Pricing Dollar Strength Risk

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Abstract

The relative strength of the U.S. dollar does not explain the cross-section of expected returns. We find, however, that signed sensitivity of individual firms' returns to moves in dollar strength matters for asset pricing. A portfolio that goes long high-dollar-sensitivity stocks and short low-dollar-sensitivity stocks earns a multi-factor alpha of 3%-7% per year. Sorting on dollar sensitivity captures firm fundamentals - in particular fraction of revenue from abroad. Dollar sensitivity has implications for profitability and fundamental momentum, as well as the relationship between momentum strategies across countries.

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Comments and suggestions welcome

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1 Introduction

The American economy has experienced an important rise in its trade openness in the last 25 years. Consequently, the fraction of revenue from abroad for U.S. firms has increased significantly as illustrated in Figure 1. Although many US firms' cash flows are exposed to the strength of the US dollar, little has been done to quantify this risk. Well known asset pricing factors such as market, and momentum are based on the performance of U.S. stocks, while factors like size and value are based on characteristics of U.S. firms. By nature, these measures do not sufficiently capture global risk. In this paper, we pursue the sensitivity of U.S. stock returns to international risks embodied in a well-defined measure of change in the U.S. currency strength. Our basic logic is to construct a tradeable factor reflecting changes in the U.S. dollar strength and then provide robust evidence that the factor matters, in the sense that loading on the other well-established factors would not be enough to explain the expected returns of firm's securities.

Insert Figure 1 Here

Attempts to capture global risk through an international version of the CAPM have had mixed results. Theoretical work such as Solnick [1974] are often at odds with the data. Lewis [2011] provides an overview of the differences between theoretical predictions and empirical facts. In our view, global risk which cannot be diversified matters for asset pricing. We propose a new asset pricing factor, based on exposure to the strength of the U.S. dollar, to explain global risk. Our analysis contributes to several strands in the literature.

First, our paper is similar in method and spirit to Frazzini and Pedersen [2014]. Our dollar strength factor is related to betting against beta (BAB), as after sorting into portfolios, we find that firms with negative dollar exposure are on average large exporters with high betas, while firms with positive dollar exposure are small firms with low betas. Excess exposure to domestic risk is a novel explanation for the BAB phenomenon, which to our knowledge, has not yet been proposed in the literature. Our results differ from Fillat and Garretto [2015], who find that exporters and multinationals earn higher average returns than purely domestic firms. One channel they propose is that fixed and variable costs of entering additional markets (operating leverage) makes exporting firms risker, which outweighs the benefit of diversified segments. We contribute to this area by looking at a larger sample of firms, and using a different method to identify international exposure. Further, we expand their sample to more recent years, when the importance of revenue from abroad has increased.

We also contribute to the literature on the US dollar as a reserve currency. Campbell et al. [2015] show "flight to quality" causes the dollar to appreciate when risky assets (i.e. world stock markets) decline in value.[1] Intuition suggests that firms which covary positively with dollar strength would have lower average returns, as they act as insurance against global risk. We find the opposite - stocks with positive exposure to dollar strength have higher average returns than those with negative dollar exposure. For our portfolios, other explanations such as industry, size and importer/exporter effects seem to dominate the safe asset effect.[2]

Our work is related to papers on asymmetric effects of risk factors such as Ang et al. [2006], and its relationship to foreign exchange returns such as Lettau et al. [2014]. We find the effect of dollar exposure depends on whether the dollar is getting stronger or weaker (although we classify these regimes ex-post). These trends are related to the industry composition, and average percent of revenue from abroad within our portfolios over time. As the dollar gets stronger, we get

[1] The authors discuss that this has also become true of the Euro, and it has, to some extent, started displacing the U.S. dollar from its role as the global reserve currency.

[2] Another reason we could be missing the safe asset effect is that exchange rates are hard to predict (see Meese and Rogoff [1983]), and exposure to exchange rates may not be well measured.

intuitive results - industries which are hurt by a strong dollar are sorted into the negative exposure portfolios. As the dollar gets weaker, however, there is not a clear pattern across importers/exporters and industries.

Lastly, our paper contributes to fundamental momentum, as discussed in Novi-Marx [2015]. Similar to the profitability factor, exposure to dollar strength is persistent and related to firm fundamentals, such as the percentage of revenue from abroad, size and market beta. We relate our factor to the return on equity factor of Hou et al. [2014], as well as the critique of Novi-Marx [2015b]. Our explanation is that dollar strength exhibits time series momentum in the spirit of Moskowitz et al. [2011], which contributes to momentum in profitability. In addition, we find our factor has predictive power for the difference between momentum strategies across countries discussed in Asness et al. [2013].

In summary, we present evidence showing that i. Exposure to the strength of the U.S. dollar is a factor which cannot be overlooked in pricing U.S. equities; ii. Revenue from abroad and industry composition of portfolios suggest our factor is not spurious; iii. GRS tests suggest our portfolios can expand the mean variance frontier; iv. Fama-MacBeth regressions reveal a risk premium on par in magnitude and statistical significance with size and value; v. The relationship to fundamental momentum is potentially caused by time series momentum in the dollar, and dollar strength risk is related to differences in performance of momentum strategies across countries.

The paper is organized as follows. In the next section, we present our empirical predictions based on a simple two-country stylized model, our method for identifying dollar strength risk, and the cross-sectional results. Section 3 explores economic explanations for our findings. Section 4 relates our findings to the momentum literature, while Section 5 concludes. An appendix presents further robustness checks of our results.

2 Asset Pricing Results

2.1 Data Sources

We measure U.S. dollar exchange rate using the *Trade Weighted US Dollar Index: Major Currencies* from FRED.[3] A higher value indicates a stronger dollar. Stock data is from CRSP. Treasury-bill rates, the TED spread and all macroeconomic series are also from FRED. Market, size, value and momentum factors, as well as size value, momentum and industry portfolios are from Ken French's data library. The Betting Against Beta (BAB) factor from Frazzini et al. [2014] and the Quality Minus Junk (QMJ) factor from Asness et al. [2014] are from AQR's website. The factors from Hou et al. [2014] were obtained from the authors. The recession indicator is from the NBER.

[3] Description from the Federal Reserve Economic Data website, "A weighted average of the foreign exchange value of the US dollar against a subset of the broad index currencies that circulate widely outside the country of issue. Major currencies index includes the Euro Area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden."

2.2 Including Dollar Returns Directly

An older literature suggested to include the change in the U.S. dollar strength directly as a risk factor like HML or SMB.[4] We follow the approach by considering the return on the dollar strength index in the two-stage technique from Fama and MacBeth [1973]. As commonly done, for test assets, we use the Fama-French 25 portfolios sorted on size and value, the 10 momentum portfolios and the 30 industry portfolios, in line for example with Lewellen et al. [2010]. In the first stage of Fama-MacBeth, to reduce the bias in estimation error, we run in 60-month rolling windows from 1986-2015, with the following factors: Market, Size, Value, Momenum, Betting Against Beta, Quality and Dollar Strength. The second stage is done using the whole sample from 1991-2015. The results are reported in Table 1. The risk premium associated with dollar strength is small, and statistically insignificant which is consistent with the older literature. We see this as a main motive for using a different technique to measure dollar exposure risk. In the next sub-section, we examine a simple model that captures the main hypotheses to be tested.

Insert Table 1 Here

2.3 Model and Hypotheses

We consider a simple two-country complete markets model in the tradition of Lucas [1982]; here countries have the same population size and the consumption good is free of transportation costs and non-storable. We use continuous time in line with the Merton [1973] ICAPM and the model uses elements of Fillat and Garetto [2015], Cochrane et al. [2008] and Brandt et al. [2006]. Foreign

[4] This approach was first suggested by Adler and Dumas [1984] and Bartov and Bodnar [1994].

consumption risk and exchange rate risk generate precautionary demands, which give firms heterogeneous expected returns based on exposures to these risks.

The domestic consumption C_t and foreign consumption C_t^* follow a geometric Brownian motions (GBM)

$$\frac{dC_t}{C_t} = \mu\, dt + \sigma\, dZ_t \tag{1a}$$

$$\frac{dC_t^*}{C_t^*} = \mu^*\, dt + \sigma^*\, dZ_t^* \tag{1b}$$

where $cov(dZ_t, dZ_t^*) = \rho$ and $\{\mu, \sigma, \mu^* \sigma^*\}$ are mean and standard deviations of consumption growth in each country and ρ is the correlation of consumption growth shocks across countries. Hence, domestic and foreign agents differ in their means, variances and stochastic shocks to consumption flows. We assume that the agent in each country has identical discount rate $\beta > 0$ and coefficient of relative risk aversion $\gamma > 0$ ($\gamma = 1$ is logarithmic utility) and utility is

$$U_t = E_t\left[\int_t^{\infty} e^{-\beta(t-s)} \frac{C_s^{1-\gamma}}{1-\gamma}\, ds\right]. \tag{2}$$

With power utility, and perfect home bias (individuals can only invest in domestic firms) the state price densities follow:

$$\frac{dM_t}{M_t} = -r\, dt - \gamma\, \sigma\, dZ_t \tag{3a}$$

$$\frac{dM_t^*}{M_t^*} = -r^*\, dt - \gamma\, \sigma^*\, dZ_t^* \tag{3b}$$

where $\{r, r^*\}$ is the risk-free rate of return in each country.

In a regime of fully flexible exchange rates, the foreign per domestic currency rate, say € per US$, follows the GBM

$$\frac{de_t}{e_t} = \mu^e\, dt + \sigma^e\, dZ_t^e \tag{4}$$

where $cov(dZ_t, dZ_t^e) = \rho_{ed}$, $cov(dZ_t^*, dZ_t^e) = \rho_{ef}$, $\{\mu^e \sigma^e\}$ are mean and standard deviations of exchange rate growth, and $\{\rho_{ed}, \rho_{ef}\}$ are the correlations of consumption growth and exchange rate growth across countries.

A firm in the domestic country can have domestic sales and export abroad (foreign sales). We assume that $\theta \in [0,1]$ denotes the share of business of the firm in the domestic market and $1 - \theta$ the share of business in the foreign market. We also assume that θ is exogenous and fixed. Consider first a domestic firm that sells only in the home market, or $\theta = 1$. The value of this firm, denoted P_t is given by the present value of discounted flow of profits [see for example Kogan and Papanikolaou (2015), Cochrane et al. (2008)]

$$P_t = E_t \left[\int_t^\infty \frac{M_s}{M_t} \pi_s^d ds \right] \tag{5}$$

where π_t^d is the flow of profits of the domestic firm. Since we have complete markets without frictions, a firm's dividend (value) is essentially equal to the consumption of the individual, e.g. Cochrane et al. (2008) and we obtain the capital gain as

$$\frac{dP_t}{P_t} = \mu \, dt + \sigma \, dZ_t. \tag{6a}$$

Using the state price density, upon integration we obtain the dividend-price ratio as:

$$\frac{\pi_t^d}{P_t} = r - \mu + \gamma \, \sigma^2. \tag{6b}$$

The return of a domestic firm that sells domestically only is dividend plus capital gains, hence the excess return is

$$\frac{1}{dt} E_t[dR_t] - r = \gamma \, \sigma^2 \tag{7}$$

where the excess return is proportional to the consumption risk (precautionary demand) weighted by the risk aversion of the agent.

Consider next a domestic firm that sells only abroad, or $\theta = 0$. The value of the firm is discounted using an adjusted stochastic discount factor, $M_t^f = \frac{M_t}{e_t}$, see e.g. Brandt et al. (2006). The value of this firm, denoted P_{ft} is given by the present value of discounted flow of profits from abroad

$$P_{ft} = E_t\left[\int_t^\infty \frac{M_s^f}{M_t^f}\pi_s^f ds\right] \tag{8}$$

where π_t^f is the flow of profits from abroad to the domestic firm. We then obtain the capital gain as

$$\frac{dP_{ft}}{P_{ft}} = \left(\mu^* + \mu^e + \sigma_{ef}\right)dt + \sigma^* \, dZ_t^* + \sigma^e \, dZ_t^e. \tag{9a}$$

Defining $\sigma_{zz*} = \rho\sigma\sigma^*$, $\sigma_{ed} = \rho_{ed}\sigma\sigma^e$ and $\sigma_{ef} = \rho_{ef}\sigma^*\sigma^e$ and using the price density, upon integration we obtain the dividend-price ratio for the foreign firm as

$$\frac{\pi_t^f e_t}{P_{ft}} = r - \mu^* - \mu^e - \sigma_{ef} + \gamma\left(\sigma_{zz*} + \sigma_{ed}\right). \tag{9b}$$

The return of a domestic firm that sells abroad only is dividend plus capital gains, hence the excess return is

$$\frac{1}{dt}E_t\left[dR_{ft}\right] - r = \gamma\left(\sigma_{zz*} + \sigma_{ed}\right). \tag{10}$$

where the precautionary demand in the excess return is proportional to the covariance of domestic and foreign consumption growth plus the covariance of consumption growth and the exchange rate, and the excess return is weighted by the risk aversion of the agent.

