion to reduce their correlation with Offshore Output, and hence we include the word "abnormal" in each variable's label. Panels A, B, and C show results based on constructing the offshoring variables using all nations, only developed nations, and only developing nations, respectively. In Panel A, we report results for the full sample in the first three rows. In row (4), we exclude firms having a CRSP market capitalization in the smallest tercile in the given month. In row (5), we exclude the smallest two terciles and thus we only retain the largest firms (those in the highest size tercile). Nation-by-nation developing versus developed status in Panels B and C is from the World Bank using data as of 1996. We also include controls for the Fama and French (1992) variables (log book to market ratio and log size), a dummy for negative book to market ratio stocks (the dummy is not displayed to conserve space and is not significant), and a control for momentum (defined as the own-firm 11-month lagged return from month $t-12$ to $t-2$). All independent variables are standardized to have a standard deviation of one for ease of comparison and interpretation. Newey West t-statistics (based on 2 lags) are displayed in parentheses.

Row	Nations Used to Construct Offshoring Variables	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Log B/M Ratio	Log Size	Past 11 Mon. Return	Obs. / RSQ
	Panel A: Offshoring based on All Nations							
(1)	Entire Sample	0.241			0.222	-0.363	0.121	793,293
		(4.24)			(1.32)	(-2.05)	(0.73)	0.025
(2)	Entire Sample	0.241	-0.063		0.233	-0.351	0.121	793,293
		(4.24)	(-1.06)		(1.48)	(-2.04)	(0.73)	0.026
(3)	Entire Sample	0.242	-0.061	-0.034	0.234	-0.354	0.121	793,293
		(4.24)	(-1.04)	(-0.95)	(1.49)	(-2.05)	(0.73)	0.026
(4)	Large and Mid Cap	0.224	-0.019	-0.045	0.180	-0.121	0.181	533,591
	Only	(4.10)	(-0.30)	(-1.45)	(1.09)	(-1.01)	(1.00)	0.040
(5)	Large Cap Only	0.167	0.016	-0.042	0.099	-0.101	0.151	266,304
		(3.28)	(0.25)	(-1.44)	(0.62)	(-1.27)	(0.79)	0.059
	Panel B: Offshoring based on Developed Nations Only							
(6)	Developed Countries	0.223			0.205	-0.368	0.119	793,293
		(4.09)			(1.21)	(-2.07)	(0.72)	0.025
(7)	Developed Countries	0.223	-0.018		0.205	-0.365	0.119	793,293
		(4.11)	(-0.41)		(1.26)	(-2.09)	(0.72)	0.025
(8)	Developed Countries	0.224	-0.018	-0.022	0.207	-0.365	0.119	793,293
		(4.12)	(-0.40)	(-0.96)	(1.27)	(-2.09)	(0.72)	0.026
	Panel C: Offshoring based on Developing Nations Only							
(9)	Developing Countries	0.083			0.160	-0.358	0.117	793,293
		(2.05)			(0.92)	(-2.04)	(0.71)	0.024
(10)	Developing Countries	0.083	-0.062		0.166	-0.351	0.117	793,293
		(2.03)	(-1.26)		(0.99)	(-2.03)	(0.71)	0.025
(11)	Developing Countries	0.083	-0.061	-0.013	0.166	-0.353	0.117	793,293
		(2.04)	(-1.23)	(-0.47)	(0.99)	(-2.04)	(0.71)	0.025

