Pricing Dollar Strength Risk

Marcelo Bianconi and Marco Sammon

September 26, 2016

Abstract

The strength of the dollar has an immediate impact on domestic firms - lowering the cost of imports, increasing the cost of exports and making US consumers richer. Stocks which covary positively with changes in a trade-weighted US dollar index earn higher expected returns than stocks which covary negatively with the index. A zero-cost tradeable factor designed to capture this effect is not priced by established factors. Our dollar strength factor has implications for profitability and fundamental momentum, as well as the relationship between momentum strategies in different countries.

1 Introduction

Both US exports and imports, have roughly doubled as a percentage of GDP over the past 25 years. See Figure 1. Almost all US firms are exposed to the strength of the US dollar, but little has been done to quantify this risk.

[Figure 1 about here.]

Asset pricing factors such as the capital asset pricing model (CAPM) of Sharpe [1964] and the momentum factor of Jegadeesh and Titman [1993] are based on the performance of US stocks. Other factors, such as size and value from Fama and French [1993] are based on firm characteristics. By nature, these measures do not sufficiently capture global risk.

Solnik [1974] and others have developed an international version of the CAPM, but the theoretical results are often at odds with the data. Harvey [1991] shows a conditional international CAPM works for some markets, but not others. Lewis [2011] provides an overview of the differences between theoretical predictions and what is observed in the data.

Global risk which cannot be diversified matters for asset pricing. To capture some of the unmeasured global risk, we propose a new asset pricing factor based on exposure to the strength of the US dollar. Our factor contributes to several themes in the literature: First, our paper is similar in method and spirit to Jagannathan and Wang [1996] in that we identify a new factor, based on the macroeconomic data, related to how investors value risky cash flows[1]. Another paper similar in method is Frazzini and Pedersen [2014], except they sort on exposure to the market, rather than the strength of the US dollar. Our factor is related to betting against beta (BAB) - after sorting into 10 portfolios, we find that firms with negative dollar exposure are large exporters with high betas, while firms with positive dollar exposure are small firms with low betas.

We also contribute to the literature on the US dollar as a reserve currency[2]. Campbell, Serfaty-De Medeiros, and Viceria [2010] show "flight to quality" causes the dollar to appreciate when risky assets (world stock markets) decline in value[3]. In this respect, we have a counterintuitive result - we find stocks with positive exposure to dollar strength have higher expected returns than those with negative dollar exposure. For our portfolios, other stories such as industry, size and importer vs. exporter effects seem to dominate the safe asset effect[4]. Using more recent data from 2008-2015 on a global equity index, we restore the intuitive result, and find our measure is negatively correlated with global equity returns.

Our work is related to the papers on downside risk such as Ang, Chen, and Xing [2006], and its relationship to foreign exchange returns such as Lettau, Maggiori, and Weber [2014]. We find the effect of dollar exposure depends on whether the dollar is getting stronger or weaker. This causes industry composition, and percent of revenue from abroad to vary within our portfolios over time. As the dollar gets stronger, we get intuitive results - industries which are hurt by a strong dollar are sorted into the negative exposure portfolios. As the dollar gets weaker, however, the industry composition does not vary as much across portfolios.

We also contribute to fundamental momentum, discussed in Novy-Marx [2015a]. Similar to a profitability factor, exposure to dollar strength is related to fundamentals, persistent and has real implications for firms. We relate our factor to the return on equity factor of Hou, Xue, and Zhang [2014], as well as the critique of Novy-Marx [2015b] that the q-Factor model isn't really pricing momentum. Our explanation is that foreign exchange assets exhibit time series momentum (shown in Moskowitz, Ooi, and Pedersen [2011]), which leads to momentum in profitability. In addition, we find our factor has predictive power for the difference between momentum strategies across countries discussed in Asness, Moskowitz, and Pedersen [2013].

Finally, we contribute to the relationship between stock returns, FX returns and equity flows. Hau and Rey [2006] and Hau and Rey [2004] predict Uncovered Equity Parity (UEP) should hold. Their mechanism is that domestic investors sell foreign equities after they perform well to reduce FX risk. Curcuru, Thomas, Warnock, and Wongswan

[1] Our method for allowing risk premia to vary over time, however, is different. We calculate risk premia in 5-year rolling windows, while Jagannathan and Wang [1996] allow them to vary by explicitly including a risk premium factor, the spread between BAA and AAA bonds.

[2] See He, Krishnamurthy, and Milbradt [2016] for related theoretical results

[3] In the paper, the authors discuss that this has also become true of the Euro, and it is, to a degree, displacing the US dollar from its role as a reserve currency.

[4] Another reason we are 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. See Section 5 for more.

[2014] find evidence for UEP, but question the mechanism of Hau and Rey [2006] [5]. We find evidence of investors rebalancing away from successful foreign momentum strategies.

The paper is organized as follows: Section 2 overviews the basic asset pricing results. Section 3 explores alternative explanations for our factor's behavior - and helps us show that it is actually picking up dollar exposure. Section 4 discusses the relationship between our factor and momentum. Section 5 goes over alternative specifications and robustness checks while Section 6 concludes.

2 Asset Pricing Results

2.1 The Data

We measure dollar strength using the *Trade Weighted US Dollar Index: Major Currencies* from FRED[6]. 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 are from Ken French's data library. The Betting Against Beta (BAB) factor from Frazzini and Pedersen [2014] and the Quality Minus Junk (QMJ) factor from Asness, Frazzini, and Pedersen [2014] are from AQR's website. The q-factors from Hou et al. [2014] were obtained from the authors. The recession indicator is from the NBER.

2.2 Identifying Dollar Strength Risk

There are several determinants of the US dollar's strength against other currencies. For example, all else fixed, a relative increase in US interest rates makes holding dollars more attractive. Dollar demand increases, and the dollar gets stronger. In reality, there are no exogenous increases in interest rates. Policy makers may raise interest rates in response to economic performance, another factor that contributes to dollar strength. For more on determinant's of dollar strength, see Campbell et al. [2010].
Ideally, we would identify changes in US dollar strength that are orthogonal to changes in interest rates. This would prevent our dollar factor from acting like an interest rate factor. Everything is simultaneously determined in equilibrium, however, so we propose a simplification. We measure the sensitivity of stock returns to changes in dollar strength, conditioning on changes in interest rate and credit risk:

$$r_{i,t} = \alpha_i + \beta_{i,DI} r_{DI,t} + \beta_{i,3M} \Delta_{3M} + \beta_{i,TED} \Delta_{TED} + \epsilon_{i,t} \tag{1}$$

[5]They argue that investors sell to avoid mean reversion. This can also be related to momentum, in the long-term under performance of the winner portfolio, see Daniel, Klos, and Rottke [2016]

[6]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."

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, Δ_{3M} is the change in the 3-month Treasury bill rate, and Δ_{TED} is the change in the TED spread[7]. We measure dollar exposure as the t-Statistic on $\beta_{i,DI}$.

2.3 Constructing a Tradeable Factor

To construct a tradeable factor, we start with the entire CRSP universe and restrict to ordinary common shares (share codes 10 and 11), traded on major exchanges (NYSE, NASDAQ and AMEX), dropping firms with market capitalization smaller than $500,000. For each stock, in each month, we run Equation 1 using data from $t-1$ to $t-60$. We require 60 non-missing returns during the calibration period, although removing this filter gives similar results[8] Finally, to be included in a portfolio at time t, the firm needs a non-missing market capitalization at $t-1$.

At the end of each $t-1$, we sort into 6 portfolios following the procedure in Fama and French [1993]. We first sort into two size portfolios based on the median market capitalization for NYSE stocks. Then, within those portfolios, we sort into 3 more portfolios based on the signed t-statistic on $\beta_{i,DI}$. 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 60 observations. We also sort into 10 portfolios based only on the signed t-statistic for $\beta_{i,DI}$ in line with momentum papers such as Jegadeesh and Titman [1993]. Portfolios are value-weighted, and used to compute returns in t. There is no look-ahead bias in our 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.

Sample length is limited by data availability - monthly TED spread first appears in FRED in January, 1986. Given our 5-year calibration period, this implies that our first portfolio returns are not available until January, 1991. Removing TED spread could give a longer sample, but we believe it captures some of the variation explained by a recession indicator. On average, $\beta_{i,TED}$ is positive from the end of 2008 to the end of 2013, and negative the rest of the sample. Independent of data availability, starting in 1991 makes sense as according to Hau and Rey [2004], global equity flows only become important in the 1990's.

We construct an HML style factor in two ways: $HML_{2\times3}$ is constructed in line with Fama and French [1993]: (1/2)(Small High + Big High) - (1/2) (Small Low + Big Low), while HML_{10-1} is constructed in-line with Jegadeesh and Titman [1993] as $r_{10} - r_1$.

[7]The TED spread is the difference between 3-Month LIBOR and 3-Month Treasury bill rates. It is a measure of credit risk, and increases when default risk is high.