Thus, a domestic firm will earn higher excess returns operating in the market according to the condition

$$\sigma^2 \gtreqless \sigma_{zz*} + \sigma_{ed}. \tag{11}$$

If the variance of the growth of domestic consumption is larger (lower) than the covariance of growth of domestic and foreign consumption plus the covariance of the growth of domestic consumption and the change in the exchange rate, then the domestic producer earns an average excess return higher (lower) than the exporting firm. For example, available sample data from FRED for U.S. and U.K. and U.S. and Australia shows that $\sigma^2 > \sigma_{zz*} + \sigma_{ed}$. We conjecture that the domestic U.S. market is relatively large and the variance of its consumption dominates the sum of the covariances. Intuitively, domestic demand in the U.S. is relatively strong and with high domestic excess returns come high domestic variance.

A firm that operates in both markets, or $\theta \in (0,1)$ has value which is a weighted average of the domestic and foreign business with excess return given by

$$\frac{1}{dt} E_t\left[dR_{ft}\right] - r = \gamma \left[\emptyset_t \sigma^2 + (1-\emptyset_t)(\sigma_{zz*} + \sigma_{ed})\right] \qquad (12)$$

where $\emptyset_t \equiv \frac{\theta P_t}{\theta P_t + (1-\theta) P_{ft}}$ is the share of domestic value over total value. The result above of course follows through for $\theta \in [0,1)$, since in the case where $\theta \in (0,1)$ the condition becomes

$$\gamma \left(1 - \emptyset_t\right) \left[\sigma^2 - (\sigma_{zz*} + \sigma_{ed})\right] \gtreqless 0 \qquad (13)$$

which is equivalent to above for $\theta \in [0,1)$.

In summary, our model predicts that i. if $\sigma^2 > \sigma_{zz*} + \sigma_{ed}$ we should expect exporting firms to earn lower excess returns than domestic firms; ii. the difference in expected returns should be proportional to $1-\emptyset_t$, the fraction of revenue from abroad; iii. the magnitude of exposure to exchange rate risk, dZ_t^e , should be informative about share of revenue from abroad, $1-\emptyset_t$. Given that we cannot observe the fraction of revenue from abroad $1-\emptyset_t$, or $1 - \theta$ directly for all firms in CRSP, we develop an instrument based on exposure to exchange rate risk in the next sub-section.

2.4 Identifying Dollar Strength Risk

There are many determinants of the U.S. dollar's strength against other currencies. For example, all else constant, a relative increase in U.S. interest rates makes holding dollars more attractive, thus increasing the demand for dollars and strengthening the currency. However, in reality, there are few purely exogenous increases in interest rates. Policy makers may raise interest rates in response to economic performance, another factor that may eventually contribute to dollar strength.[5]

Ideally, we would like to identify changes in U.S. dollar strength that are orthogonal to changes in interest rates, to prevent our dollar factor from acting as an interest rate factor. With this objective in mind, we propose to measure the sensitivity of stock returns to changes in dollar strength, conditional on changes in the interest rate and credit risk. Hence, we project the change in the dollar strength on stock returns controlling for changes in interest rates and credit risk with the following regression specification

$$r_{i,t} = \alpha_i + \beta_{i,DI} r_{DI,t} + \beta_{i,3M} \Delta_{3M,t} + \beta_{i,TED} \Delta_{TED,t} + \varepsilon i, t \qquad (14)$$

where $r_{i,t}$ is the return on stock i in month t, $r_{DI,t}$ is the percent change in the dollar strength index in month t, $\Delta_{3M,t}$ is the change in the 3-month Treasury bill rate, and $\Delta_{TED,t}$ is the change in the TED spread. We then measure stock returns' dollar exposure as the signed t-Statistic on the coefficient $\beta_{i,DI}$.[6] While the coefficient itself measures the slope of the stock return function given changes in the percent change of the dollar index, we identify the stock returns dollar exposure with the signed t-Statistic. In turn, the higher the t-Statistic (in absolute value) the more significant the exposure of the stock returns to the dollar. The positive (negative) sign for the t-Statistic indicates a

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[5] For more on determinants of dollar strength, see Campbell et al. [2010].

[6] We estimate Equation 14 using simple OLS. We also tried using White's robust standard errors, as well as Newey-West HAC standard errors and the results are not sensitive to these alternatives.

positive (negative) impact on a company stock return which provides potential information on whether the firm is ultimately sensitive to demand from foreign sources.

We proceed using the signed t-Statistic to construct a tradeable factor that can be appropriately priced.

2.5 Constructing a Tradeable Factor

We start with data for the entire CRSP universe and restrict to ordinary common shares (share codes 10 and 11), traded on major exchanges (NYSE, NASDAQ and AMEX). Portfolios are formed once a year in July, as in Fama and French [1993].[7] In addition, we follow Jagannathan and Wang [1996] and allow the sensitivity to dollar exposure to vary over time: Each July (time t) we run Equation 14 using data from $t-1$ to $t-60$. We require 48 non-missing monthly returns during the calibration period.[8] To be included in a portfolio at time t, the firm needs a non-missing market capitalization at $t-1$, as portfolios are value-weighted. Note also here that we basically follow the general procedure in Hou et al. [2017] and control for factors that they deem important as well.

We proceed with sorts in two basic alternative ways. First, at the end of each $t-1$, we sort into 6 portfolios following the procedure in Fama and French [1993]. These portfolios are the intersection of two portfolios formed on size, and three portfolios formed on the t-statistic on $\beta_{i,DI}$. The breakpoints are calculated using NYSE firms, but the portfolios include all NYSE, AMEX and Nasdaq firms that meet the filters described above. Sorting on $\beta_{i,DI}$ itself gives weaker results, as sorting on the t-statistics filters out some of the noise inherent in coefficients estimated with at most

[7] Rebalancing monthly instead of annually yields similar results.

[8] Reducing the required observations to 36 does not meaningfully change the results. The results are also robust to using daily data instead of monthly data to calculate the t-Statistics.

60 observations. Second, we sort into 10 portfolios based only on the signed t-statistic for $\beta_{i,DI}$, following momentum papers such as Jegadeesh and Titman [1993]. In addition, in the appendix we provide another alternative for portfolios sorted on sensitivity to individual currencies, as opposed to aggregate dollar strength. There is no look-ahead bias in our portfolio construction, as all data used to form portfolios is available as of month $t - 1$. Our results are improved by adding an interaction term between $r_{DI,t}$ and the NBER recession indicator, but this is not produced in real time, so we omit it to avoid the look-ahead bias.

Our sample length is limited by data availability, as the monthly TED spread is only available in FRED starting in January, 1986. Given our 5-year calibration period, this implies that our first portfolio returns are not available until January, 1991. Removing the TED spread would yield a longer sample, but in unreported results, we find that including the TED spread is important for identifying sensitivity to dollar strength controlling for changes in interest rates.[9] On average, the slope coefficient on the TED spread, $\beta_{i,TED}$ is positive from the end of 2008 to the end of 2013, and negative the rest of the sample. Regardless of data availability, focusing on 1990 onward is reasonable, given the increased importance over the past 20 years of revenue from abroad for U.S. firms.

Finally, we construct an HML style dollar strength factor in two alternative ways: i. The 2×3 factor denominated HML2×3 is constructed following [30]: (1/2)(Small High + Big High) - (1/2) (Small Low + Big Low); ii. The momentum factor denominated HML$10 - 1$ is constructed following Jegadeesh and Titman [1993] as Top Decile - Bottom Decile.

[9] In addition, the TED spread picks of a lot of the variation captured by the NBER recession indicator, without introducing a look-ahead bias.

In the next sub-section, we provide evidence of the relationship between our measure of exposure to change in dollar strength, i.e. the t-Statistic on the coefficient $\beta_{i,DI}$ and the share of revenue from abroad since we expect that the magnitude of and sign of exposure to exchange rate risk should be informative about share of revenue from abroad. This is important because it gives us a sense of the validity of our exposure measure as an instrument for sensitivity of a firm's return to revenue from abroad. Then, we provide summary statistics of the two tradeable factors obtained and their relationship to our model's hypothesis.

2.6 Summary Statistics and Model Hypotheses

First, Table 2 presents evidence for the hypothesis that the magnitude of exposure to exchange rate risk should be informative about share of revenue from abroad. Given that percent of revenue from abroad is only available for Compustat firms, we want to make sure that sorting on sensitivity to U.S. dollar is a valid proxy. There is a monotonic relationship between portfolio and percent of revenue from abroad for the firms we can match in Compustat in our sample. This confirms intuition that firms with a large fraction of revenue from abroad are negatively impacted by a strong dollar, that is a negative and significant t-Stat on $\beta_{i,DI}$. Intuitively, as their goods become relatively more expensive for foreign buyers they tend to be negatively impacted by changes in dollar strength.

Insert Table 2 Here

Having confirmed the validity of our instrument, we proceed with the two factor specifications. Table 3 shows summary statistics for the 2x3 sort. For both small and large firms, returns are monotonically increasing across the t-Stat dimension. This is evidence in favor of our model prediction that exporting firms tend to earn lower excess returns than domestic firms. For both small and large firms, market betas and average size are decreasing across the t-Stat dimension. The HML factor has an average annualized return of 2.23% per year over our 1991-2015 sample. This is similar in magnitude to well-established factors, such as SMB and HML, with average annualized returns of 2.57% and 3.49% over the same period.

Insert Table 3 Here

Table 4 shows the results for the 10 portfolio sort. We find an average difference of 3.98% per year between the positive/high extreme (10) and negative/low extreme (1) exposure portfolios. This shows that our model prediction that exporting firms tend to earn lower excess returns than domestic firms is robust to the sorting strategy. As with the 2×3 sort, we have almost monotonically decreasing beta and market capitalization from portfolio 1 to portfolio 10. But, we have more noise in expected returns for the middle portfolios since the majority of t-Statistics in those portfolios are not significant. Note also that our factor is not, however, just a size effect, as removing the bottom 20% of firms by market capitalization each month does not change the results.

Insert Table 4 Here

As a summary of the evidence in Tables 3 and 4, we note that across both sorts, small, low market beta firms, have larger t-Statistics on $\beta_{i,DI}$, and do well as the dollar strengthens. This evidence matches the flight-to-quality story of Campbell et al. [2010] and Cho et al. [2012] on both dimensions. First, large firms, potentially multinationals, have a larger percentage of revenue from abroad, and as a result, suffer more than small domestic firms after global downturns. Focusing on the 10 sort portfolios, Figures 8, 9 and 10 show the average annual percentage of revenue from abroad by portfolio.[10] From 1991-2000 and from 2009-2015 the 1 portfolio (large) firms had more

[10] The numbers in the figure seem high, but this is caused by a selection problem - only some of the firms in our sample are in Compustat, and even fewer have non-missing data for pretax foreign income. We do, however, match about an equal number of firms per portfolio/year. These results should only be taken as suggestive

than double the share of revenue from abroad as the 10 portfolio (small) firms. Second, low market beta firms represent defensive stocks that lose less during economic downturns.

All else equal, our finding that large firms sort into the bottom decile of dollar sensitivity is quite plausible. If large firms are exporters, when the dollar goes up in value, their products become more expensive to foreign buyers, and they should sell less. In the next sub-section, we consider the relationship between our two dollar factors and other commonly used factors in the literature.

Insert Figures 8, 9 and 10 Here

2.7 Relationship to Other Asset Pricing Factors

We regress the excess returns[11] of our 2 × 3 and 10 sorted portfolio returns on two sets of regressors: i. the q-Factor model of Hou et al. [2014]; ii. an augmented Fama and French [1993] model, where we add the momentum (MOM) factor of Jegadeesh and Titman [1993], the betting against beta (BAB) factor of Frazzini and Pedersen [2014] and the quality minus junk (QMJ) factor of Asness et al. [2014]. We test for the joint significance of the alphas using the method in Gibbons et al. [1989]. Tables 5 and 6 show the results for the 2 × 3 sorted portfolios. Applying the Gibbons et al. [1989] GRS test to the 2 × 3 sorted portfolios, we reject the null that they are on the mean variance frontier for both the q-Factor model and the augmented Fama-French model. Thus, our

evidence, not proof that all firms in the 1 portfolio are large exporters. It could also be a pure firm-size effect, see Figure 11.