Table 4: Offshoring Return Premium and Trade Network Centrality

Fama-MacBeth regressions with own-firm excess monthly stock return as the dependent variable. One observation is one firm month from July 1998 to June 2015. The independent variables include three types of offshoring activities: (1) the sale of output in foreign nations (Offshore Output), (2) the procurement of input in foreign nations (Offshore Input), and (3) the extent to which foreign input is bought directly from an external party rather than produced by own-firm foreign assets (Offshore External Input). The latter two measures are constructed in a fashion to reduce their correlation with Offshore Output, and hence we include the word "abnormal" in each variable's label. To contrast contributions from nations with different degree of concentration in the global trade network, we construct these independent variables separately for the set of nations in the highest, middle, and lowest tercile of trade network centrality. The trade network centrality is the eigenvector centrality constructed using directed (Panel A) and undirected (Panel B) bilateral trades. For each year, we run a cross-sectional regression of each nation's directed or undirected trade value with another nation on the two nations' log GDPs and/or the log distance and take the residuals of the regression as the weights for bilateral trade pairs. The directed and undirected trade values are imports and exports separately, and the average of imports and exports, respectively. We use the centrality estimates for 1997, the start of our sample. We thus include nine variables: three offshoring variables for each tercile as noted in the column headers. The fourth row in each panel indicates that "FX Controls" are included, and we add 40 additional control variables based on exchange rate exposures to each nation's currency using five year rolling return versus exchange rate change regressions. We also include controls for the Fama and French (1992) variables (log book to market ratio and log size), a dummy for negative book to market ratio stocks (not displayed to conserve space), and a control for momentum (defined as the own-firm 11-month lagged return from month $t-12$ to $t-2$). All independent variables are standardized for ease of comparison and interpretation. Newey West t-statistics (based on 2 lags) are displayed in parentheses. Superscripts "a" and "b" in the high centrality nations columns indicate that coefficients are statistically significantly different from the low centrality nations at the 1% and 5% level, respectively.

Panel A: Centrality from Directed Network

		High Centrality Nations			Medium Centrality Nations			Low Centrality Nations							
Row	Nations Used to Construct Offshoring Vars	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Log B/M Ratio	Log Size	Past 11 Mon Return	FX Ctls	Obs. / RSQ
(1)	See Column	0.194^a			0.047			-0.037			0.196	-0.369	0.118	No	793,293
	Headers	(3.44)			(1.08)			(-1.39)			(1.15)	(-2.09)	(0.71)		0.025
(2)	See Column	0.193^a	-0.069		0.052	0.001		-0.040	-0.020		0.206	-0.352	0.117	No	793,293
	Headers	(3.46)	(-1.47)		(1.22)	(0.02)		(-1.49)	(-0.89)		(1.27)	(-2.04)	(0.71)		0.027
(3)	See Column	0.193^a	-0.068	-0.035	0.053	-0.001	-0.001	-0.040	-0.020	-0.015	0.206	-0.356	0.117	No	793,293
	Headers	(3.46)	(-1.46)	(-1.21)	(1.24)	(-0.03)	(-0.03)	(-1.46)	(-0.87)	(-0.77)	(1.28)	(-2.06)	(0.71)		0.028
(4)	See Column	0.137^a	-0.104^b	-0.052	0.058	0.002	0.004	-0.016	-0.007	-0.025	0.042	-0.400	0.018	Yes	696,757
	Headers	(2.55)	(-2.49)	(-1.77)	(1.32)	(0.04)	(0.21)	(-0.54)	(-0.30)	(-1.15)	(0.33)	(-2.46)	(0.11)		0.065

Panel B: Centrality from Undirected Network (with Distance Control)

		High Centrality Nations			Medium Centrality Nations			Low Centrality Nations							
Row	Nations Used to Construct Offshoring Vars	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Log B/M Ratio	Log Size	Past 11 Mon Return	FX Ctls	Obs. / RSQ
(1)	See Column	0.200^a			0.041			-0.041			0.197	-0.370	0.119	No	793,293
	Headers	(3.54)			(0.96)			(-1.51)			(1.16)	(-2.09)	(0.71)		0.025
(2)	See Column	0.199^a	-0.066		0.043	-0.008		-0.040	-0.006		0.206	-0.354	0.117	No	793,293
	Headers	(3.57)	(-1.42)		(1.03)	(-0.25)		(-1.54)	(-0.25)		(1.27)	(-2.06)	(0.71)		0.027
(3)	See Column	0.199^a	-0.064	-0.037	0.043	-0.010	0.002	-0.039	-0.006	-0.014	0.206	-0.358	0.118	No	793,293
	Headers	(3.56)	(-1.40)	(-1.25)	(1.02)	(-0.30)	(0.11)	(-1.44)	(-0.26)	(-0.72)	(1.28)	(-2.07)	(0.71)		0.028
(4)	See Column	0.140^a	-0.103^b	-0.053	0.062	0.004	0.011	-0.021	-0.000	-0.031	0.042	-0.404	0.019	Yes	696,757
	Headers	(2.64)	(-2.45)	(-1.81)	(1.48)	(0.11)	(0.57)	(-0.71)	(-0.01)	(-1.49)	(0.32)	(-2.48)	(0.12)		0.065