[8]Using 3 years of data instead of 5, and using daily data instead of monthly data do change the results. See Section 5 for more on the robustness checks.

2.4 Summary Statistics

Table 1 shows summary statistics for the 2x3 sort. For large firms, returns are monotonically increasing across the $\beta_{i,DI}$ dimension. Among large firms, those with the smallest market capitalization have the largest t-statistic on $\beta_{i,DI}$. For both small and large firms, market betas are decreasing across the $\beta_{i,DI}$ dimension.

[Table 1 about here.]

Table 2 shows the results for the 10 portfolio sort. We have more noise in expected returns for the middle portfolios, but there is an average difference of 2.35% per year between the positive/high (10) and negative/low (1) exposure portfolios. We have monotonically decreasing beta and market capitalization from portfolio 1 to portfolio 10. 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 (see Section 5).

[Table 2 about here.]

Small, low market beta firms, have larger t-Statistics on $\beta_{i,DI}$, and do well as the dollar strengthens. This is in line with the flight-to-quality story of Campbell et al. [2010] and Cho, Choi, Kim, and Kim [2012] on both dimensions. First, large firms (multinationals) have a larger percentage of revenue from abroad, and as a result, suffer more than small domestic firms after global downturns. Figures 11, 12 and 13 show the average annual percentage of revenue from abroad by portfolio[9]. From 1991-2000 and from 2009-2015 the 1 portfolio (large firms) had more 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.

Even if you do not buy the flight to quality story, large firms being sorted into portfolio 1 still makes sense. If large firms are exporters, when the dollar goes up in value, their products become more expensive to foreigners, and they sell less.

2.5 Relationship to Other Asset Pricing Factors

We regress the excess returns[10] our 2×3 and 10 sorted portfolio returns on two sets of regressors: the q-Factor model of Hou et al. [2014] and 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 joint significance of the alphas using the method in Gibbons, Ross, and Shanken [1989]. Tables 3 and 4 show the results for the 2×3 sorted portfolios.

[9] The numbers in the figure seem too high, and 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 evidence, not proof that all firms in the 1 portfolio are large exporters.

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

[Table 3 about here.]

[Table 4 about here.]

Applying the GRS test to the 2×3 sorted portfolios, we cannot reject the null that they are on the mean variance frontier. Tables 5 and 6 show the results for the 10 sorted portfolios.

[Table 5 about here.]

[Table 6 about here.]

Applying the GRS test to the 10 sorted portfolios, we reject the null that they are on the mean variance frontier for both the q-Factor model ($p = 0.011$) and the augmented Fama-French model ($p = 0.023$). This is evidence that we have discovered a new asset pricing factor, as the variation in excess returns across our portfolios is not explained by established factors.
For both sorts, the $HML_{2\times3}$ and HML_{10-1} factors' loading on ROE is economically large and statistically significant. Exposure to US dollar strength is a fundamental characteristic of a firm, just like size or book-to-market. Given the time series momentum in FX returns (see Moskowitz et al. [2011]), it makes sense that our factor is related to something persistent like profitability (see Novy-Marx [2015a]). A full discussion of the relationship between our factor, profitability and momentum is in Section 4.

2.6 Fama MacBeth results

To understand the risk premium associated with holding dollar strength risk, we use the two-stage technique in Fama and MacBeth [1973]. Given that our 2×3 portfolios do not expand the mean variance frontier, from here on, we only use the HML_{10-1} factor. 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, Nagel, and Shanken [2010]). The first stage is run in 60-month rolling windows:

$$\begin{aligned} R^e_{i,t} = \alpha_i + \beta_{i,mkt}mkt_t + \beta_{i,smb}smb_t + \beta_{i,hml}hml_t + \beta_{i,mom}mom_t + \\ \beta_{i,qmj}qmj_t + \beta_{i,bab}bab_t + \beta_{i,dollar}HML_{10-1,t} + \epsilon_{i,t} \end{aligned} \tag{2}$$

where $R^e_{i,t}$ 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:

$$\begin{aligned} E[R^e_{i,t}] = \alpha_0 + \lambda_m kt\beta_{i,mkt} + \lambda_{smb}\beta_{i,smb} + \lambda_{hml}\beta_{i,hml} + \lambda_{mom}\beta_{i,mom} + \\ \lambda_{qmj}\beta_{i,qmj} + \lambda_{bab}\beta_{i,bab} + \lambda_{dollar} + \beta_{i,dollar} + \tilde{\epsilon_i} \end{aligned} \tag{3}$$

Figure 2 plots the evolution of selected λ's from the second stage:

[Figure 2 about here.]

Figure 3 plots the associated t-Statistics on the λ's:

[Figure 3 about here.]

We repeat the first stage using the q-Factor model:'

$$\begin{aligned} R^e_{i,t} = \alpha_i + \beta_{i,mkt} mkt_t + \beta_{i,me} me_t + \beta_{i,ia} ia_t + \\ \beta_{i,roe} roe_t + \beta_{i,dollar} HML_{10-1,t} + \epsilon_{i,t} \end{aligned} \tag{4}$$

And the second stage:

$$\begin{aligned} E[R^e_{i,t}] = \alpha_0 + \lambda_m kt \beta_{i,mkt} + \lambda_{me} \beta_{i,me} + \lambda_{ia} \beta_{i,ia} + \\ \lambda_{roe} \beta_{i,roe} + \lambda_{dollar} + \beta_{i,dollar} + \tilde{\epsilon_i} \end{aligned} \tag{5}$$

In Figure 4 we plot selected λ's from the second stage:

[Figure 4 about here.]

And Figure 5 plots the associated t-Statistics:

[Figure 5 about here.]

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. This is more evidence that we have found a viable new factor.

3 Explanations

Having established the economic and statistical significance of our dollar exposure factor, we explore for economic explanations for its behavior. These results also alleviate some concerns of a spurious factor[11].

3.1 Imports/Exports

Some of the correlation between imports, exports and dollar strength is driven by behavior in recessions. Figure 6 plots the 3 series from 1991-2015. The dollar is used for international transactions, but it is also a reserve currency. A crisis causes imports and exports to fall but the demand for dollar reserves increases. As a result, correlations between the series maybe be biased during contractions.

[Figure 6 about here.]

Given the trends in both series Figures 7 and 8 plot the series in percent changes, and compute correlations. Excluding the crisis years, 2007-2009, we restore the expected sign on the correlation between imports and dollar strength.

[11] For more on spurious factors, see Bryzgalova [2015].

[Figure 7 about here.]

[Figure 8 about here.]

Changes in exports are more correlated with changes in dollar strength than changes in imports, and the magnitude of correlation is significant. This implies changes in dollar strength should have a real effect on exporting firms. For example, a strong dollar is bad for US export industries, such as such as aircraft and pharmaceutical companies. We discuss the industry breakdown by portfolio in a subsection below.

The weak relationship between dollar strength and imports is surprising, as a strong dollar should make Americans effectively richer. For example: A strong dollar makes oil products less expensive, giving Americans more disposable income to spend on consumption. Figure 9 plots the relationship between real consumption and dollar strength. The correlation is negative, and excluding the crisis years it is essentially zero.

[Figure 9 about here.]

The relationship between dollar strength, imports and consumptions is weak, but the relationship between dollar strength and exports is promising. In Section 2, we speculated that firms in portfolio 1 were more likely to be exporters, but we can 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[12]. Not all firms in CRSP are in Compustat and not all firms in Compustat have non-missing data. We do not match an equal number of firms across portfolios, as Compustat has better data on large firms. We consistently match 50-100% more firms in portfolio 1 than portfolio 10.

To get around the matching problem, we add up total total domestic and foreign pretax income within each portfolio/year observation, and calculate total percent of revenue from abroad at the portfolio level. This eliminates most of the problems with negative values[13]. 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 10 motivates breaking the sample into 3 periods based on the direction the dollar is moving.

[Figure 10 about here.]

As expected, the portfolio 1 is populated with exporters. Figure 11 shows we get nearly monotonically decreasing revenue from abroad from portfolio 1 to 10 in the first dollar strengthening episode from 1991-2000.

[Figure 11 about here.]

As the dollar weakens from 2001-2008, Figure 12 shows there is essentially no relationship between our sort and revenue from abroad.

[12] This creates a selection bias, but otherwise percent of revenue from abroad is not always well defined

[13] For example: A large firm makes a small positive profit, but it is foreign revenues are big and negative and domestic revenues are big and positive. Then we are dividing a big negative number by a number near zero, and we get an even bigger negative number

[Figure 12 about here.]

Figure 13 shows that as the dollar strengthens again after the crisis, the near monotonic relationship between export revenue and portfolio sorts returns.

[Figure 13 about here.]

3.2 Global Downturn Risk

Another possible story is that our factor measures exposure to global downturn risk. In the style of Campbell 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 get some preliminary results. Figure 14 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 -42.43% with the VTWSX and a correlation of -31.15% 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.

[Figure 14 about here.]