[11] We use excess returns over the risk-free rate available at Ken French's data library.

HML2×3 portfolio expands the mean-variance frontier providing evidence that we found a new factor.[12]

Insert Tables 5, 6 Here

Tables 7 and 8 show the results for the 10 sorted portfolios. Applying the GRS test to the 10 sorted portfolios, we also reject the null for both the q-Factor model and the augmented Fama-French model at well below the 1% level, evidence for the robustness of our new factor. Thus, our HML10-1 portfolio expands the mean-variance frontier, providing further evidence that we found a new factor.

Insert Tables 7, 8 Here

For both sorts, the HML2 × 3 and HML10 − 1 factors' loading on ROE is economically large and statistically significant. We find that exposure to U.S. dollar strength is a fundamental characteristic of a firm, just like size or book-to-market. Given the time series momentum in foreign exchange returns discussed in Moskowitz et al. [2011], it is plausible that our factor is related to something persistent like profitability. We provide a full discussion of the relationship between our factor, profitability and momentum is in Section 4 below. But, first, in the next sub-section, we provide evidence on the risk premium associated with our dollar strength risk measure.

2.8 Fama-MacBeth results

We examine the risk premium associated with holding dollar strength risk using the two-stage technique in Fama and MacBeth [1973]. Here, we focus on the 2 × 3 portfolios, and the

[12] We are confident our results are not driven by the monotonically decreasing average market capitalization across our portfolios, as the size effect was weak during our sample. See, for example, Van Dijk (2011).

corresponding HML2 × 3 factor.[13] For test assets, we use the Fama-French 25 portfolios sorted on size and value, the 10 momentum portfolios and the 30 industry portfolios (in line with Lewellen et al. [2010]). The first stage regressions are done in 60-month rolling windows according to the model,

$$R_{i,t}^{e} = \alpha_i + \beta_{i,mkt} mkt_t + \beta_{i,smb} smb_t + \beta_{i,hml} hml_t + \beta_{i,mom} mom_t + \beta_{i,qmj} qmj_t + \beta_{i,bab} bab_t + \beta_{i,dollar} HML_{2\times 3,t} + \epsilon_{i,t} \tag{15}$$

where $R_{i,t}^{e}$ is the excess return over the risk free rate on test asset i. The second stage is run with cross-sectional data using the results from the first stage according to the expression

$$E\left[R_{i,t}^{e}\right] = \alpha_o + \lambda_{mkt}\beta_{i,mkt} + \lambda_{smb}\,\beta_{i,smb} + \lambda_{hml}\beta_{i,hml} + \lambda_{mom}\beta_{i,mom} + \lambda_{qmj}\beta_{i,qmj} + \lambda_{bab}\,\beta_{i,bab} + \lambda_{dollar}\beta_{i,dollar} + \tilde{\epsilon}_{i,t}. \tag{16}$$

Figure 2 plots the evolution of selected λ's from the second stage, while Figure 3 plots the associated t-Statistics. The initial evidence is promising and points to a viable factor.

Insert Figure 2 and Insert Figure 3 Here

We seek robustness by repeating the first stage, but now using the q-Factor model

$$R_{i,t}^{e} = \alpha_i + \beta_{i,mkt} mkt_t + \beta_{i,me} me_t + \beta_{i,ia} ia_t + \beta_{i,roe} roe_t + \beta_{i,dollar} HML_{2\times 3,t} + \epsilon_{i,t} \tag{17}$$

and the corresponding the second stage model is given by

$$E\left[R_{i,t}^{e}\right] = \alpha_o + \lambda_{mkt}\beta_{i,mkt} + \lambda_{me}\,\beta_{i,me} + \lambda_{ia}\beta_{i,ia} + \lambda_{roe}\beta_{i,roe} + \lambda_{dollar}\beta_{i,dollar} + \tilde{\epsilon}_{i,t}. \tag{18}$$

In Figure 4 we plot selected λ's from the second stage, and Figure 5 plots the associated t-Statistics.

Insert Figure 4 and Insert Figure 5 Here

[13] Results for the other sorts are available upon request.

Our results indicate that over the past 20 years, our dollar exposure factor has a level of economic and statistical significance comparable to accepted factors such as size, value and profitability, even when including size and value themselves in the Fama-MacBeth specification. We take this as additional evidence that the existing factors in the literature do not price dollar strength risk.

As mentioned above, revenue from abroad has increased dramatically from 2002-2015, which suggests the dollar factor should have gained more explanatory power in recent years. We verify this conjecture running three regressions using 30 industry portfolios according to the general model

$$r_t^e = \alpha + \gamma_{mkte} mkt_t^e + \gamma_{smb} SMB_t + \gamma_{hml} HML_t + \gamma_{dollar} HML_{2\times 3,t} + \epsilon_t \quad (19a)$$

where we impose the restrictions

$$\gamma_{smb} = \gamma_{hml} = \gamma_{dollar} = 0$$
$$\gamma_{smb} = \gamma_{hml} = 0 \quad (19b)$$
$$\gamma_{dollar} = 0$$

and where r_t^e denotes the portfolio excess return, mkt_t^e denotes the market excess return, HML2 × 3 is our dollar factor, SMB is the size factor and HML is the value factor.

Table 9 presents the R-squared value for each portfolio for two regimes, 1991-2002 and 2002-2015. The average ratio of the 2nd and 3rd columns is 0.915, while the average ratio of the 4th and 5th columns is 0.997, suggesting the dollar has become as powerful for explaining returns as size and value over the past decade.

Insert Table 9 Here

In summary, our evidence suggests that our dollar exposure factor has robust statistical significance. Next, we explore for potential economic mechanisms that explain our results, specifically using firm financial data, imports/exports, industries, global downturn risk, interest rates, and momentum.

3 Explanations

In this section, we explore economic explanations for the behavior of our dollar exposure factor. Relating the factor to firm fundamentals alleviate some concerns of a spurious factor, as discussed in Brysgalova [2015].

3.1 Firm Financial Data

Ideally, we would obtain net foreign exchange positions for all firms in our sample. Although this is not possible, we can get a rough idea using data from Compustat. Among the variables measuring foreign exchange exposure, we choose the least sparsely-populated field, foreign exchange income (FCA). Using annual FCA data, we match on average 80-100 firms per portfolio/year. Figure 6 shows that although the relationship is not strictly monotonic, the firms with negative dollar strength exposure have negative FCA, while firms with positive dollar strength exposure have positive FCA. A possible explanation is that firms in portfolio 1 are purchasing FX hedges (insurance) to protect themselves from dollar appreciation, but like most insurance contracts, they lose money on average.

Insert Figure 6 Here

3.2 Imports/Exports

In Section 2, we speculated that firms in portfolio 1 were more likely to be exporters, but we can partially test this prediction with data. Using Compustat, we obtain total pretax income, domestic pretax income and foreign pretax income. We drop all firms with missing values for any of these fields.[14] Not all firms in CRSP are in Compustat and not all firms in Compustat have non-missing data. In addition, Compustat has better data on large firms, so we do not match an equal number of firms across portfolios. We consistently match over 50% more firms in portfolio 1 than portfolio 10. Table 10 provides summary statistics. Consistent with our predictions, we find that firms in portfolio 1 earn a larger percentage of their revenue from abroad, and this decreases monotonically going from portfolio 1-10. Similar to Fillat and Garetto [2015], we find that exporting firms are more leveraged than domestic firms, but this could be a pure size effect.

Insert Table 10 Here

For robustness, we re-do this calculation over several time periods. Similar to papers like Ang et al. [2006], we get different results for times when the dollar is getting stronger, and when the dollar is getting weaker. Figure 7 motivates breaking the sample into 3 periods based on the direction the dollar is moving. This creates some look-ahead bias, as these regimes were identified ex-post, but we proceed to analyze the evidence.

Insert Figure 7 Here

As expected, the portfolio 1 is populated with exporters. Figure 8 shows we get nearly monotonically decreasing revenue from abroad from portfolio 1 to 10 in the first dollar strengthening episode from 1991-2000. As the dollar weakens from 2001-2008, Figure 9 the relationship weakens. Figure 10 shows that as the dollar strengthens again after the crisis, a somewhat monotonic relationship between export revenue and portfolio sorts returns.

[14] This may create a selection bias, but otherwise percent of revenue from abroad is not always well defined.

Insert Figure 8 and Insert Figure 9 Here

However, it is important to interpret this evidence carefully. We sort into 10 portfolios based on market capitalization in Figure 11, with the same sample used to form dollar sensitivity portfolios. As expected, percent of revenue from abroad is almost monotonically increasing in market capitalization thus indicating that the evidence of a monotonic relationship between export revenue and portfolio sorts returns along with dollar strengthening could be related to a size effect.

Insert Figure 10 and Insert Figure 11 Here

3.3 Industries

Intuition suggests that some industries will benefit more than others from a strong dollar. We examine the industry composition of selected portfolios over time using SIC Divisions. As above, we break the time series into up and down dollar strength trends. Figure 12 shows that from 1991-2000 the low/negative sensitivity portfolios (1 & 3) have more mining stocks, while the high/positive sensitivity portfolios (7 & 10) have more financial firms and retail firms. Mining firms being sorted into portfolios 1 & 3 is consistent with the global macroeconomic risk story - when the global economy does poorly, demand for basic materials goes down, as the dollar goes up. Retail portfolios being sorted into portfolios 7 & 10 is consistent with US consumers becoming effectively richer when the dollar gets stronger, and increasing consumption.

Insert Figure 12 Here

Figure 13 shows that in the 2000-2008 period, the main differences between the high and low portfolios are more construction and retail firms in the high portfolios.

Insert Figure 13 Here

Figure 14 shows that post crisis, we go back to the original pattern, with the lower portfolios loading up on the mining firms and the high portfolios loading on the financial and retail firms.

Insert Figure 14 Here

One possible explanation for the different industry composition across dollar strength regimes is that dollar weakness has a net zero effect on U.S. firms - imports become more expensive, but it is compensated by more exports. Differences between up and down dollar regimes are consistent with the results in Figure 9 where the revenue from abroad does not have a clear pattern across portfolios.

We also wanted to be sure our results were not being driven by one industry, so within each industry, we sorted into 3 portfolios to see if the results still hold. First, we sort the whole sample into 3 portfolios to see if the 10 portfolio sort was driving our result, see Table 11.

Insert Table 11 Here

Having established that the pattern still holds for the 3 portfolio sort, we sort by SIC major group (excluding Agriculture, as the portfolios were too sparse) and present the evidence in Table 12. The hypothesis that exporting firms earn lower excess returns than domestic firms is robust across almost every major industry group, the exceptions being mining and wholesale. The mining result could be driven by mining firms hedging dollar risk in derivatives markets, which we cannot observe in our data. In the appendix we present additional evidence for sorting on sensitivity to specific currencies by industry.

Insert Table 12 Here

3.4 Global Downturn Risk

Another possible explanation is that our factor measures exposure to global downturn risk. In the style of Cambell et al. [2010], we examine the relationship between $HML_{10-1}$and the performance of global risky assets. We get the Vanguard Total World Stock Index (VTWSX) from Yahoo Finance. We do not have a long sample, as the series starts in June 2008, but we can obtain preliminary results. Figure 15 shows the global index, our dollar factor and the dollar strength index from 2008 to 2015. Our HML_{10-1} factor has a correlation of -32% with the VTWSX and a correlation of -26% with the market. The stronger negative correlation with the global index over the domestic index is evidence that our factor is a hedge against global risk.

Insert Figure 15 Here

3.5 Interest Rates

Even though we sorted on exposure to changes in the dollar index conditional on changes in interest rate, it is possible that there are other interest rate variables such as long term bonds, and corporate debt, that our factor is picking up. All the series in levels (yields) are persistent, hence Table 13 computes all of the correlations in first differences. The highest correlations are with long-term interest rates, but all these are around or below 15%, and hence we are not concerned that our results are an interest rate factor in disguise.

Insert Table 13 Here

4 Relationship to Momentum

4.1 Fundamental Momentum

In the 2×3 sorts and 10 portfolio sort, the alpha on the HML factor is larger, and more statistically significant in the augmented Fama-French model than the q-factor model of Hou et al. [2014]. In the q-factor model, one of the largest loadings, both economically and statistically, is on the ROE factor. This suggests the dollar exposure factor is somehow related to profitability.