Table 5: Offshoring Return Premium and Consumption Risk

Fama-MacBeth regressions with own-firm excess monthly stock return as the dependent variable. One observation is one firm month from July 1998 to June 2015. The independent variables include three types of offshoring activities: (1) the sale of output in foreign nations (Offshore Output), (2) the procurement of input in foreign nations (Offshore Input), and (3) the extent to which foreign input is bought directly from an external party rather than produced by own-firm foreign assets (Offshore External Input). The latter two measures are constructed in a fashion to reduce their correlation with Offshore Output, and hence we include the word "abnormal" in each variable's label. To contrast contributions from nations with different global consumption risk (Panel A) and U.S. consumption risk (Panel B), we construct these independent variables separately for the set of nations in the highest, middle, and lowest tercile of global and U.S. consumption risk, respectively. Global consumption risk is measured using the pre-sample covariance between each nation's total annual consumption growth and worldwide annual consumption growth. U.S. consumption risk is measured analogously using U.S. consumption growth instead of global consumption growth. We thus include nine variables: three offshoring variables for each tercile as noted in the column headers. The fourth row in each panel indicates that "FX Controls" are included, and we add 40 additional control variables based on exchange rate exposures to each nation's currency using five year rolling return versus exchange rate change regressions. We also include controls for the Fama and French (1992) variables (log book to market ratio and log size), a dummy for negative book to market ratio stocks (not displayed to conserve space), and a control for momentum (defined as the own-firm 11-month lagged return from month $t-12$ to $t-2$). All independent variables are standardized to have a standard deviation of one for ease of comparison and interpretation. Newey West t-statistics (based on 2 lags) are displayed in parentheses. Superscripts "a" and "b" in the high risk nations columns indicate that coefficients are statistically significantly different from the low centrality nations at the 1% and 5% level, respectively.

Panel A: Global Consumption Risk

		High Risk Nations			Medium Risk Nations			Low Risk Nations							
Row	Nations Used to Construct Offshoring Vars	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Log B/M Ratio	Log Size	Past 11 Mon Return	FX Ctls	Obs. / RSQ
(1)	See Column	0.207^{a}			0.043			-0.014			0.194	-0.378	0.115	No	793,293
	Headers	(4.23)			(0.63)			(-0.30)			(1.15)	(-2.13)	(0.70)		0.026
(2)	See Column	0.202^{a}	-0.038		0.047	0.017		-0.013	-0.018		0.201	-0.369	0.115	No	793,293
	Headers	(4.24)	(-0.93)		(0.68)	(0.57)		(-0.29)	(-0.53)		(1.25)	(-2.15)	(0.70)		0.028
(3)	See Column	0.202^{b}	-0.040	-0.016^{b}	0.049	0.021	-0.073	-0.016	-0.021	0.052	0.203	-0.373	0.115	No	793,293
	Headers	(4.25)	(-0.97)	(-0.86)	(0.71)	(0.69)	(-2.14)	(-0.34)	(-0.61)	(2.14)	(1.27)	(-2.16)	(0.70)		0.028
(4)	See Column	0.149^{b}	-0.038	-0.026^{b}	0.031	0.001	-0.087	-0.004	-0.053	0.062	0.045	-0.411	0.018	Yes	696,757
	Headers	(3.42)	(-1.06)	(-1.30)	(0.53)	(0.03)	(-2.67)	(-0.10)	(-1.44)	(2.35)	(0.35)	(-2.53)	(0.11)		0.066