3.3 Industries

Some industries 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 15 shows that from 1991-2000 the low/negative sensitivity portfolios (1 & 3) have more mining stocks, while the 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.

[Figure 15 about here.]

Figure 16 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.

[Figure 16 about here.]

Figure 17 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.

[Figure 17 about here.]

The industry composition could be different during dollar up and dollar down periods for several reasons. One explanation is that dollar weakness has a net zero effect - where imports become more expensive, but it is compensated by more exports - while dollar strength has a real effect on firms. The differences between up and down periods is in line with the results in Figure 12 where the revenue from abroad does not have a clear pattern across portfolios.

3.4 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, so Table 7 computes all of the correlations in first differences. Even though we conditioned on changes in the 3-month rate, changes in the 3-month treasury bill have the strongest correlation with our HML_{10-1} factor. All of the correlations are less than 10% so we are not concerned that we have just created an interest rate factor.

[Table 7 about here.]

3.5 Looking at Firm Financial Data

Ideally, we would like all 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). In our baseline specification, each month, on average there are 325 firms per portfolio. Using annual FCA data, we match 80/100 firms per portfolio/year. Figure 18 shows that although the relationship is not 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.

[Figure 18 about here.]

4 Relationship to Momentum

4.1 Fundamental Momentum

In the 2×3 sorts we see that the alpha on the HML_{10-1} factor is statistically significant in the augmented Fama French model, but not in the q-factor model of Hou et al. [2014]. In the q-factor model, the largest loading, both economically and statistically, is on the ROE factor. This shows the dollar exposure factor is somehow related to profitability.
Novy-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 Novy-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. 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 (t-statistic of over 4). 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 correlation between the dollar index and MOM/ROE, which is around 10% for both. This is because our factor picks up *sensitivity* to moves in the dollar, a fundamental characteristic, not just moves in the dollar itself.

In Table 8, we take the 10 momentum portfolios from Jegadeesh and Titman [1993] and regress their returns on the 3 Fama-French Factors, later adding our HML_{10-1} factor and Hou et al. [2014]'s ROE factor. Our factor remains significant, or becomes significant after adding ROE factor for almost all portfolios.

[Table 8 about here.]

Going even simpler we test the relationship between the factors using linear regression in Table 9. In a univariate regression, our HML_{10-1} factor alone takes all the alpha out of winner minus loser (MOM) portfolio. The big different using Newey-West standard errors suggests autocorrelation in the series, which is not surprising - after all, these are factors related to momentum.

[Table 9 about here.]

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 US and the UK, each with their own currencies, the dollar and the pound. If the dollar is experiencing positive momentum, the pound must be experiencing "negative" momentum. 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 US investor, a US momentum strategy can be decomposed into:

$$r_t^{MOM,US} = a + a_1 ROE_t^{US} + a_2 FX_t^{dollar} \tag{6}$$

And the UK momentum strategy can be decomposed into:

$$\begin{aligned} r_t^{MOM,UK} &= b + b_1 ROE_t^{UK} + b_2 FX_t^{pound} = \\ r_t^{MOM,UK} &= b + b_1 ROE_t^{UK} - b_2 FX_t^{dollar} = \end{aligned} \tag{7}$$

Where the second line follows from our assumption of only two countries: 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 (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 US and foreign momentum on our HML_{10-1} factor. We exclude Japan, as momentum in Japan is weak during our sample period. Table 10 shows the results from the univariate regressions.

[Table 10 about here.]

Our sign is consistent with the uncovered equity parity result discussed in Hau and Rey [2006]. Consider a US momentum investor. Suppose UK momentum does well relative to US momentum ($US^{MOM} - UK^{MOM} < 0$). To rebalance away from pound exposure, the US investor sells some of his UK momentum position. The flow of funds from the UK to the US would increase the value of the dollar, and benefit stocks with positive dollar exposure (so HML_{10-1} should be> 0). 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.

5 Robustness Checks

We check the robustness of our results with daily data, alternative calibration periods, alternative filters, alternative measures of dollar strength and checking for outliers[14].

5.1 Repeat Analysis with Daily Data

Using monthly data for Equation 1 only allows 60 observations, which may lead to measurement errors in the $\beta_{i,DI}$. We did not use daily data in our baseline specification, as at the daily level, especially later in the sample, there is a lack of variation in ΔTED spread and Δ3-Month T-bill yield (most of the observations are zero).
When using the daily calibration, the direction of expected return reverses: Now the low/negative exposure portfolios have higher expected returns. See Table 11. This is in line with the safe asset story - the dollar increasing in value is a sign of a crisis, so assets that covary positively should have low expected returns. Table 12 shows it is

[14]We have also assembled a panel of S&P500 companies with firm fundamentals at a quarterly frequency. Using data from 2000 to 2016, we estimate several panel data models, in the style of Fama and French [1992]. We find a consistently negative average risk premia for the dollar index across all specifications. Those results are available upon request.

being driven by small firms, as the direction does not reverse for portfolios 4, 5 and 6. All of the alphas however, are statistically insignificant. The HML factors computed with daily data load heavily on Betting Against Beta in the augmented Fama-French model, and load on size and return on equity in the q-Factor model.

It is not fair to claim it is caused by noisy betas at the daily level, as the t-Statistics are larger, which is not surprising as we go from 60 observations to over 1,000. The large difference between the daily results and the monthly results suggest that the underlying factors that drive daily dollar returns, conditional on changes in interest rates, are different than the factors that drive monthly returns.

Figure 19 shows the value of $1 invested in the monthly calibrated HML_{10-1}, vs the daily calibrated HML_{10-1}. The correlation between the three series (all in percent changes) is not high, with a maximum of 26%. This is not the result of conditioning on changes in interest rates in 1. Figure 20 shows the effect of conditioning on interest rates. The daily HML_{10-1} is more highly correlated with the changes in dollar strength, but this is not surprising as the $\beta_{i,DI}$ are better measured. Our measure does not track dollar strength well, but Meese and Rogoff [1983] showed it is to predict FX moves, so it is not surprising. Future work will explore the underlying drivers of daily and monthly movements in dollar strength.

[Figure 19 about here.]

[Figure 20 about here.]

[Table 11 about here.]

[Table 12 about here.]

[Table 13 about here.]

5.2 Compare using 3-year and 5-year calibration periods

Instead of using the previous 5 years of data, we run Equation 1 using the previous 3 years of data. To make it an apples-to-apples comparison, we require the previous 60 returns to be non-missing, so we are sorting on the same universe of stocks as before. The results are significantly different, and we offer two explanations. The first is similar to our explanation of the results using daily data - the underlying factors driving dollar changes at the shorter horizons are different than factors driving dollar changes at longer horizons. A second explanation is that these betas are not as well measured. As you can see in Tables 14 and 15 the average t-Statistics on $\beta_{i,DI}$ are closer to zero for almost all portfolios.

[Table 14 about here.]

[Table 15 about here.]

5.3 Relaxing filter on non-missing returns

Requiring 60 non-missing observations out of 60 possible observations seems like a harsh filter. We re-form the portfolios by running Equation 1 on the previous 5 years of data, but this time, we only require 36 non-missing observations. Tables 16 and 17 show that the results are essentially unchanged.

[Table 16 about here.]

[Table 17 about here.]

5.4 Sorting on $\beta_{i,DI}$ as opposed to t-Statistics

We wanted to know if $\beta_{i,DI}$ had some information outside the t-statistic[15]. The $HML_{2\times3}$ and HML_{10-1} portfolios have similar alphas on established asset pricing factors. Table 18 shows, however, that this sort generates a smaller spread in expected returns. Also, Table 19 shows we lose the monotonicity in expected returns among the small portfolios in the 2×3 sort. This suggests the $\beta_{i,DI}$ are noisy and using the t-Statistic instead is correct.

[Table 18 about here.]

[Table 19 about here.]

5.5 Value vs. Equal weighted portfolios (Outliers)

it is possible our results are being driven by a few large firms, so we repeat the analysis using equal weights, as opposed to value weights. Changing to equal weights is similar to sorting on $\beta_{i,D}$ as opposed to the t-statistics: it introduces more noise. As above, the alpha's on our HML portfolio are about the same using equal weights. As Table 20 shows, the relationship in the large portfolios is similar, while the relationship in the small portfolios falls apart. It also reduces spread in returns across the 10-sorted portfolios. We do not believe this is a lack of robustness, just a problem of too many small firms in selection universe adding noise[16]. Table 21 shows that for the 10 portfolio sort, not much changes when using equal weights

[Table 20 about here.]

[Table 21 about here.]

[15] For example - given the short calibration period, all stocks might have small t-statistics, so they're not very informative

[16] Recall: we only removed those with market capitalization less than $500,000

5.6 Removing Small Firms

To make sure we are not just creating a new size factor, we drop the bottom 20% of firms by market capitalization each month and sort into portfolios as before. Table 22 shows our results are essentially unchanged. This is not surprising, as our portfolios are value-weighted, so small firms do not have a large impact. We only show the 10 portfolio sort, as dropping small firms has an asymmetric effect on the 2×3 sorted portfolios[17].