Novi-Marx [2015a] argues that momentum in earnings is the primary driver of price momentum in stocks. The ROE factor of Hou et al. [2014] prices portfolios sorted on past returns, but Novi-Marx [2015b] argues that their ROE factor is responsible. As we argued above, just like size and book to market, dollar exposure is a fundamental, persistent, firm characteristic.[15] Moskowitz et al. [2011] show that foreign exchange assets exhibit time series momentum - if they go up in the past, they are likely to keep going up in the near future. Panel C of Figure 1 in Moskowitz et al. [2011] shows the strong predictability in FX returns at the 1 month horizon with a t-statistic of over four.

We believe our factor ties these things together. If dollar exposure is persistent, and dollar moves are persistent, we could see persistence in profitability. Our factor has a contemporaneous correlation of about 20% with the price momentum factor, but of over 50% with the ROE factor. This is much higher than the correlation between changes in the dollar index itself and MOM/ROE, which is around 10% for both. This is because our factor picks up sensitivity to changes in dollar strength, a fundamental firm characteristic.

We test the relationship between the factors using linear regression in Table 14. In a univariate regression, our HML_{10-1} factor alone takes almost all the alpha out of the winner minus loser (MOM) portfolio. The difference when using Newey-West standard errors suggests autocorrelation in the series, which is not surprising - after all, these are factors related to momentum. The row labeled OLS reports standard t-statistics, while the row labeled Newey-West

[15] We find that the turnover in the dollar strength portfolio is about equal to the turnover in book to market sorted portfolios and we take this as evidence suggesting persistence. Results are available upon request.

reports the t-statistics adjusted for serial correlation. We selected 3 lags based on the Akaike information criterion and the Bayesian information criterion.

Insert Table 14 Here

We proceed further to consider momentum strategies across countries.

4.2 Relationship to Momentum across Countries

Asness et al. [2013] show that momentum strategies are related across countries. We believe this relationship could be dampened by currency momentum. Suppose there are only two countries, the U.S. and the U.K., each with their own currencies, the dollar and the pound. If the dollar is experiencing positive momentum, the pound must be experiencing "negative" momentum as the dollar has to be appreciating against something. We can formalize this as follows. Suppose momentum is driven by two fundamentals, profitability (ROE) and currency exposure, FX^{dollar} or FX^{pound}. From the prospective of a U.S. investor, a U.S. momentum strategy can be decomposed into

$$r_t^{MOM,US} = a + a_1 ROE_t^{US} + a_2 FX_t^{dollar} \tag{20}$$

and the UK momentum strategy can be decomposed into:

$$r_t^{MOM,UK} = b + b_1\, ROE_t^{UK} + b_2 FX_t^{pound} = b + b_1 ROE_t^{UK} - b_2 FX_t^{dollar} \tag{21}$$

where the second line follows from our assumption of only two countries, that is gains in the dollar translate one for one with losses in the pound (and vice versa). The sign of b_2 might depend on the role of the foreign country, relative to the domestic country importer/exporter. For example, if one country is a larger exporter, it will benefit from currency depreciation, while an importer would not.

With this example in mind, we use our dollar exposure factor to explain differences in momentum strategies across countries. First, we generate a winner minus loser (WML) portfolio in each country using data from Asness et al. [2013]. WML is the difference between the third momentum portfolio and the first momentum portfolio. We then regress the difference between U.S. and foreign momentum on our HML_{10-1} factor. We exclude Japan, as momentum in Japan is weak during our sample period.

Table 15 shows the results from the univariate regressions. Our sign is consistent with the uncovered equity parity result discussed in Hau and Rey [2006]. Consider a U.S. momentum investor. Suppose UK momentum does well relative to U.S. momentum ($\text{USMOM} - \text{UKMOM} < 0$). To rebalance away from pound exposure, the U.S. investor sells some of her UK momentum position. The flow of funds from the UK to the U.S. would increase the value of the dollar, and benefit stocks with positive dollar exposure and thus our HML_{10-1} factor would be positive. This would imply a negative coefficient and t-statistic, which is confirmed in the table. As a robustness check, we repeated the analysis using changes in the dollar strength index itself and found correlations and t-statistics near zero. As mentioned above, our factor is picking moves in exposure to dollar risk combined with moves in the dollar, not just moves in the dollar itself.

Insert Table 15 Here

5 Conclusions

We provide evidence that exposure to the strength of the US dollar is a factor that cannot be overlooked in the cross-section of U.S. equity returns. Data on revenue from abroad and industry composition of portfolios suggest our factor is not spurious. The GRS test suggests our HML factor is not priced by existing factors, and Fama-Macbeth regressions reveal a risk premium on par in magnitude and statistical significance with size and value.

Our factor contributes to the debate on momentum in two ways. First, persistence in foreign exchange returns together with exposure to dollar strength risk give our factor strong explanatory power for a return on equity factor. We take the fundamental momentum argument one step deeper - and suggest it is caused by time series momentum in the dollar. Second, we find that dollar strength risk is related to differences in performance of momentum strategies across countries. It is possible the effects of equity flows dampen the already high correlation between momentum strategies across countries, providing an even bigger puzzle than before.

This paper opens the door for more research on the relationship between dollar strength and equity returns. It is worth analyzing exposure to higher moments of foreign exchange risk in the cross section. Applying our analysis using individual currencies, as opposed to an aggregate dollar index also seems worthwhile. The dollar strengthening against the Yen will have a different effect on firms than the dollar strengthening against the Euro, which is not captured in the aggregate dollar index. Finally, given the role of the US dollar as a reserve currency, we think it makes sense to connect our factor with measures of systemic risk in future work.

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Table 1: Naive Use of Dollar Strength in Fama-MacBeth Regression

Factor	Annualized Risk Premium	t-Stat
Market	-1.25%	-0.604
SMB	0.87%	1.428
HML	1.15%	1.667
MOM	5.78%	4.812
QMJ	4.50%	5.670
BAB	-6.32%	-2.076
Dollar	-1.23%	-0.767

Table 2: Firm Characteristics

Portfolio	Num. Firms	t-Stat on $\beta_{i,\,DI}$	Matched in CCM	Pct Rev Abroad
1	283	-2.38	40.07%	30.28%
2	292	-1.74	37.92%	24.26%
3	308	-1.40	35.93%	21.53%
4	315	-1.11	35.87%	20.82%
5	339	-0.87	34.24%	20.01%
6	336	-0.63	33.42%	18.82%
7	344	-0.38	33.82%	16.60%
8	361	-0.11	32.01%	16.07%
9	383	0.22	30.03%	13.59%
10	456	0.86	26.72%	11.25%

Table 3: Summary Statistics for 2 × 3 Sort

		Annualized			Average Within Portfolio		
		Mean	St. Dev.	$Beta M$	Mkt. Cap. ($M)	t-Stat on $\beta i, DI$	# Firms
Small	Low t-Stat	12.03%	19.89%	1.09	$376	-1.42	667
	Med t-Stat	13.56%	18.15%	1.03	$367	-0.38	954
	Hi t-Stat	14.04%	17.27%	0.90	$356	0.65	793
Large	Low t-Stat	10.17%	15.70%	1.13	$15,200	-1.52	250
	Med t-Stat	11.00%	14.33%	1.10	$12,700	-0.44	310
	Hi t-Stat	12.61%	13.62%	0.99	$11,000	0.60	219
	HML	2.23%	7.80%				

Monthly means are multiplied by 12, while monthly standard deviations are multiplied by $\sqrt{12}$. $Beta_M$ is measured using a univariate regression of monthly excess returns on the three Fama-French factors from $t - 60$ to $t - 1$, market capitalization is measured at the end of $t - 1$, and t-Stat $\beta_{i,DI}$ is our portfolio sorting variable.

Table 4: Summary Statistics for 10 Sort

	Annualized			Average Within Portfolio		
	Mean	St. Dev.	$Beta M$	Mkt. Cap. ($M)	t-Stat on $\beta i, DI$	# Firms
1	9.13%	17.17%	1.10	$5,605	-2.02	314
2	11.47%	15.88%	1.10	$5,129	-1.37	297
3	10.65%	15.80%	1.08	$4,480	-1.02	306
4	10.32%	15.47%	1.08	$4,113	-0.76	301
5	11.17%	14.67%	1.06	$3,954	-0.52	316
6	12.03%	15.54%	1.02	$3,115	-0.29	324
7	12.37%	15.24%	1.03	$2,982	-0.05	323
8	12.41%	14.84%	0.99	$3,044	0.20	333
9	11.55%	14.09%	0.94	$2,867	0.54	333
10	13.11%	14.54%	0.83	$2,393	1.17	346
HML	3.98%	13.76%				

Monthly means are multiplied by 12, while monthly standard deviations are multiplied by $\sqrt{12}$. $Beta_M$ is measured using a univariate regression of monthly excess returns on the three Fama-French factors from $t - 60$ to $t - 1$, market capitalization is measured at the end of $t - 1$, and t-Stat $\beta_{i,DI}$ is our portfolio sorting variable.

Table 5: 2 × 3 q-Factor Model Regressions

Size	DI Exposure	Alpha	Mkt.	ME	IA	ROE
	Low	-0.01	1.00	0.82	0.20	-0.13
		(0.74)	(46.50)	(31.62)	(4.79)	(4.06)
Small	Med	0.00	0.94	0.79	0.31	-0.06
		(0.58)	(62.57)	(43.25)	(10.65)	(2.37)
	High	0.00	0.92	0.76	0.36	0.04
		(0.49)	(46.62)	(31.79)	(9.49)	(1.42)
	Low	0.02	0.98	-0.13	-0.11	-0.12
		(1.96)	(52.81)	(5.86)	(3.08)	(4.15)
Large	Med	-0.01	1.03	-0.15	0.31	0.23
		(1.67)	(62.70)	(7.30)	(9.71)	(8.96)
	High	0.00	0.97	-0.09	0.44	0.32
		(0.34)	(40.57)	(3.07)	(9.61)	(8.83)
	HML	-0.03	-0.05	-0.01	0.36	0.30
		(2.18)	(1.65)	(0.29)	(6.29)	(6.63)

Alphas are multiplied by 12 to annualize. The numbers below the coefficients in parenthesis are the t-statistics. Mkt. is the market factor, ME is the size factor, IA is the investment factor and ROE is the return on equity factor from Hou et al. [2014].

Table 6: 2 × 3 Augmented Fama-French Model Regressions

Size	DI Exposure	Alpha	Mkt.	SMB	HML	MOM	BAB	QMJ
	Low	0.00	1.02	0.92	0.25	0.00	0.23	0.32
		(0.44)	(43.67)	(32.54)	(8.87)	(0.22)	(7.17)	(6.15)
Small	Med	0.00	0.98	0.88	0.27	0.00	0.08	0.41
		(0.41)	(68.84)	(51.43)	(15.41)	(0.07)	(2.29)	(6.66)
	High	-0.01	0.99	0.88	0.28	-0.03	0.28	0.53
		(0.95)	(54.99)	(40.44)	(12.55)	(2.16)	(4.52)	(5.08)
	Low	0.02	0.97	-0.10	-0.03	-0.01	0.00	0.00
		(1.87)	(44.49)	(3.96)	(1.01)	(0.70)	_bab	_qmj
Large	Med	-0.01	1.06	-0.11	0.18	-0.02	-0.09	0.02
		(1.98)	(59.87)	(5.25)	(8.49)	(1.38)	(3.96)	(0.53)
	High	-0.01	1.01	-0.06	0.21	-0.01	0.00	0.06
		(1.01)	(38.60)	(1.86)	(6.46)	(0.68)	(0.18)	(2.54)
	HML	-0.04	0.00	0.01	0.12	-0.02	0.08	0.20
		(3.05)	(0.05)	(0.17)	(3.01)	(0.78)	(4.18)	(6.55)

Alphas are multiplied by 12 to annualize. The numbers below the coefficients in parenthesis are the t-statistics. Mkt. is the market factor, SMB is the size factor and HML is the value factor from Fama and French [1993]. MOM is the momentum factor from Jegadeesh and Titman [1993], while QMJ is the quality factor from Asness et al. [2014] and BAB is the betting against beta factor from Frazzini and Pedersen [2014].