Panel B: U.S. Consumption Risk

		High Risk Nations			Medium Risk Nations			Low Risk Nations							
Row	Nations Used to Construct Offshoring Vars	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Log B/M Ratio	Log Size	Past 11 Mon Return	FX Ctls	Obs. / RSQ
(1)	See Column	0.185^{b}			0.072			-0.021			0.196	-0.371	0.119	No	793,293
	Headers	(3.62)			(1.37)			(-0.40)			(1.16)	(-2.09)	(0.72)		0.026
(2)	See Column	0.182^{b}	-0.069^{b}		0.077	-0.003		-0.023	0.022		0.203	-0.363	0.119	No	793,293
	Headers	(3.61)	(-1.63)		(1.45)	(-0.10)		(-0.46)	(0.71)		(1.27)	(-2.11)	(0.73)		0.027
(3)	See Column	0.184^{b}	-0.067^{b}	-0.038^{b}	0.076	-0.003	-0.035	-0.025	0.020	0.032	0.205	-0.366	0.120	No	793,293
	Headers	(3.64)	(-1.59)	(-1.53)	(1.44)	(-0.08)	(-1.56)	(-0.49)	(0.66)	(1.65)	(1.28)	(-2.12)	(0.73)		0.028
(4)	See Column	0.130^{b}	-0.075^{b}	-0.069^{b}	0.068	-0.031	-0.012	-0.022	0.010	0.027	0.044	-0.407	0.021	Yes	696,757
	Headers	(2.99)	(-1.86)	(-2.83)	(1.43)	(-0.90)	(-0.48)	(-0.48)	(0.32)	(1.33)	(0.34)	(-2.50)	(0.13)		0.065

Table 6: Offshoring Return Premium and Stock Market Risk

Fama-MacBeth regressions with own-firm excess monthly stock return as the dependent variable. One observation is one firm month from July 1998 to June 2015. The independent variables include three types of offshoring activities: (1) the sale of output in foreign nations (Offshore Output), (2) the procurement of input in foreign nations (Offshore Input), and (3) the extent to which foreign input is bought directly from an external party rather than produced by own-firm foreign assets (Offshore External Input). The latter two measures are constructed in a fashion to reduce their correlation with Offshore Output, and hence we include the word "abnormal" in each variable's label. To contrast contributions from nations with different global stock market risk (Panel A) or U.S. stock market risk (Panel B), we construct these variables separately for the set of nations in the highest, middle, and lowest tercile of global and U.S. stock market risk, respectively. Global stock market risk is measured using the pre-sample covariance between each nation's monthly stock market returns using its Datastream index and a worldwide stock market return index returns computed as the market capitalization weighted returns over all nations having the Datastream data. U.S. stock market risk is the covariance between each nation's stock market returns and the U.S. stock market returns. We thus include nine variables: three offshoring variables for each tercile as noted in the column headers. We also include controls for the Fama and French (1992) variables (log book to market ratio and log size), a dummy for negative book to market ratio stocks (not displayed to conserve space), and a control for momentum (defined as the own-firm 11-month lagged return from month $t-12$ to $t-2$). All independent variables are standardized to have a standard deviation of one for ease of comparison and interpretation. Newey West t-statistics (based on 2 lags) are displayed in parentheses. Superscripts "a" and "b" in the high risk nations columns indicate that coefficients are statistically significantly different from the low centrality nations at the 1% and 5% level, respectively.

Panel A: Global Stock Market Risk

		High Risk Nations			Medium Risk Nations			Low Risk Nations							
Row	Nations Used to Construct Offshoring Vars	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Log B/M Ratio	Log Size	Past 11 Mon Return	FX Ctls	Obs. / RSQ
(1)	See Column	0.109			0.101			0.036			0.191	-0.377	0.118	No	793,293
	Headers	(1.88)			(2.56)			(1.01)			(1.12)	(-2.11)	(0.71)		0.025
(2)	See Column	0.108	-0.044		0.100	0.013		0.036	-0.014		0.195	-0.374	0.116	No	793,293
	Headers	(1.85)	(-1.04)		(2.55)	(0.34)		(1.02)	(-0.37)		(1.20)	(-2.15)	(0.70)		0.027
(3)	See Column	0.107	-0.042	-0.014	0.102	0.012	-0.038	0.034	-0.016	0.016	0.196	-0.375	0.116	No	793,293
	Headers	(1.85)	(-1.01)	(-0.64)	(2.62)	(0.32)	(-1.88)	(0.96)	(-0.42)	(0.72)	(1.21)	(-2.15)	(0.71)		0.028
(4)	See Column	0.071	-0.063	-0.037[b]	0.068	0.013	-0.043	0.045	-0.039	0.039	0.037	-0.415	0.017	Yes	696,757
	Headers	(1.51)	(-1.50)	(-1.66)	(1.97)	(0.40)	(-2.00)	(1.29)	(-0.99)	(1.62)	(0.28)	(-2.54)	(0.10)		0.065