[Table 22 about here.]

6 Conclusion

We provide evidence that exposure to the strength of the US dollar is a factor that cannot be overlooked in pricing US equities. Data on revenue from abroad and industry composition of portfolios suggest our factor is not spurious. The GRS test suggests our portfolios can expand the mean variance frontier, 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. We are currently working on another paper which analyzes exposure to higher moments of foreign exchange risk in the cross section. We also plan on repeating our analysis using individual currencies, as opposed to an aggregate dollar index. 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.

[17] Despite this, the 2×3 results do not change much

References

Ang, A., J. Chen, and Y. Xing (2006): "Downside Risk," *The Review of Financial Studies*, 19, 1191–1239.

Asness, C. S., A. Frazzini, and L. H. Pedersen (2014): "Quality Minus Junk," *SSRN*.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen (2013): "Value and Momentum Everywhere," *The Journal of Finance*, 68, 929–986.

Bryzgalova, S. (2015): "Spurious Factors in Linear Asset Pricing Models," *Working Paper*.

Campbell, J. Y., K. Serfaty-De Medeiros, and L. M. Viceria (2010): "Global Currency Hedging," *The Journal of Finance*, 65, 87–121.

Cho, J.-W., J. H. Choi, T. Kim, and W. Kim (2012): "Flight-to-Quality and Correlations between Currency and Stock Returns," *SSRN Working Paper*.

Curcuru, S. E., C. P. Thomas, F. E. Warnock, and J. Wongswan (2014): "Uncovered Equity Parity and Rebalancing in international Portfolios." *NBER Working Paper*.

Daniel, K., A. Klos, and S. Rottke (2016): "Betting Against Winners," *Working Paper*.

Fama, E. F. and K. R. French (1992): "The Cross-Section of Expected Stock Returns," *The Journal of Finance*, 47, 427–465.

——— (1993): "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics*, 33, 3–56.

Fama, E. F. and J. D. MacBeth (1973): "Risk, Return, and Equilibrium: Empirical Tests," *The Journal of Polotical Economy*, 81, 607–636.

Frazzini, A. and L. H. Pedersen (2014): "Betting against beta," *Journal of Financial Economics*, 111, 1–25.

Gibbons, M., S. Ross, and J. Shanken (1989): "A Test of the Efficency of a Given Portfolio," *Econometrica*, 57, 1121–1152.

Harvey, C. R. (1991): "The World Price of Covariance Risk," *The Journal of Finance*, 46, 111–157.

Hau, H. and H. Rey (2004): "Can Portfolio Rebalancing Explain the Dynamics of Equity Returns, Equity Flows, and Exchange Rates?" *American Economic Review*, 94, 126–133.

——— (2006): "Exchange Rates, Equity Prices, and Capital Flows," *Review of Financial Studies*, 19, 273–317.

He, Z., A. Krishnamurthy, and K. Milbradt (2016): "A Model of Safe Asset Determination," *NBER Working Paper No. 22271*.

Hou, K., C. Xue, and L. Zhang (2014): "Digesting Anomalies: An Investment Approach," *Review of Financial Studies*, 28, 650–705.

Jagannathan, R. and Z. Wang (1996): "The Conditional CAPM and the Cross-Section of Expected Returns," *The Journal of Finance*, 51, 3–53.

Jegadeesh, N. and S. Titman (1993): "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *The Journal of Finance*, 48, 65–91.

Lettau, M., M. Maggiori, and M. Weber (2014): "Conditional Risk Premia in Currency Markets and Other Assets Classes," *Journal of Financial Economics*, 114, 197–225.

Lewellen, J., S. Nagel, and J. Shanken (2010): "A Skeptical Appraisal of Asset Pricing Tests," *Journal of Financial Economics*, 96, 175–194.

Lewis, K. K. (2011): "Global Asset Pricing," *Annual Review of Financial Economics*, 3, 435–466.

Meese, R. A. and K. Rogoff (1983): "Empirical Exchange Rate Models of the Seventies: Do they fit out of sample?" *Journal of International Economics*, 14, 3–24.

Moskowitz, T. J., Y. H. Ooi, and L. H. Pedersen (2011): "Time Series Momentum," *Journal of Financial Economics*, 104, 228–250.

Novy-Marx, R. (2015a): "Fundamentally, Momentum is Fundamental Momentum," *NBER Working Paper*.

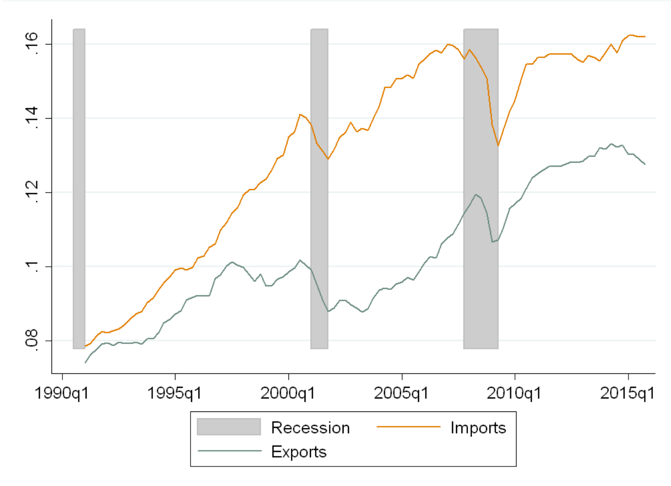
——— (2015b): "How Can a Q-Theoretic Model Price Momentum?" *NBER Working Paper*.

Sharpe, W. F. (1964): "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk," *The Journal of Finance*, 19, 425–442.

Solnik, B. H. (1974): "An Equilibrium Model of the International Capital Market," *Journal of Economic Theory*, 8, 500–524.

List of Figures

Figure 1: Exports and Imports as a Percentage of GDP

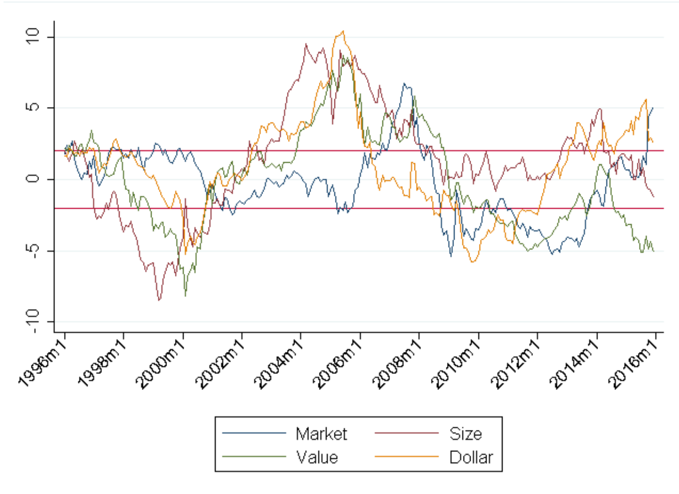


Imports and exports have increased from about 8% in 1991 to 13% and 16% in 2015

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

Risk premia are computed using Fama and MacBeth [1973] style regressions. We include the following factors: MKT, SMB, HML, MOM, QMJ, BAB and our HML_{10-1}. We multiply by 12 to annualize monthly risk premia.