Table 7: 10-Portfolio q-Factor Model Regressions

DI Exposure	Alpha	Mkt.	ME	IA	ROE
Low	0.02	0.90	-0.03	-0.22	-0.33
	(1.63)	(28.06)	(0.74)	(3.53)	(6.60)
2	0.02	1.01	-0.10	0.03	-0.02
	(1.36)	(41.54)	(3.36)	(0.66)	(0.50)
3	0.00	1.04	-0.09	0.09	0.09
	(0.30)	(42.32)	(2.90)	(1.82)	(2.44)
4	-0.02	1.05	-0.08	0.34	0.14
	(1.56)	(40.69)	(2.41)	(6.70)	(3.40)
5	0.00	1.00	-0.15	0.19	0.21
	(0.23)	(37.87)	(4.76)	(3.79)	(5.18)
6	-0.01	1.05	-0.05	0.49	0.24
	(1.00)	(34.02)	(1.31)	(8.24)	(5.06)
7	-0.01	1.02	0.01	0.34	0.28
	(0.51)	(33.57)	(0.29)	(5.76)	(5.88)
8	-0.01	1.00	-0.02	0.48	0.22
	(0.48)	(34.73)	(0.53)	(8.62)	(4.94)
9	-0.01	0.96	-0.03	0.42	0.30
	(0.96)	(32.88)	(0.87)	(7.47)	(6.57)
High	-0.01	0.97	0.10	0.47	0.37
	(0.58)	(30.29)	(2.47)	(7.61)	(7.49)
HML	-0.06	0.06	0.12	0.69	0.69
	(2.45)	(1.26)	(1.99)	(6.95)	(8.69)

Alphas are multiplied by 12 to annualize. The numbers below the coefficients in parenthesis are the t-statistics. Mkt. is the market factor, ME is the size factor, IA is the investment factor and ROE is the return on equity factor from Hou et al. [2014].

Table 8: 10-Portfolio Augmented Fama-French Model Regressions

DI Exposure	Alpha	Mkt.	SMB	HML	MOM	BAB	QMJ
Low	0.03	0.90	0.04	-0.04	-0.04	-0.19	-0.13
	(1.63)	(23.47)	(0.86)	(0.94)	(1.37)	(4.95)	(1.95)
2	0.02	0.99	-0.12	0.09	0.04	-0.07	-0.09
	(1.88)	(35.19)	(3.49)	(2.48)	(1.82)	(2.51)	(1.85)
3	-0.01	1.07	-0.06	0.02	-0.01	0.02	0.13
	(0.82)	(37.10)	(1.59)	(0.67)	(0.28)	(0.78)	(2.68)
4	-0.02	1.07	-0.02	0.21	-0.03	0.01	0.18
	(1.45)	(36.05)	(0.44)	(5.66)	(1.53)	(0.37)	(3.53)
5	-0.01	1.04	-0.12	0.07	-0.01	0.08	0.22
	(0.95)	(35.39)	(3.45)	(1.81)	(0.64)	(2.72)	(4.40)
6	-0.01	1.06	0.01	0.31	-0.11	0.06	0.27
	(0.55)	(31.77)	(0.37)	(7.64)	(4.67)	(1.73)	(4.72)
7	-0.01	1.08	0.04	0.24	0.06	0.05	0.26
	(1.02)	(31.04)	(0.91)	(5.54)	(2.24)	(1.39)	(4.38)
8	-0.01	1.02	0.01	0.25	-0.03	0.16	0.15
	(0.79)	(32.01)	(0.14)	(6.32)	(1.25)	(5.02)	(2.83)
9	-0.03	1.02	0.04	0.14	-0.06	0.23	0.32
	(2.30)	(32.98)	(0.97)	(3.70)	(2.56)	(7.17)	(6.15)
High	-0.02	1.04	0.17	0.29	-0.01	0.08	0.41
	(1.02)	(29.03)	(3.82)	(6.68)	(0.46)	(2.29)	(6.66)
HML	-0.07	0.15	0.13	0.33	0.02	0.28	0.53
	(2.64)	(2.37)	(1.74)	(4.39)	(0.46)	(4.52)	(5.08)

Alphas are multiplied by 12 to annualize. The numbers below the coefficients in parenthesis are the t-statistics. Mkt. is the market factor, SMB is the size factor and HML is the value factor from Fama and French [1993]. MOM is the momentum factor from Jegadeesh and Titman [1993], while QMJ is the quality factor from Asness et al. [2014] and BAB is the betting against beta factor from Frazzini and Pedersen [2014].

Table 9: R-Squared Values

The Mkt. column is the R^2 from a univariate regression of the portfolio return on the market factor. The $+HML_{2\times3}$ column adds our dollar HML factor to the previous regression. The $+SMB+HML$ column adds the Fama-French size and value factors to the market, instead of the $HML_{2\times3}$ factor.

	1991-2002			2003-2015		
Industry	Mkt.	$+HML2\times3$	$+SMB+HML$	Mkt.	$+HML2\times3$	$+SMB+HML$
Food	0.176	0.400	0.303	0.593	0.602	0.616
beer	0.161	0.306	0.230	0.344	0.345	0.440
smoke	0.043	0.096	0.102	0.228	0.231	0.249
games	0.515	0.517	0.566	0.735	0.736	0.743
books	0.548	0.634	0.607	0.723	0.724	0.747
hshld	0.295	0.399	0.339	0.534	0.534	0.552
clths	0.342	0.404	0.412	0.615	0.628	0.636
hlth	0.364	0.398	0.407	0.576	0.590	0.607
chems	0.423	0.462	0.595	0.770	0.786	0.770
txtls	0.245	0.320	0.520	0.561	0.586	0.623
cnstr	0.500	0.584	0.613	0.763	0.763	0.817
steel	0.623	0.654	0.670	0.681	0.701	0.703
fabpr	0.639	0.651	0.708	0.784	0.818	0.805
elceq	0.648	0.655	0.682	0.772	0.783	0.798
autos	0.345	0.365	0.539	0.669	0.673	0.687
carry	0.335	0.379	0.484	0.729	0.732	0.735
mines	0.111	0.118	0.192	0.387	0.460	0.388
coal	0.093	0.097	0.120	0.244	0.332	0.254
oil	0.244	0.248	0.370	0.430	0.541	0.448
util	0.062	0.181	0.374	0.365	0.366	0.384
telcm	0.583	0.583	0.604	0.780	0.783	0.789
servs	0.752	0.802	0.855	0.826	0.827	0.865
buseq	0.678	0.810	0.776	0.774	0.777	0.822
paper	0.376	0.450	0.546	0.773	0.773	0.778
trans	0.465	0.541	0.602	0.703	0.704	0.714
whlsl	0.481	0.528	0.569	0.810	0.810	0.847
rtail	0.532	0.583	0.544	0.636	0.708	0.648
meals	0.317	0.437	0.455	0.644	0.674	0.654
fin	0.602	0.780	0.820	0.805	0.815	0.856
other	0.460	0.466	0.488	0.675	0.676	0.734

Table 10: Compustat Match and Summary Statistics

Portfolio	Matched in CCM	Pct Rev Abroad	Leverage
1	40.07%	30.28%	0.36
2	37.92%	24.26%	0.32
3	35.93%	21.53%	0.30
4	35.87%	20.82%	0.28
5	34.24%	20.01%	0.25
6	33.42%	18.82%	0.26
7	33.82%	16.60%	0.27
8	32.01%	16.07%	0.26
9	30.03%	13.59%	0.26
10	26.72%	11.25%	0.24

These are medians by portfolio.
Percent of Revenue From Abroad is computed as $\frac{Pretax\ Foreign\ Income}{Pretax\ Income}$.
Leverage is computed as $\frac{Book\ Value\ of\ Debt}{Book\ Value\ of\ Equity}$.

Table 11: 3 Portfolio Sort

Portfolio	Mean	SD	Sharpe	Num Firms	Mkt Cap ($M)	Sorting Variable
1	6.48%	16.84%	0.38	880	882	-1.83
2	8.48%	14.85%	0.57	1339	407	-0.75
3	9.12%	14.22%	0.64	1210	215	0.34
HML	2.64%	11.54%	0.23			

All firm characteristics are medians by portfolio.

Table 12: 3 Portfolio Sort

Industry	Portfolio	Mean	SD	Sharpe	Num Firms	Mkt Cap ($M)	Pct Rev Abroad
Mining	1	7.33%	22.08%	0.33	35	1,753	45.40%
Mining	2	8.42%	20.63%	0.41	52	862	26.09%
Mining	3	5.48%	22.92%	0.24	57	288	16.16%
Mining	HML	-1.86%	14.45%	-0.13			
Construction	1	4.20%	26.69%	0.16	14	686	27.13%
Construction	2	8.43%	27.23%	0.31	15	566	86.18%
Construction	3	6.99%	29.51%	0.24	13	329	-672.24%
Construction	HML	2.79%	23.34%	0.12			
Manufacturing	1	7.71%	18.86%	0.41	364	965	28.87%
Manufacturing	2	8.65%	15.95%	0.54	542	407	23.50%
Manufacturing	3	9.71%	14.80%	0.66	516	184	17.07%
Manufacturing	HML	2.00%	14.42%	0.14			
TTU	1	4.70%	16.28%	0.29	84	1,507	23.51%
TTU	2	6.21%	14.73%	0.42	115	1,046	7.74%
TTU	3	6.90%	13.99%	0.49	100	844	7.53%
TTU	HML	2.20%	14.39%	0.15			
Wholesale	1	7.77%	19.03%	0.41	34	589	19.30%
Wholesale	2	11.52%	17.22%	0.67	45	422	18.99%
Wholesale	3	5.53%	17.69%	0.31	48	151	11.77%
Wholesale	HML	-2.25%	18.95%	-0.12			
Retail	1	6.84%	17.74%	0.39	73	674	9.51%
Retail	2	10.07%	18.43%	0.55	84	522	6.62%
Retail	3	8.85%	16.66%	0.53	71	498	4.71%
Retail	HML	2.01%	12.15%	0.17			
Finance	1	6.77%	20.56%	0.33	184	957	13.96%
Finance	2	7.80%	19.30%	0.40	234	391	16.18%
Finance	3	10.24%	19.31%	0.53	219	248	17.31%
Finance	HML	3.47%	9.69%	0.36			
Services	1	6.70%	22.21%	0.30	148	712	18.01%
Services	2	11.38%	20.65%	0.55	197	348	13.49%
Services	3	12.26%	19.47%	0.63	177	194	11.17%
Services	HML	5.56%	17.61%	0.32			

All firm characteristics are medians by portfolio.
Percent of revenue from abroad is only calculated for firms matched from CRSP to Compustat.

Table 13: Correlations between HML_{10-1} and Interest Rate Variables

Variable	Correlation with HML_{10-1}
3-Month Treasury	-0.0207
1-Year Treasury	-0.0499
5-Year Treasury	-0.1301
10-Year Treasury	-0.1627
aaa Corprate Yield	-0.1156
baa Corporate Yield	-0.0543

All of the variables are measured in first differences, except HML_{10-1}, an excess return.

Table 14: Explaining Variation in MOM and ROE Factors using HML_{10-1}

Regressand	Alpha	Beta on HML_{10-1}	R^2
MOM Factor	0.0001	0.0017	0.0180
OLS	(1.89)	(2.32)	
Newey-West	(1.65)	(0.93)	
ROE Factor	0.0000	0.0035	0.2455
OLS	(2.44)	(9.75)	
Newey-West	(2.28)	(7.25)	

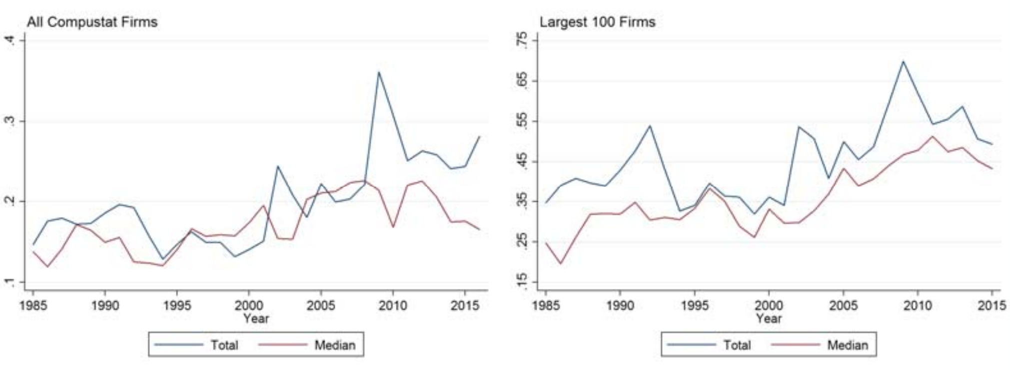
The row labeled OLS reports standard t-statistics, while the row labeled Newey-West reports the t-statistics adjusted for serial correlation. We selected 3 lags based on the Akaike information criterion and the Bayesian information criterion.