Panel B: U.S. Stock Market Risk

		High Risk Nations			Medium Risk Nations			Low Risk Nations							
Row	Nations Used to Construct Offshoring Vars	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Offshore Output	Abnormal Offshore Input	Abnormal Offshore External Input	Log B/M Ratio	Log Size	Past 11 Mon Return	FX Ctls	Obs. / RSQ
(1)	See Column	0.069			0.178			-0.010			0.192	-0.373	0.113	No	793,293
	Headers	(1.16)			(1.90)			(-0.38)			(1.14)	(-2.10)	(0.69)		0.026
(2)	See Column	0.065	-0.031		0.178	-0.009		-0.010	-0.017		0.200	-0.364	0.113	No	793,293
	Headers	(1.08)	(-0.72)		(1.90)	(-0.28)		(-0.37)	(-0.45)		(1.26)	(-2.12)	(0.70)		0.028
(3)	See Column	0.065	-0.034	-0.014	0.180	-0.006	-0.047	-0.012	-0.016	0.025	0.202	-0.368	0.114	No	793,293
	Headers	(1.08)	(-0.78)	(-0.78)	(1.92)	(-0.20)	(-1.67)	(-0.44)	(-0.44)	(1.06)	(1.27)	(-2.13)	(0.70)		0.029
(4)	See Column	0.029	-0.042	-0.024[b]	0.164	-0.016	-0.065	-0.015	-0.044	0.045	0.046	-0.409	0.017	No	696,757
	Headers	(0.59)	(-1.13)	(-1.21)	(2.31)	(-0.47)	(-2.30)	(-0.56)	(-1.10)	(1.73)	(0.36)	(-2.52)	(0.10)		0.066

Table 7: Calendar Time Portfolios and Trade Network Centrality

We report OLS coefficients and factor loadings based on calendar time zero investment portfolios investing long in various high offshore output firms and short in low or zero offshore output firms. All reported alphas are expressed as percent monthly returns and portfolios are equal (EW) or value weighted (VW) as noted in the second column. We form zero-cost portfolios using the optimized method in Fama (1976), Hoberg and Welch (2009), and Back, Kapadia, and Ostdiek (2015). These studies show that Fama-MacBeth regression coefficients are tradeable portfolio returns having unique properties making them ideally suited for testing more sophisticated trading strategies where rigorous controls are needed. In our setting in Panel A, we run Fama-MacBeth monthly returns regressions based on the models in Table 3 and extract the time series of coefficients on the offshore output term. These coefficients are the monthly returns of a calendar time portfolio that loads one standard deviation long on offshore output, and has exactly zero exposure to size, book to market, momentum, document size, and the other two offshoring variables. Rows (3) and (4) are based on sorting firms monthly into market cap terciles, and row (3) retains the middle and large tercile whereas row (4) retains only the large cap tercile. In Panels B and C, we consider the Fama-MacBeth models in Table 4, and in particular, focus on the coefficients for high, medium, and low centrality nations. As such we examine whether a firm with one standard deviation higher offshoring output to highly central nations, with all controls held to zero, has a monthly alpha that is different from zero. For each such calendar time portfolio, we regress its calendar time portfolio returns on the Fama-French three factors and display the results below. Newey West t-statistics (based on 2 lags) are displayed in parentheses.