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

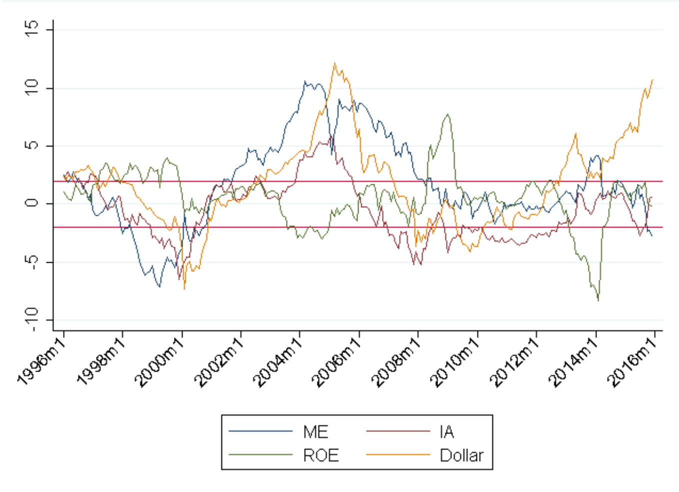


Horizontal lines indicate 95% critical values

Figure 4: Annualized Risk Premia from q-Factor Model

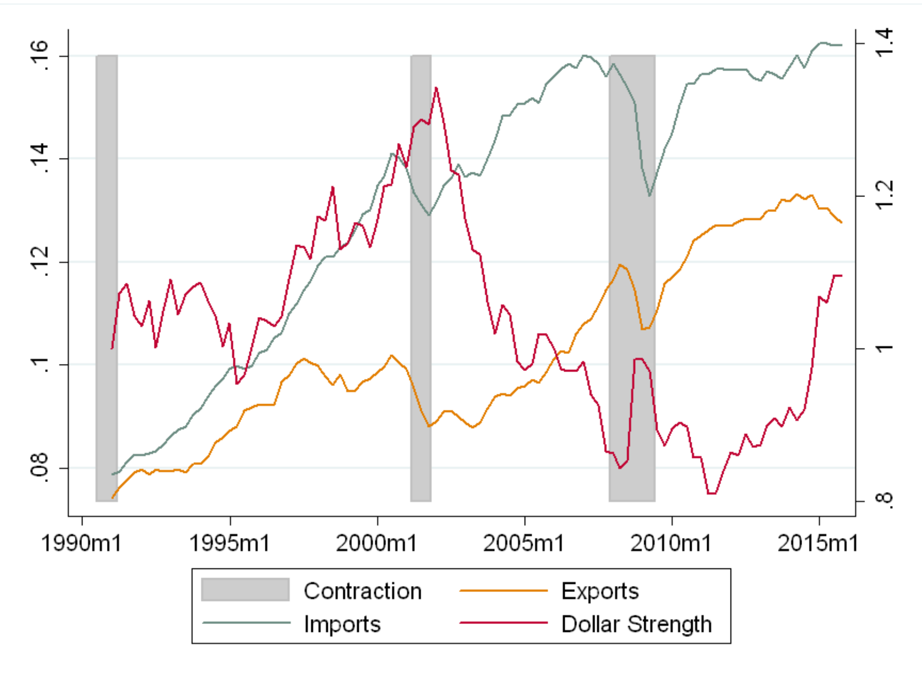
Risk premia are computed using Fama and MacBeth [1973] style regressions. We include the following factors: MKT, ME, IA, ROE and our HML_{10-1}. We multiply by 12 to annualize monthly risk premia.

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



Horizontal lines indicate 95% critical values

Figure 6: Dollar Strength, Imports and Exports



Real exports and imports as a percentage of real GDP

Figure 7: Changes in Exports and Dollar Strength

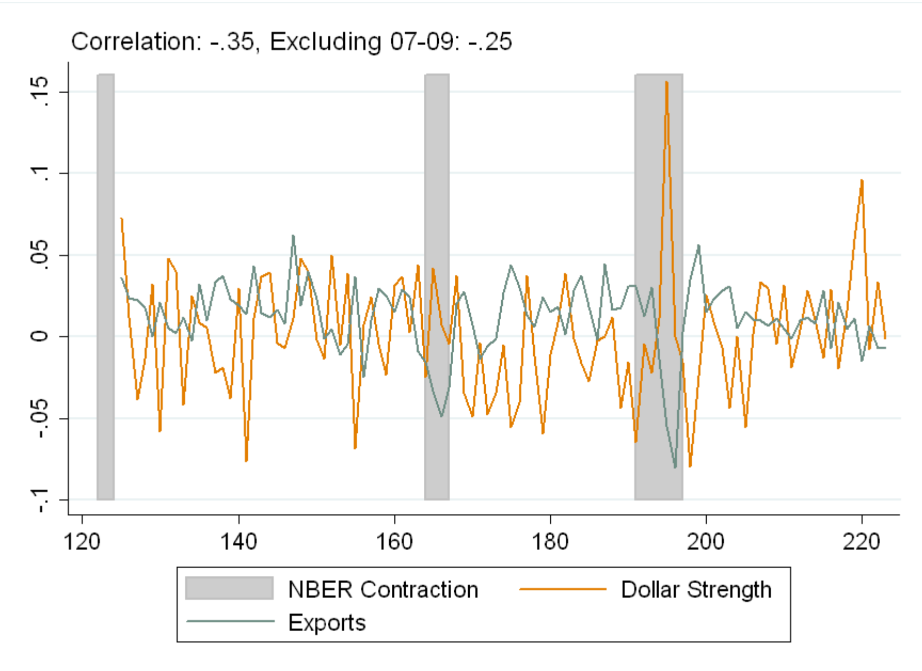


Figure 8: Changes in Imports and Dollar Strength

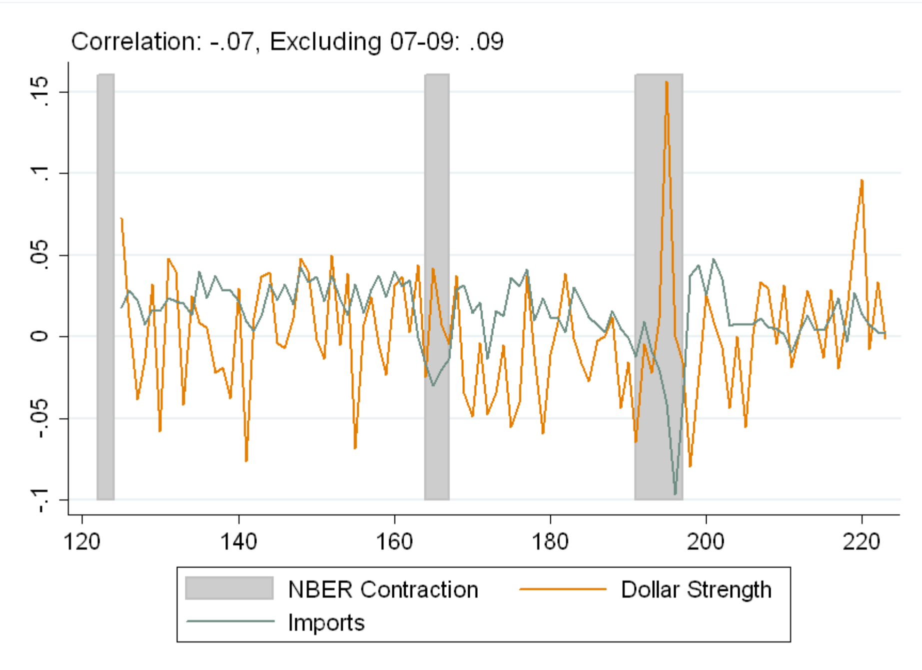


Figure 9: Changes in Consumption and Dollar Strength

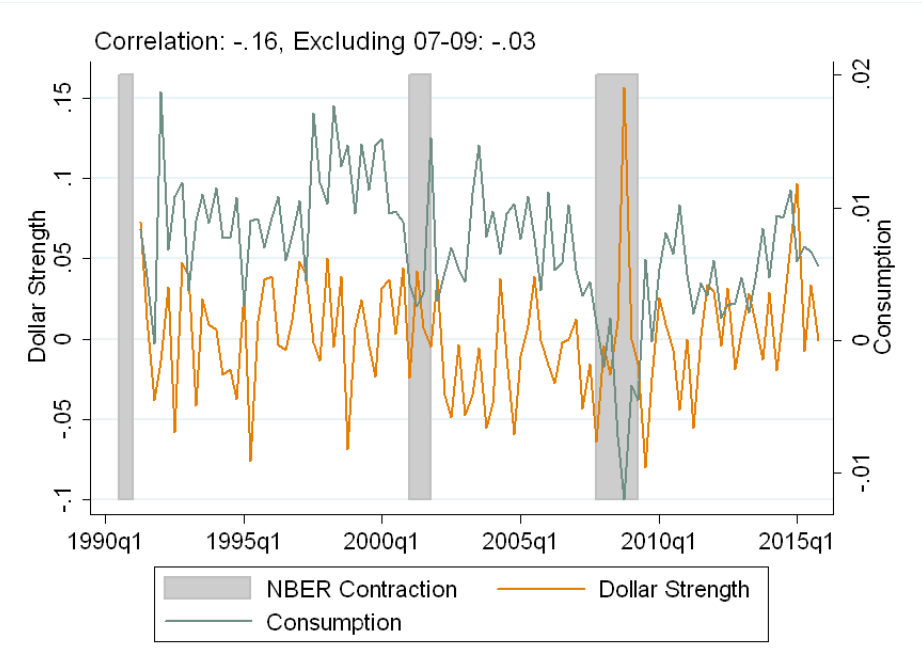
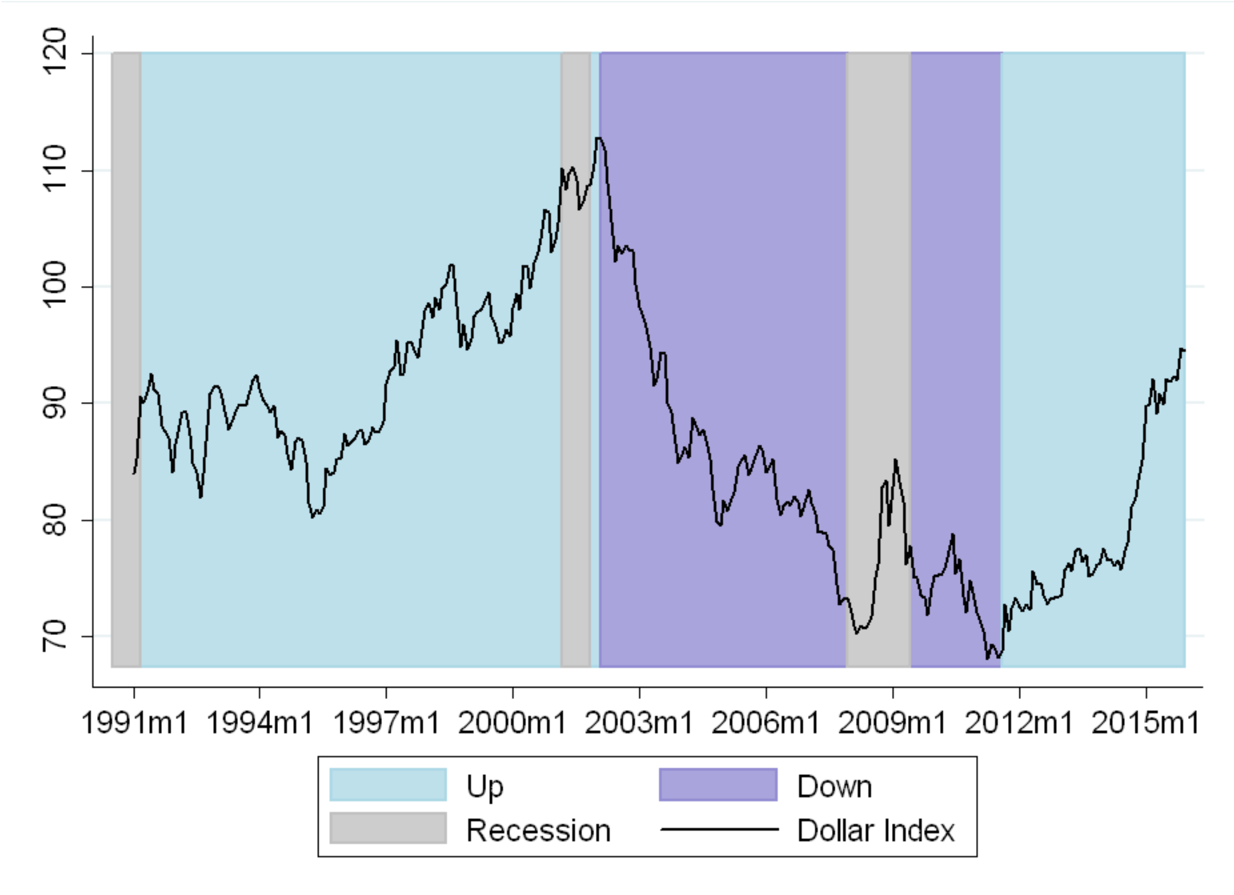