Table 15: Differences in Momentum Strategies across the U.S., UK and EU

Countries	t-Stat on HML_{10-1}	Correlation
$US^{MOM} - UK^{MOM}$	-2.24	-0.1389
$US^{MOM} - EU^{MOM}$	-3.70	-0.2253

Using the data from Asness et al. [2013], we construct winner minus loser (WML) factors for all 3 countries.
U.S.-UK is the difference between WML_t^{US} and WML_t^{UK} and U.S.-EU replaces WML_t^{UK} with WML_t^{EU}.
We then run a regressions of the form:
$$[US - UK]_t = \alpha + \beta \, HML_{10-1,t} + \epsilon_t$$
and take the t-statistics on the β.

Figure 1: Pretax Income From Abroad as Fraction of Total Pretax Income

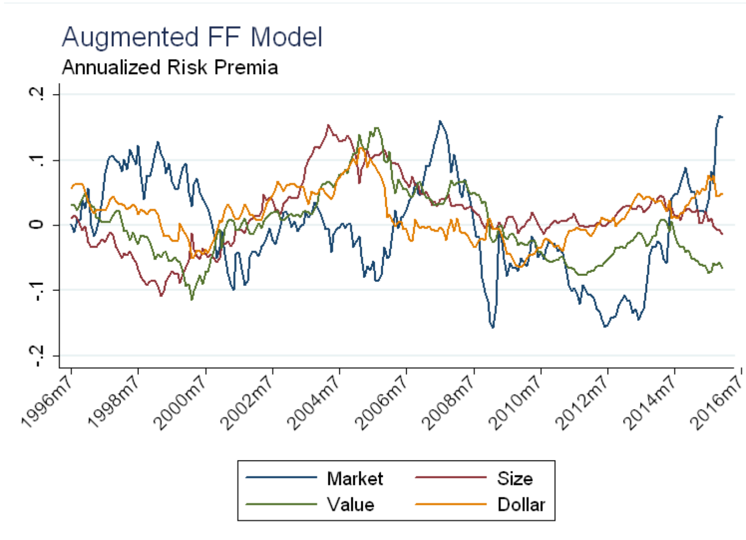


Percent of revenue from abroad increased from about 10% in 1985 to almost 30% in 2016 for all Compustat firms.

The effect was even larger for the largest 100 firms by market capitalization.

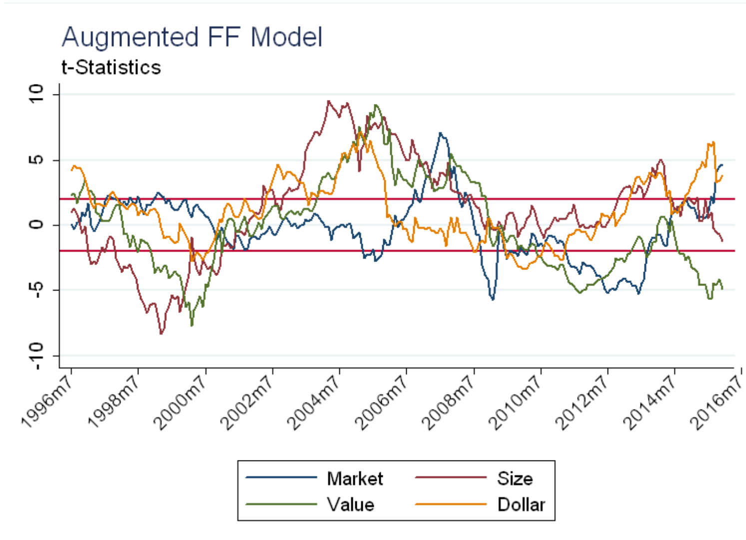
Total reflects adding across all firms, while median is the median across all firms in a given year

Figure 2: Annualized Risk Premia from Augmented Fama-French Model



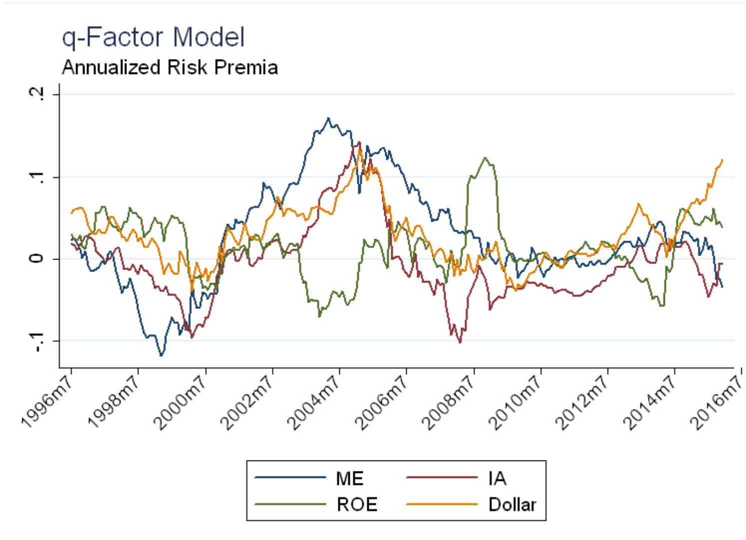
Risk premia computed using Fama and MacBeth [1973] style regressions. We include the following factors: MKT, SMB, HML, MOM, QMJ, BAB and our $HML_{2\times3}$.
We multiply by 12 to annualize monthly risk premia.

Figure 3: t-Statistics on Risk Premia from Augmented Fama-French Model



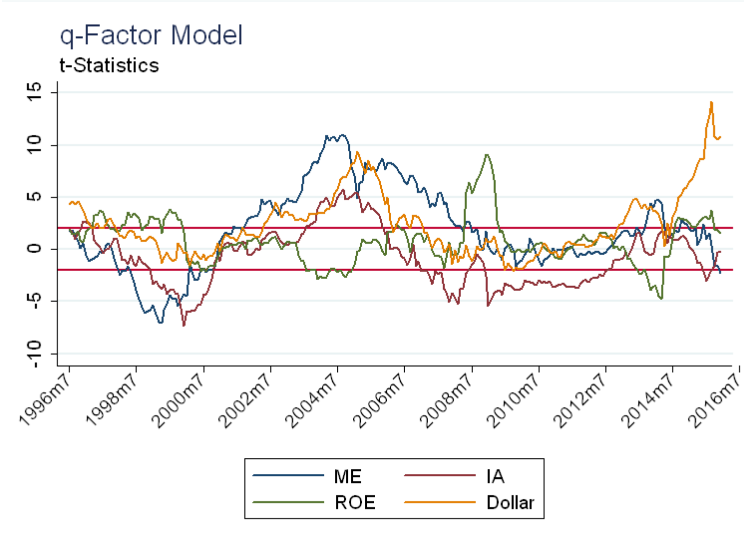
Horizontal lines indicate 95% critical values

Figure 4: Annualized Risk Premia from q-Factor Model



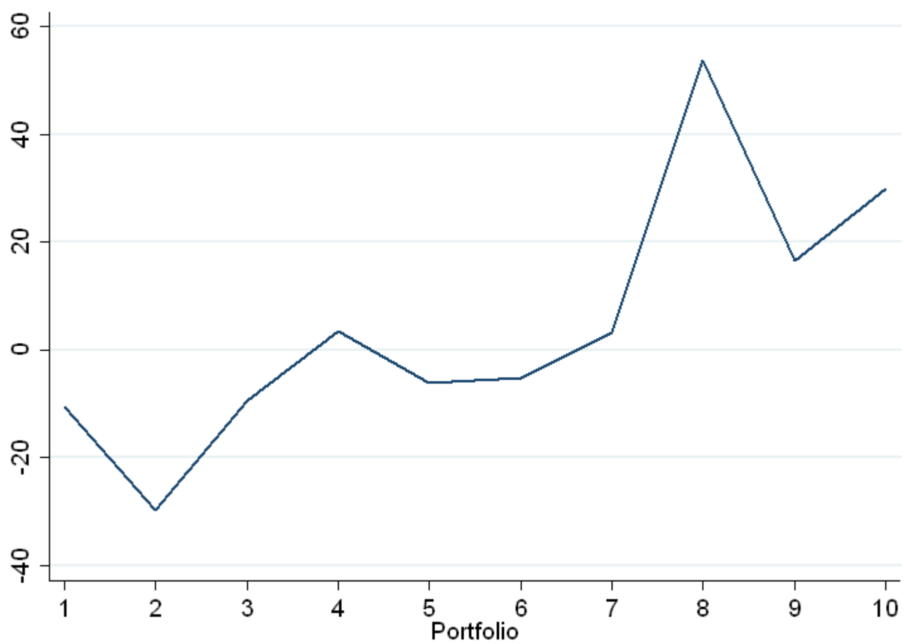
Risk premia are computed using Fama and MacBeth [1973] style regressions. We include the following factors: MKT, ME, IA, ROE and our $HML_{2\times3}$.
We multiply by 12 to annualize monthly risk premia.

Figure 5: t-Statistics on Risk Premia from q-Factor Model



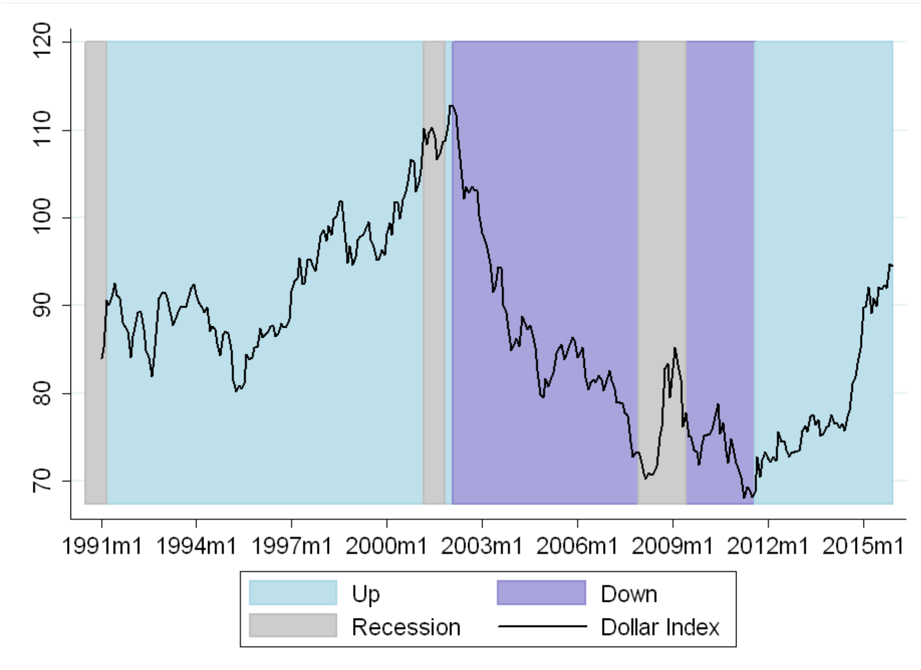
Horizontal lines indicate 95% critical values

Figure 6: Average Foreign Exchange Income (Loss) by Portfolio



Represents annual foreign exchange income (loss) in millions of dollars

Figure 7: Trend in the Dollar Index



Up from January 1991-Feburary 2002, down from March 2002 to December 2007 (when contraction starts), down again after contraction until August 2011, up until December 2015.