Row	Sample / Horizon	Alpha	MKT	HML	SMB	R^2/Obs.	Sharpe
			Panel A: Full Sample Results				
(1)	Full Sample (EW)	0.206	0.029	-0.017	0.076	0.210/204	1.088
		(3.74)	(1.97)	(-0.78)	(5.16)		
(2)	Full Sample (VW)	0.129	0.022	0.054	0.035	0.080/204	0.696
		(3.15)	(1.76)	(2.93)	(2.12)		
(3)	Large+Mid Caps (EW)	0.180	0.034	0.011	0.086	0.205/204	0.889
		(3.29)	(2.17)	(0.50)	(5.49)		
(4)	Large Caps Only (EW)	0.127	0.039	0.005	0.073	0.172/204	0.607
		(2.60)	(3.12)	(0.25)	(3.87)		
			Panel B: Trade Network Centrality (directed network) Subsamples				
(5)	Most Risky (EW)	0.178	-0.000	0.034	0.027	0.088/204	1.052
		(3.80)	(-0.03)	(2.51)	(2.01)		
(6)	Middle Tercile (EW)	0.021	0.044	-0.085	0.080	0.372/204	0.104
		(0.36)	(3.17)	(-3.89)	(4.39)		
(7)	Least Risky (EW)	0.001	-0.017	0.061	-0.047	0.311/204	0.010
		(0.04)	(-1.69)	(5.74)	(-2.92)		
(8)	Most-Least Risky (EW)	0.177	0.017	-0.027	0.074	0.150/204	0.658
		(2.42)	(0.95)	(-1.30)	(2.73)		
(9)	Most Risky (VW)	0.199	-0.023	-0.013	0.031	0.053/204	0.795
		(3.26)	(-1.28)	(-0.47)	(1.33)		
(10)	Middle Tercile (VW)	-0.045	0.032	0.030	0.031	0.091/204	-0.213
		(-0.92)	(2.42)	(1.43)	(1.58)		
(11)	Least Risky (VW)	-0.047	-0.004	0.087	-0.057	0.220/204	-0.227
		(-0.84)	(-0.22)	(3.62)	(-2.87)		
(12)	Most-Least Risky (VW)	0.246	-0.018	-0.099	0.088	0.111/204	0.614
		(2.45)	(-0.54)	(-2.38)	(2.41)		
			Panel C: Trade Network Centrality (undirected network) Subsamples				
(13)	Most Risky (EW)	0.152	0.023	-0.006	0.056	0.139/204	0.846
		(3.07)	(2.00)	(-0.37)	(4.19)		
(14)	Middle Tercile (EW)	0.055	0.032	-0.066	0.058	0.370/204	0.367
		(1.34)	(2.97)	(-4.10)	(3.49)		
(15)	Least Risky (EW)	-0.005	-0.029	0.082	-0.058	0.451/204	-0.033
		(-0.12)	(-2.87)	(7.52)	(-3.73)		
(16)	Most-Least Risky (EW)	0.156	0.053	-0.088	0.113	0.331/204	0.572
		(2.08)	(2.71)	(-3.85)	(4.36)		
(17)	Most Risky (VW)	0.209	0.003	0.001	0.060	0.061/204	0.829
		(3.46)	(0.13)	(0.04)	(2.77)		
(18)	Middle Tercile (VW)	-0.066	0.030	0.001	-0.001	0.024/204	-0.316
		(-1.38)	(2.35)	(0.04)	(-0.03)		
(19)	Least Risky (VW)	-0.022	-0.028	0.095	-0.057	0.307/204	-0.114
		(-0.42)	(-1.57)	(4.51)	(-3.41)		
(20)	Most-Least Risky (VW)	0.232	0.031	-0.094	0.117	0.173/204	0.590
		(2.31)	(0.88)	(-2.39)	(3.57)		

Table 8: Calendar Time Portfolios and Consumption Risk

We report OLS coefficients and factor loadings based on calendar time zero investment portfolios investing long in various high offshore output firms and short in low or zero offshore output firms. All reported alphas are expressed as percent monthly returns and portfolios are equal (EW) or value weighted (VW) as noted in the second column. We form zero-cost portfolios using the optimized method in Fama (1976), Hoberg and Welch (2009), and Back, Kapadia, and Ostdiek (2015). These studies show that Fama-MacBeth regression coefficients are tradable portfolio returns having unique properties making them ideally suited for testing more sophisticated trading strategies where rigorous controls are needed. In our setting in Panel A, we run Fama-MacBeth monthly return regressions based on the models in Table 3 and extract the time series of coefficients on the offshore output term. These coefficients are the monthly returns of a calendar time portfolio that loads one standard deviation long on offshore output, and has exactly zero exposure to size, book to market, momentum, document size, and the other two offshoring variables. Rows (3) and (4) are based on sorting firms monthly into market cap terciles, and row (3) retains the middle and large tercile whereas row (4) retains only the large cap tercile. In Panels B and C, we consider the Fama-MacBeth models in Table 5, and in particular, focus on the coefficients for high, medium, and low consumption risk nations. As such we examine whether a firm with one standard deviation higher offshoring output to high consumption risk nations, with all controls held to zero, has a monthly alpha that is different from zero. For each such calendar time portfolio, we regress its calendar time portfolio returns on the Fama-French three factors and display the results below. Newey West t-statistics (based on 2 lags) are displayed in parentheses.