Figure 10: Trend in the Dollar Index



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

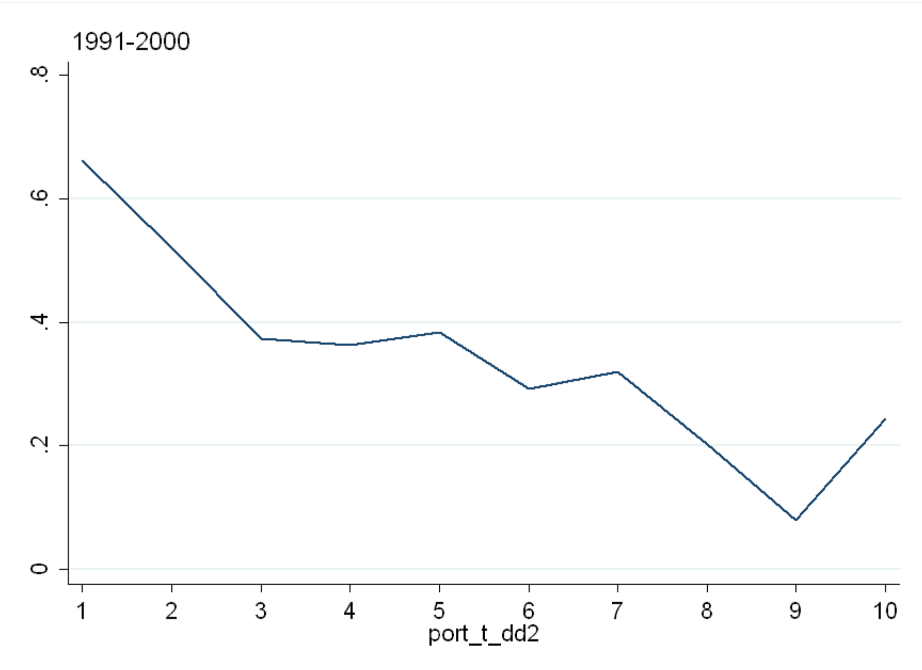


Figure 12: Average Annual Percent of Revenue from Abroad by Portfolio, 2009-2015

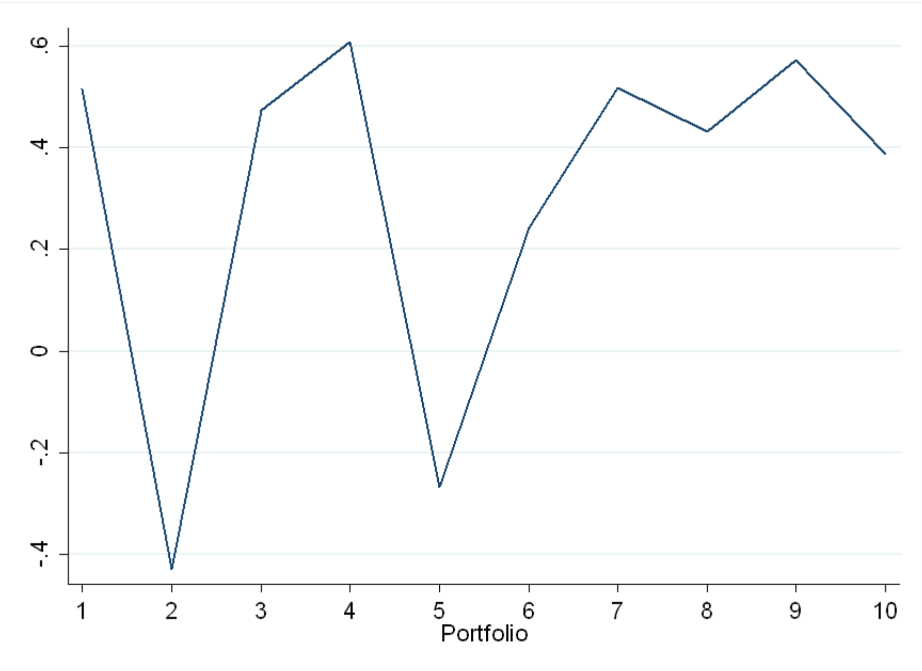


Figure 13: Average Annual Percent of Revenue from Abroad by Portfolio, 2009-2015