Figure 8: Average Annual Percent of Revenue from Abroad by Portfolio, 1991-2000

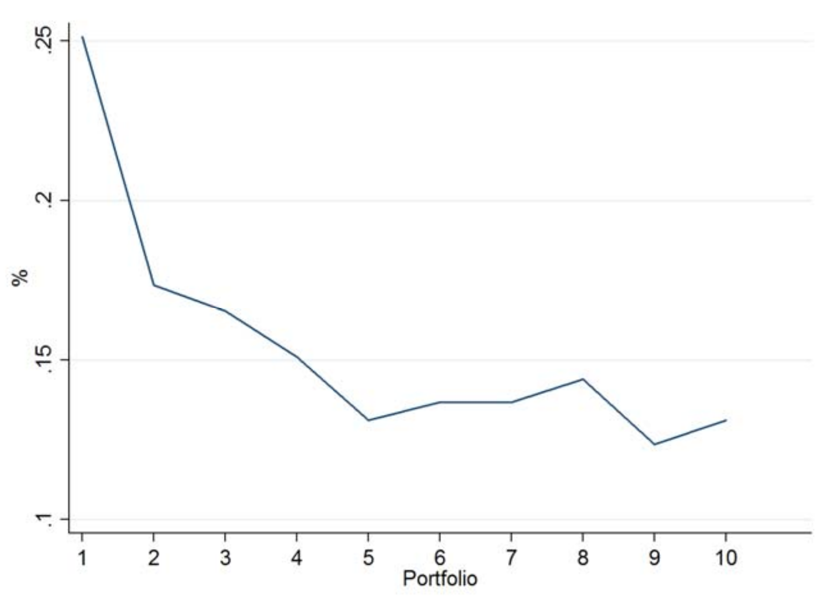


Figure 9: Average Annual Percent of Revenue from Abroad by Portfolio, 2001-2008

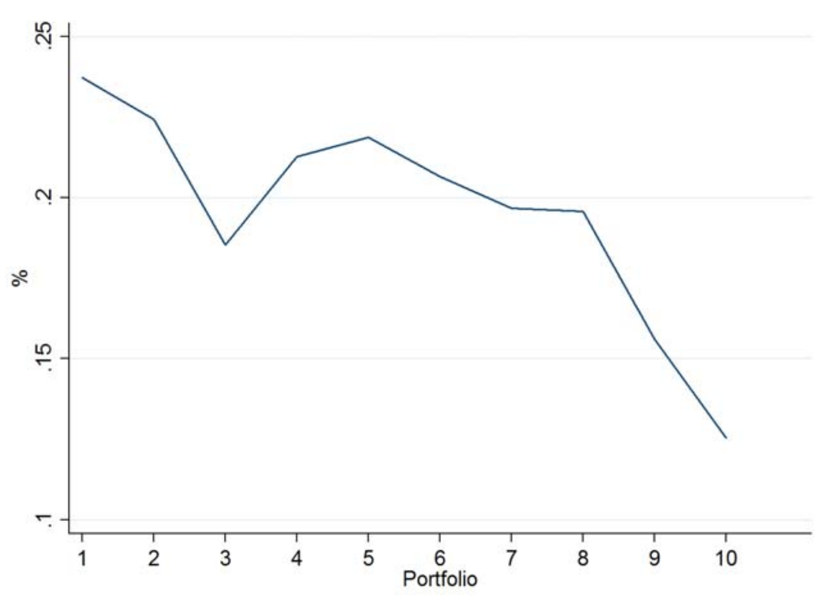


Figure 10: Average Annual Percent of Revenue from Abroad by Portfolio, 2009-2015

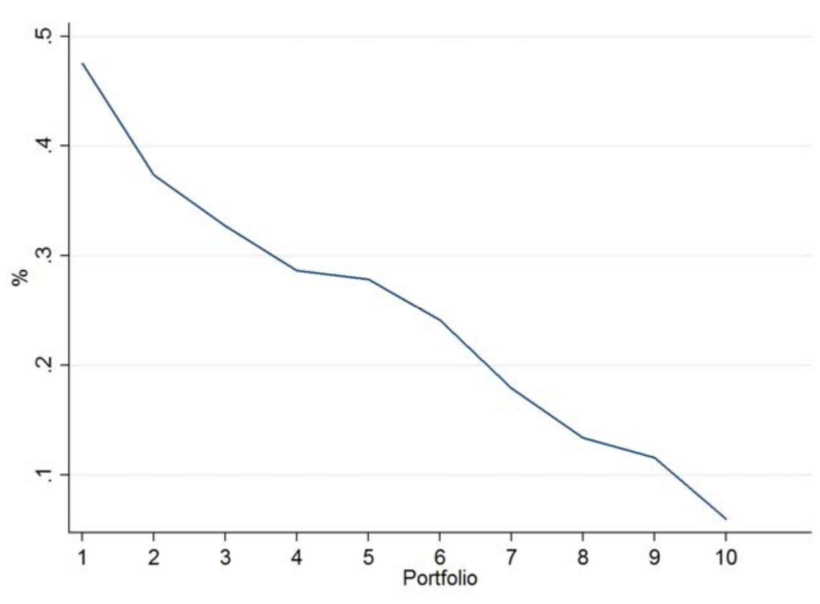


Figure 11: Average Annual Percent of Revenue from Abroad Across 10 Size Portfolios

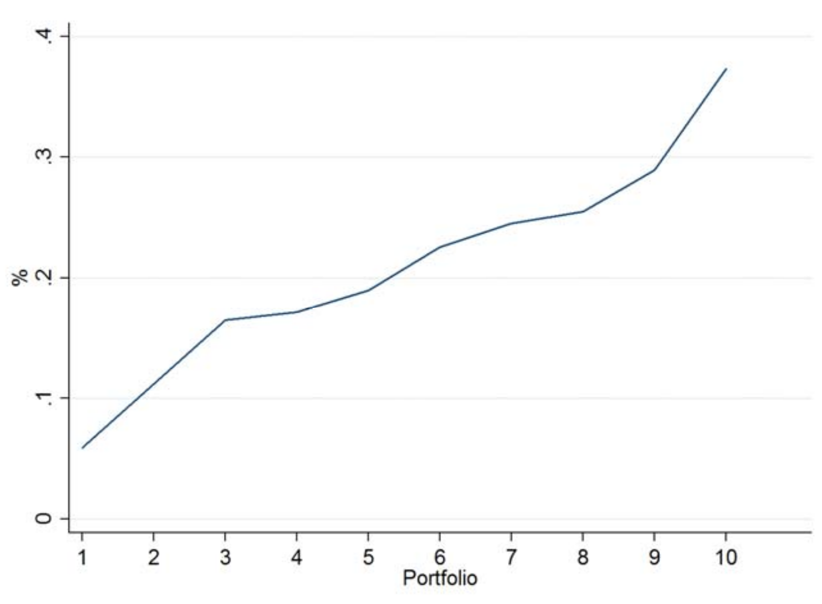


Figure 12: Distribution of Industries by Portfolio, 1991-2000

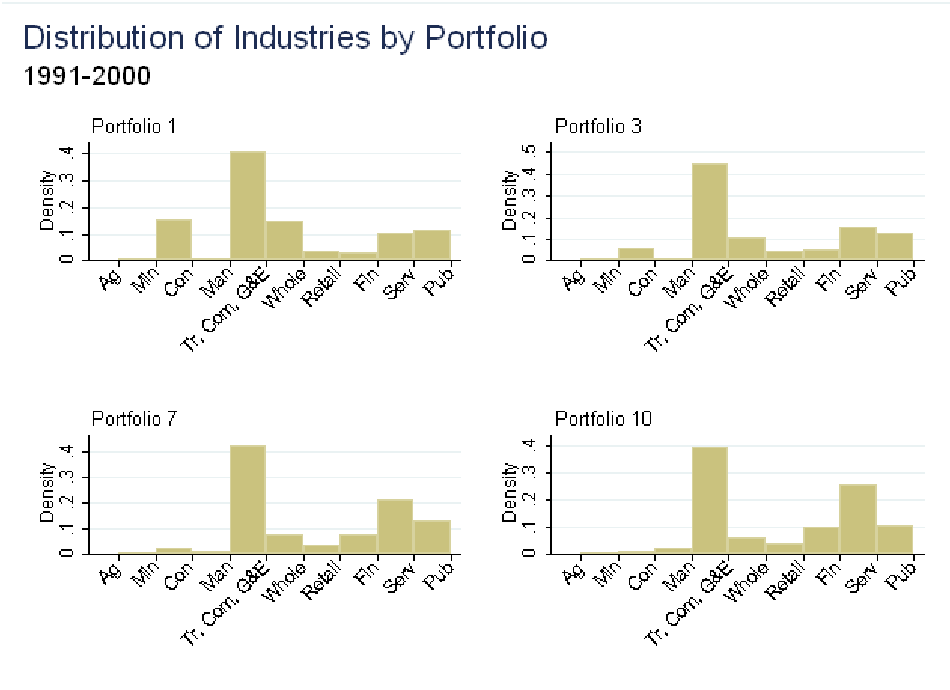


Figure 13: Distribution of Industries by Portfolio, 2001-2008

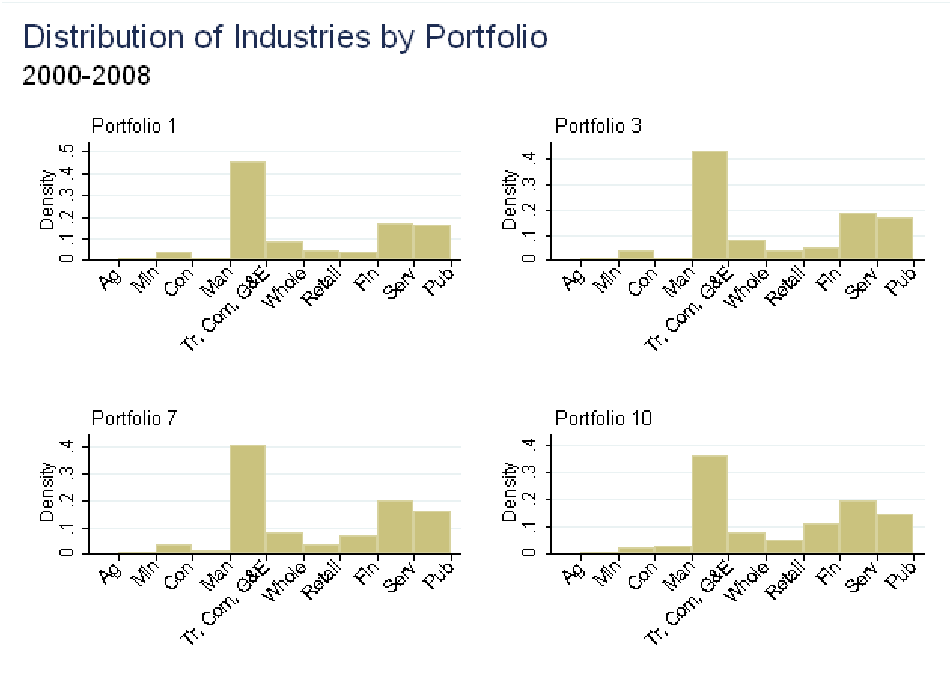


Figure 14: Distribution of Industries by Portfolio, 2009-2015

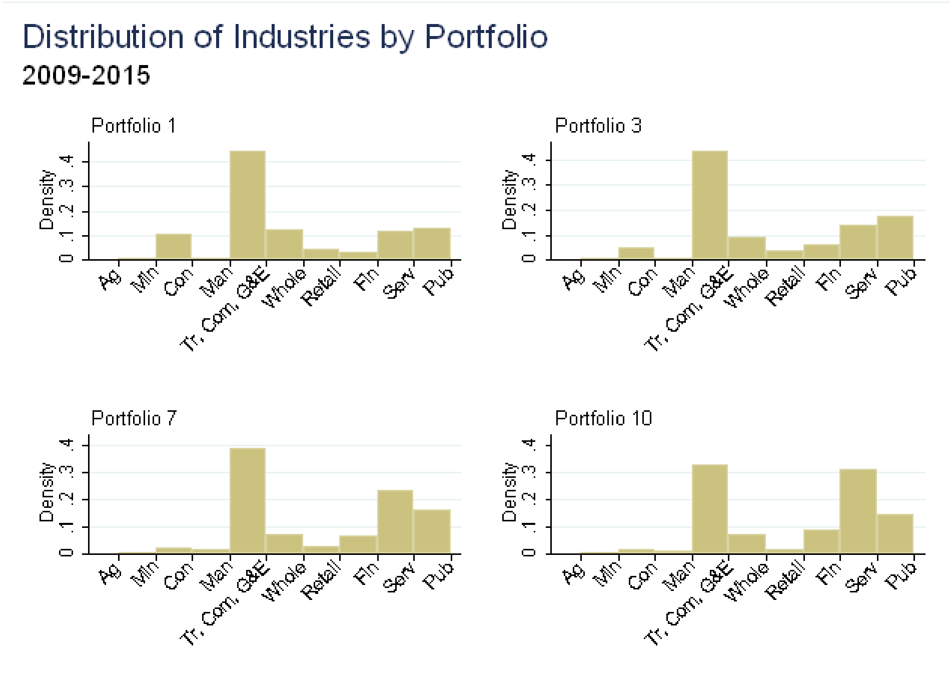
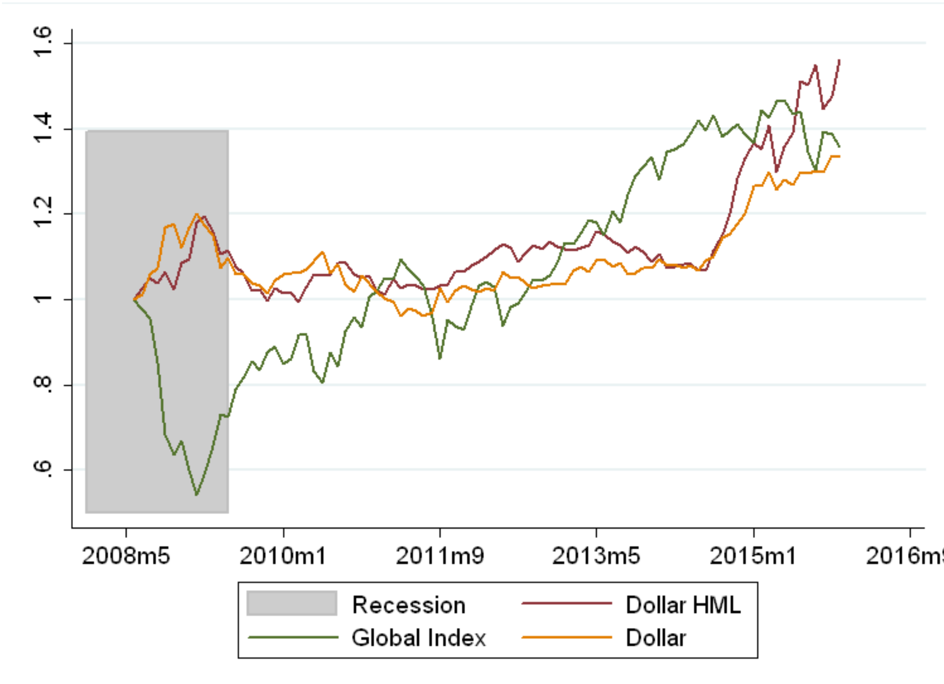