Row	Sample / Horizon	Alpha	MKT	HML	SMB	R^2/Obs.	Sharpe
			Panel A: Full Sample Results				
(1)	Full Sample (EW)	0.206	0.029	-0.017	0.076	0.210/204	1.088
		(3.74)	(1.97)	(-0.78)	(5.16)		
(2)	Full Sample (VW)	0.129	0.022	0.054	0.035	0.080/204	0.696
		(3.15)	(1.76)	(2.93)	(2.12)		
(3)	Large+Mid Caps (EW)	0.180	0.034	0.011	0.086	0.205/204	0.889
		(3.29)	(2.17)	(0.50)	(5.49)		
(4)	Large Caps Only (EW)	0.127	0.039	0.005	0.073	0.172/204	0.607
		(2.60)	(3.12)	(0.25)	(3.87)		
			Panel B: Global Consumption Risk Subsamples				
(5)	Most Risky (EW)	0.157	0.031	0.006	0.059	0.133/204	0.821
		(2.84)	(2.38)	(0.31)	(5.05)		
(6)	Middle Tercile (EW)	0.075	-0.023	-0.004	-0.024	0.066/204	0.520
		(1.70)	(-2.32)	(-0.35)	(-2.12)		
(7)	Least Risky (EW)	-0.048	0.003	0.019	0.005	0.016/204	-0.479
		(-1.75)	(0.50)	(2.29)	(0.60)		
(8)	Most-Least Risky (EW)	0.205	0.028	-0.013	0.054	0.099/204	0.936
		(3.51)	(1.78)	(-0.61)	(3.77)		
(9)	Most Risky (VW)	0.115	0.019	0.060	0.008	0.059/204	0.588
		(2.61)	(1.66)	(2.47)	(0.51)		
(10)	Middle Tercile (VW)	0.020	-0.021	0.043	-0.015	0.133/204	0.136
		(0.56)	(-2.10)	(3.78)	(-1.13)		
(11)	Least Risky (VW)	0.002	-0.006	0.003	0.006	-0.013/204	0.020
		(0.10)	(-1.01)	(0.25)	(0.63)		
(12)	Most-Least Risky (VW)	0.113	0.026	0.058	0.002	0.039/204	0.483
		(2.16)	(1.81)	(1.95)	(0.10)		
			Panel B: U.S. Consumption Risk Subsamples				
(13)	Most Risky (EW)	0.164	0.030	0.003	0.059	0.130/204	0.852
		(2.97)	(2.31)	(0.18)	(4.93)		
(14)	Middle Tercile (EW)	0.058	-0.015	0.011	-0.025	0.059/204	0.401
		(1.33)	(-1.64)	(0.96)	(-2.25)		
(15)	Least Risky (EW)	-0.042	-0.003	0.005	0.007	-0.010/204	-0.412
		(-1.57)	(-0.45)	(0.66)	(0.95)		
(16)	Most-Least Risky (EW)	0.205	0.032	-0.002	0.051	0.086/204	0.908
		(3.29)	(1.87)	(-0.08)	(3.59)		
(17)	Most Risky (VW)	0.114	0.014	0.061	0.015	0.055/204	0.578
		(2.49)	(1.20)	(2.48)	(0.95)		
(18)	Middle Tercile (VW)	0.021	-0.020	0.047	-0.024	0.170/204	0.145
		(0.59)	(-1.92)	(3.99)	(-1.79)		
(19)	Least Risky (VW)	-0.003	-0.003	0.003	0.006	-0.016/204	-0.032
		(-0.15)	(-0.43)	(0.29)	(0.69)		
(20)	Most-Least Risky (VW)	0.117	0.017	0.057	0.008	0.028/204	0.487
		(2.17)	(1.09)	(1.88)	(0.42)		