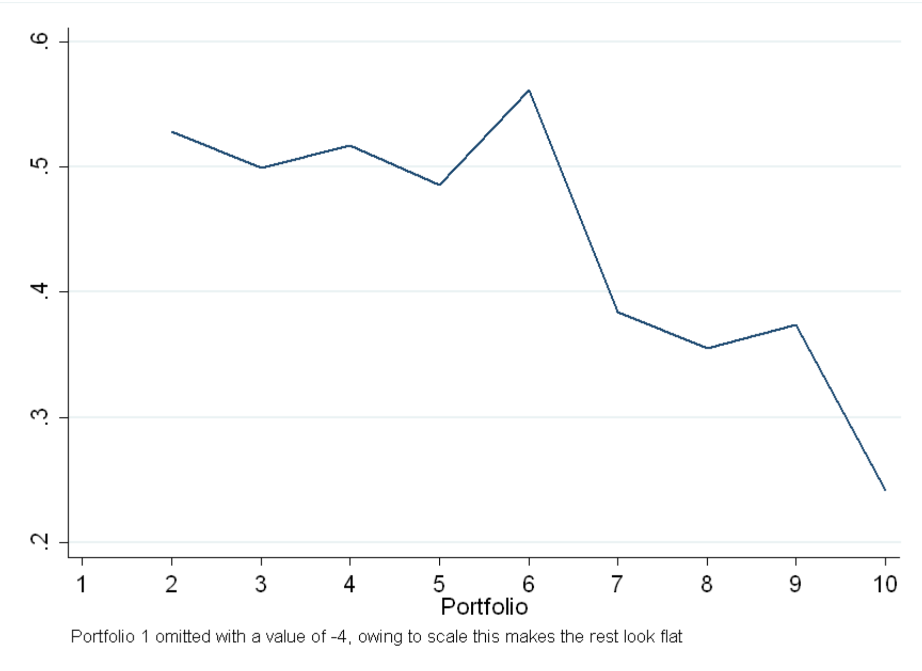


Figure 14: Value of $1 Invested in June 2008

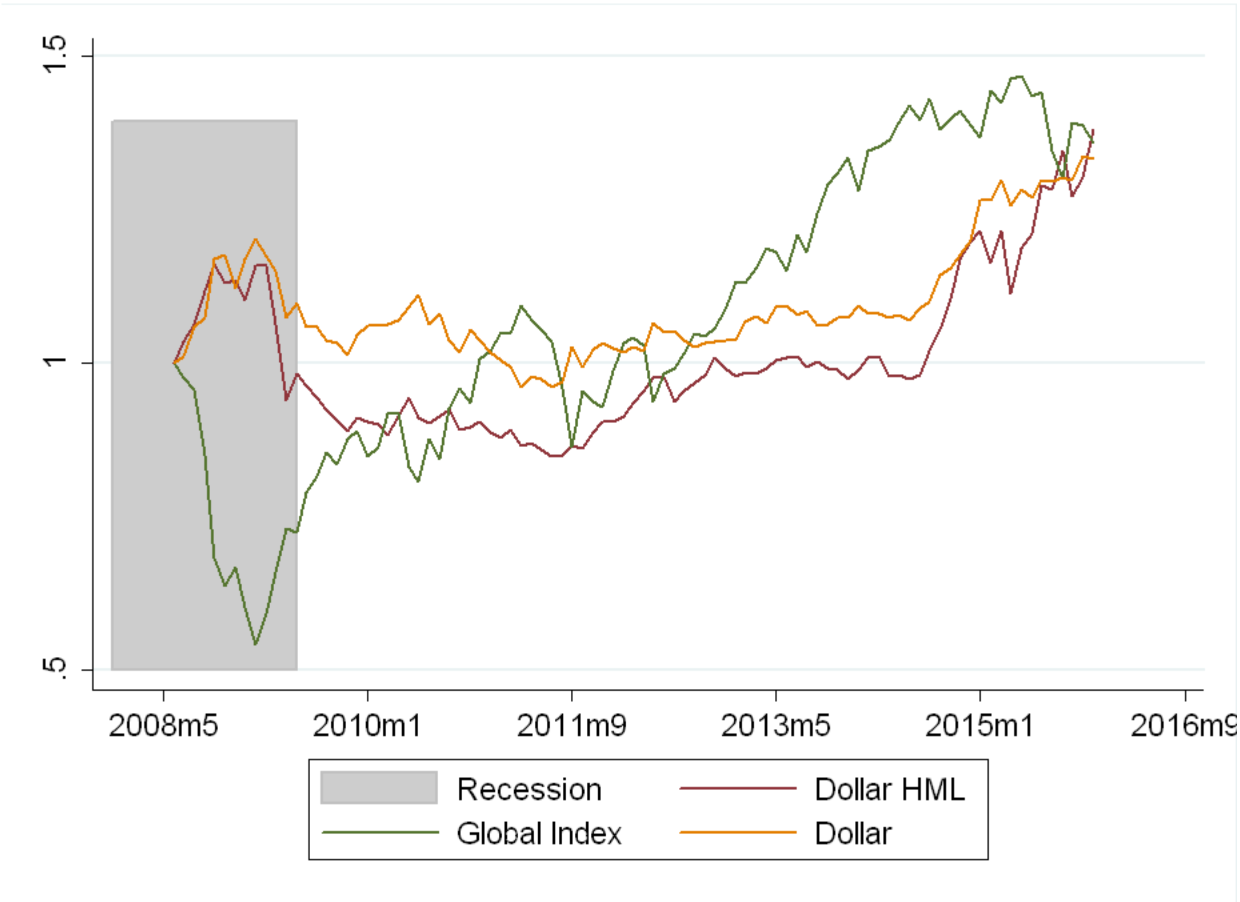


Figure 15: Distribution of Industries by Portfolio, 1991-2000

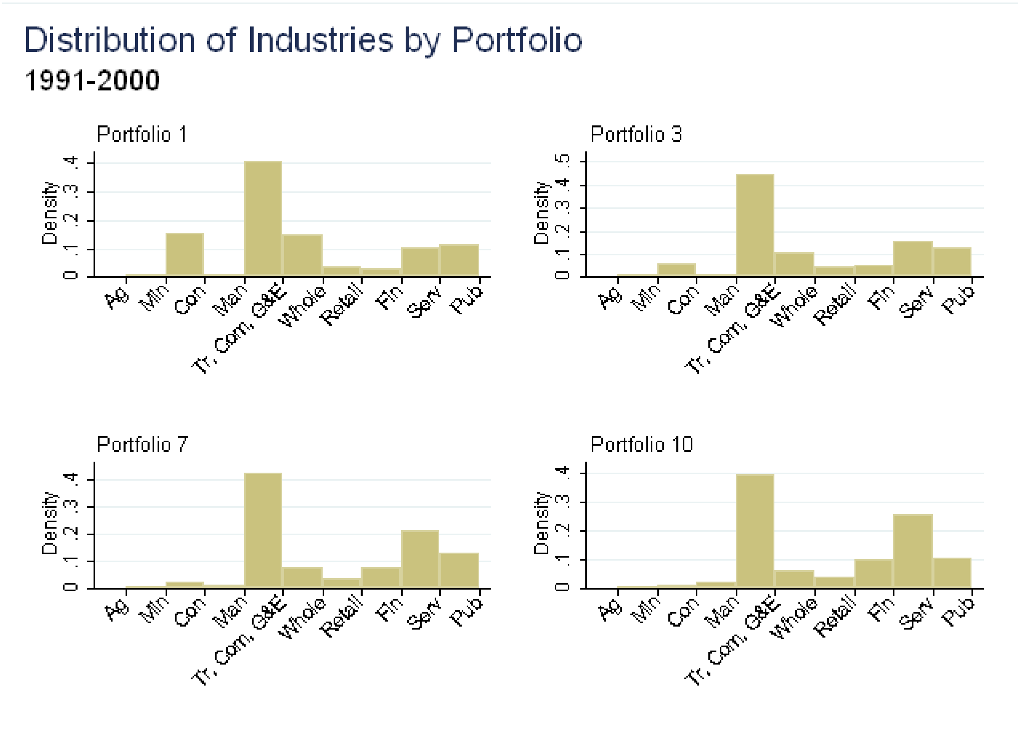


Figure 16: Distribution of Industries by Portfolio, 2001-2008