Figure 15: Value of $1 Invested in June 2008



APPENDIX

A1 Removing Financial Firms

Financial firms are likely to hold many non-dollar-denominated assets, and hedge their foreign exchange risk in derivatives markets. To make sure our results are not driven entirely by financial firms, Table A1-1 shows the results of a 10-portfolio sort excluding financial firms (SIC codes 6000-6999). Although the effect is weaker, the qualitative prediction of Hypothesis 1 is robust.

Table A1-1: Excluding Financial Firms

Portfolio	Mean	SD	Sharpe	Num Firms	Mkt Cap ($M)	Sort
1	5.96%	18.87%	0.32	225	1,368	-2.38
2	6.67%	18.44%	0.36	235	834	-1.74
3	7.91%	17.72%	0.45	251	564	-1.40
4	8.85%	16.20%	0.55	258	529	-1.11
5	8.23%	15.64%	0.53	274	449	-0.87
6	8.88%	15.35%	0.58	277	398	-0.63
7	9.82%	15.09%	0.65	285	361	-0.38
8	8.66%	14.85%	0.58	289	292	-0.11
9	8.34%	14.41%	0.58	315	246	0.22
10	9.15%	13.95%	0.66	364	192	0.86
HML	3.20%	16.34%	0.20			

A2 Double Sorts

To ensure our results are not driven by the 3 common factors, we perform a double sort. First, sort into 3 portfolios based on size/beta/loading on value factor. Note that most of the firms in our sample are not in Compustat, so we cannot calculate book value of equity. We then sort further into 3 portfolios based on sensitivity to changes in the U.S. dollar. Tables A2-1-3 show our result is robust to almost all double sorts.

Table A2-1: Size and DI

	Portfolio	Mean	SD	Sharpe	Num Firms	Mkt Cap ($M)	Size	DI
Small	Low DI	10.15%	21.74%	0.47	487	158	158	-1.74
	2	9.82%	20.25%	0.48	823	136	136	-0.73
	High DI	11.41%	19.82%	0.58	832	91	91	0.38
Medium	Low DI	8.40%	18.46%	0.45	247	1,482	1,482	-1.88
	2	9.66%	16.67%	0.58	336	1,347	1,347	-0.78
	High DI	11.05%	16.03%	0.69	245	1,302	1,302	0.24
Large	Low DI	6.20%	16.86%	0.37	145	9,434	9,434	-1.97
	2	8.45%	14.84%	0.57	180	8,871	8,871	-0.80
	High DI	8.89%	14.11%	0.63	133	8,686	8,686	0.26

Table A2-2: Beta and DI

	Portfolio	Mean	SD	Sharpe	Num Firms	Mkt Cap ($M)	Beta	DI
Low Beta	Low DI	4.93%	15.97%	0.31	289	764	0.50	-1.76
	2	7.45%	13.13%	0.57	445	395	0.47	-0.71
	High DI	8.53%	12.53%	0.68	519	164	0.42	0.43
Medium Beta	Low DI	7.55%	16.27%	0.46	302	1,264	1.00	-1.81
	2	8.17%	14.97%	0.55	464	581	0.99	-0.76
	High DI	10.33%	15.03%	0.69	381	315	0.98	0.29
High Beta	Low DI	6.21%	23.16%	0.27	286	762	1.66	-1.83
	2	11.14%	20.89%	0.53	428	341	1.66	-0.78
	High DI	9.18%	21.51%	0.43	307	230	1.65	0.23

Table A2-3: HML Loading and DI

	Portfolio	Mean	SD	Sharpe	Num Firms	Mkt Cap ($M)	HML	DI
Low Value	Low DI	6.77%	19.19%	0.35	362	1,151	-0.47	-1.83
	2	7.99%	16.23%	0.49	510	456	-0.47	-0.76
	High DI	9.31%	15.15%	0.61	435	195	-0.44	0.34
Medium Value	Low DI	6.60%	14.53%	0.45	297	1,073	0.36	-1.84
	2	8.87%	13.85%	0.64	435	559	0.36	-0.76
	High DI	9.56%	13.89%	0.69	391	319	0.36	0.31
High Value	Low DI	8.99%	18.20%	0.49	218	599	1.10	-1.80
	2	11.00%	18.65%	0.59	391	323	1.16	-0.74
	High DI	9.75%	17.98%	0.54	382	221	1.18	0.34

A3 Individual Currency Results

In the body of the paper, we use an aggregate measure of the US dollar's strength against a basket of other currencies. In this section, we run 14 except we replace $r_{DI,t}$ with the percent change of the dollar against the Euro and the Yen. Table A3-1 shows that the hypothesis that exporting firms earn lower excess returns than domestic firms does not hold for Euro exposure, but Table A3-2 shows the effect is strong for Yen exposure.

Table A3-1: Euro

Portfolio	Mean	SD	Sharpe	Num Firms	Mkt Cap ($M)	Sort
1	6.55%	13.93%	0.47	489	275	-0.34
2	9.78%	17.02%	0.57	396	358	0.34
3	7.72%	14.83%	0.52	359	438	0.68
4	9.59%	14.50%	0.66	332	519	0.96
5	9.72%	15.24%	0.64	317	623	1.22
6	8.53%	14.40%	0.59	296	745	1.45
7	8.09%	14.83%	0.55	279	887	1.70
8	6.66%	15.16%	0.44	261	1,089	1.99
9	9.02%	15.42%	0.59	258	1,276	2.34
10	8.30%	15.51%	0.54	252	1,876	2.96
HML	1.75%	9.07%	0.19			

Table A3-2: Yen

Portfolio	Mean	SD	Sharpe	Num Firms	Mkt Cap ($M)	Sort
1	5.62%	16.33%	0.34	371	247	-1.13
2	7.55%	17.27%	0.44	344	284	-0.56
3	6.51%	15.90%	0.41	338	307	-0.25
4	7.10%	16.48%	0.43	334	340	-0.01
5	7.50%	15.69%	0.48	334	370	0.21
6	8.35%	15.23%	0.55	328	373	0.40
7	7.62%	15.49%	0.49	336	408	0.61
8	9.01%	15.16%	0.59	338	438	0.84
9	10.86%	15.46%	0.70	340	415	1.14
10	9.60%	14.62%	0.66	354	520	1.68
HML	3.99%	13.17%	0.30			

A4 Individual Industries by Currency

Different industries are more/less exposed to specific currency risk. As above, we calculate sensitivity to the Euro and the Yen, and sort into 3 portfolios within each industry based on this sensitivity, the results are in Tables A4-1 and A4-2.

Table A4-1: Euro Industry

Industry	Portfolio	Mean	SD	Sharpe	Num Firms	Mkt Cap ($M)	Sort
Mining	1	8.27%	26.92%	0.31	52	498	0.93
Mining	2	13.75%	22.39%	0.61	46	1,573	2.00
Mining	3	9.40%	22.28%	0.42	33	3,261	2.78
Mining	HML	1.12%	14.41%	0.08			
Construction	1	8.94%	30.70%	0.29	14	544	0.48
Construction	2	6.64%	29.75%	0.22	12	1,227	1.27
Construction	3	-1.68%	29.36%	-0.06	11	862	2.27
Construction	HML	-10.62%	23.81%	-0.45			
Manufacturing	1	8.50%	15.73%	0.54	521	299	0.25
Manufacturing	2	11.03%	14.36%	0.77	484	631	1.36
Manufacturing	3	6.82%	15.50%	0.44	295	1,476	2.42
Manufacturing	HML	-1.68%	7.03%	-0.24			
TTU	1	7.55%	12.64%	0.60	87	1,147	0.21
TTU	2	9.75%	12.80%	0.76	107	1,322	1.23
TTU	3	7.47%	14.08%	0.53	74	1,924	2.24
TTU	HML	-0.08%	9.38%	-0.01			
Wholesale	1	7.90%	16.72%	0.47	41	280	0.36
Wholesale	2	14.28%	16.84%	0.85	44	821	1.48
Wholesale	3	9.96%	16.46%	0.60	24	834	2.57
Wholesale	HML	2.05%	13.73%	0.15			
Retail	1	11.39%	15.65%	0.73	67	907	-0.19
Retail	2	7.19%	15.76%	0.46	77	989	0.78
Retail	3	11.94%	14.66%	0.81	67	960	1.67
Retail	HML	0.55%	11.02%	0.05			
Finance	1	5.16%	19.58%	0.26	243	252	0.25
Finance	2	3.77%	20.38%	0.18	222	610	1.32
Finance	3	4.95%	20.09%	0.25	162	1,567	2.40
Finance	HML	-0.21%	10.13%	-0.02			
Services	1	9.92%	17.67%	0.56	211	338	0.21
Services	2	10.62%	16.98%	0.63	197	660	1.23
Services	3	10.88%	17.25%	0.63	140	1,157	2.13
Services	HML	0.95%	10.18%	0.09			

Table A4-2: Yen Industry

Industry	Portfolio	Mean	SD	Sharpe	Num Firms	Mkt Cap ($M)	Sort
Mining	1	10.07%	21.20%	0.47	43	680	-0.84
Mining	2	4.37%	22.37%	0.20	55	776	-0.09
Mining	3	5.57%	23.42%	0.24	46	739	0.75
Mining	HML	-4.50%	16.63%	-0.27			
Construction	1	5.11%	25.27%	0.20	15	347	-0.12
Construction	2	7.48%	27.84%	0.27	16	557	0.68
Construction	3	8.48%	30.96%	0.27	11	621	1.38
Construction	HML	3.36%	24.32%	0.14			
Manufacturing	1	7.46%	17.62%	0.42	437	240	-0.61
Manufacturing	2	7.94%	15.52%	0.51	539	367	0.26
Manufacturing	3	9.94%	15.51%	0.64	441	416	1.12
Manufacturing	HML	2.48%	12.67%	0.20			
TTU	1	5.13%	16.56%	0.31	89	1,612	-0.71
TTU	2	5.58%	14.61%	0.38	113	1,041	0.18
TTU	3	7.86%	13.91%	0.56	96	906	1.07
TTU	HML	2.72%	15.53%	0.18			
Wholesale	1	6.75%	16.80%	0.40	41	197	-0.59
Wholesale	2	8.56%	17.38%	0.49	47	348	0.30
Wholesale	3	9.61%	18.88%	0.51	39	488	1.11
Wholesale	HML	2.87%	18.14%	0.16			
Retail	1	10.02%	19.27%	0.52	75	489	-0.38
Retail	2	7.52%	16.74%	0.45	85	572	0.49
Retail	3	8.81%	17.46%	0.50	67	665	1.33
Retail	HML	-1.20%	14.57%	-0.08			
Finance	1	8.07%	21.33%	0.38	221	295	-0.40
Finance	2	8.85%	19.39%	0.46	231	340	0.45
Finance	3	9.17%	20.35%	0.45	184	553	1.32
Finance	HML	1.10%	11.40%	0.10			
Services	1	8.47%	23.19%	0.37	173	203	-0.53
Services	2	9.81%	20.87%	0.47	198	328	0.37
Services	3	10.24%	18.14%	0.56	149	425	1.23
Services	HML	1.77%	16.11%	0.11			