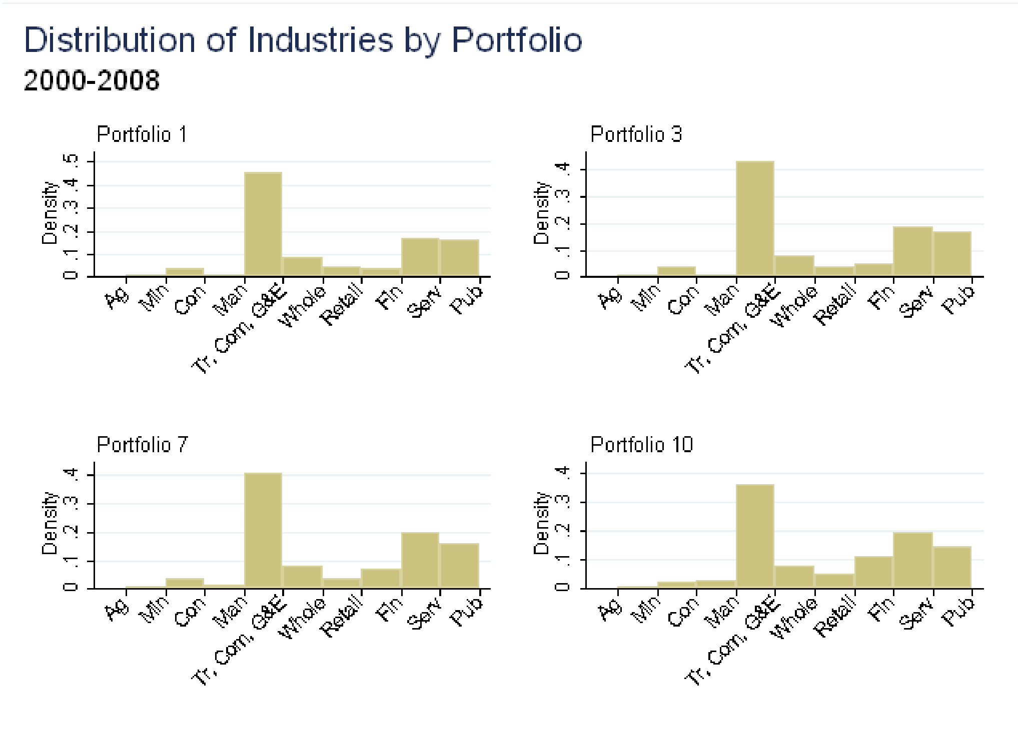


Figure 17: Distribution of Industries by Portfolio, 2009-2015

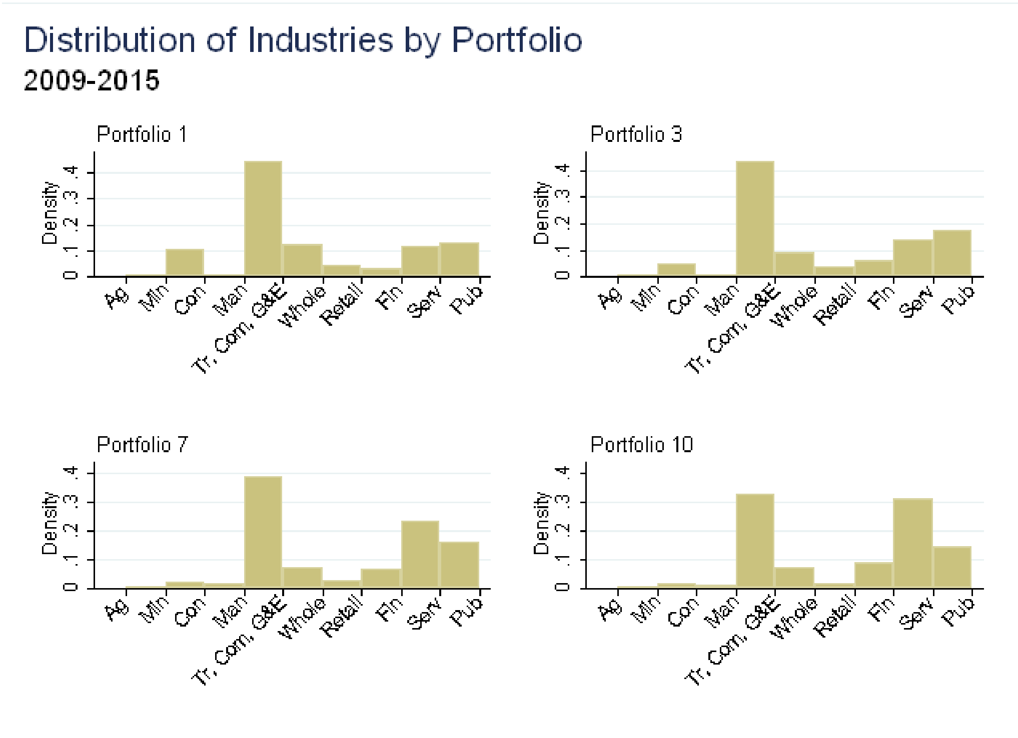
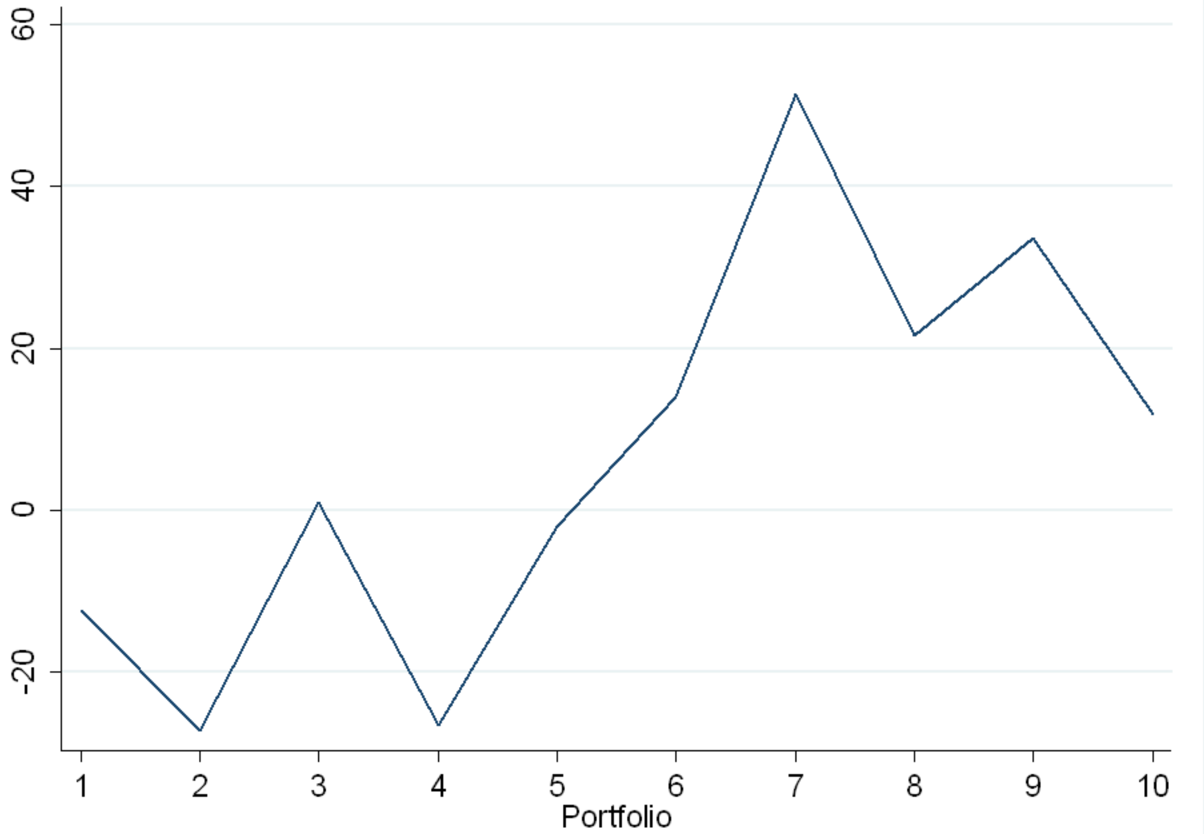
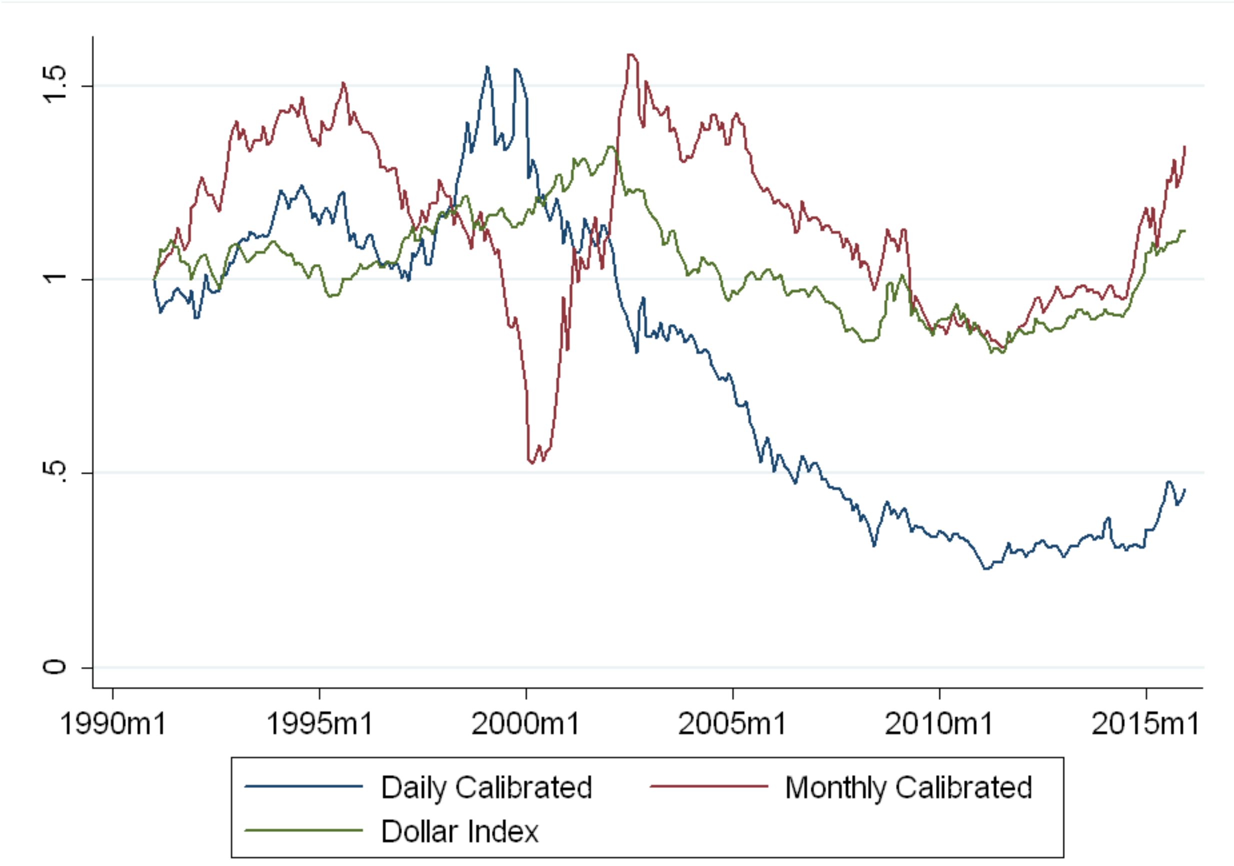


Figure 18: Average Foreign Exchange Income (Loss) by Portfolio



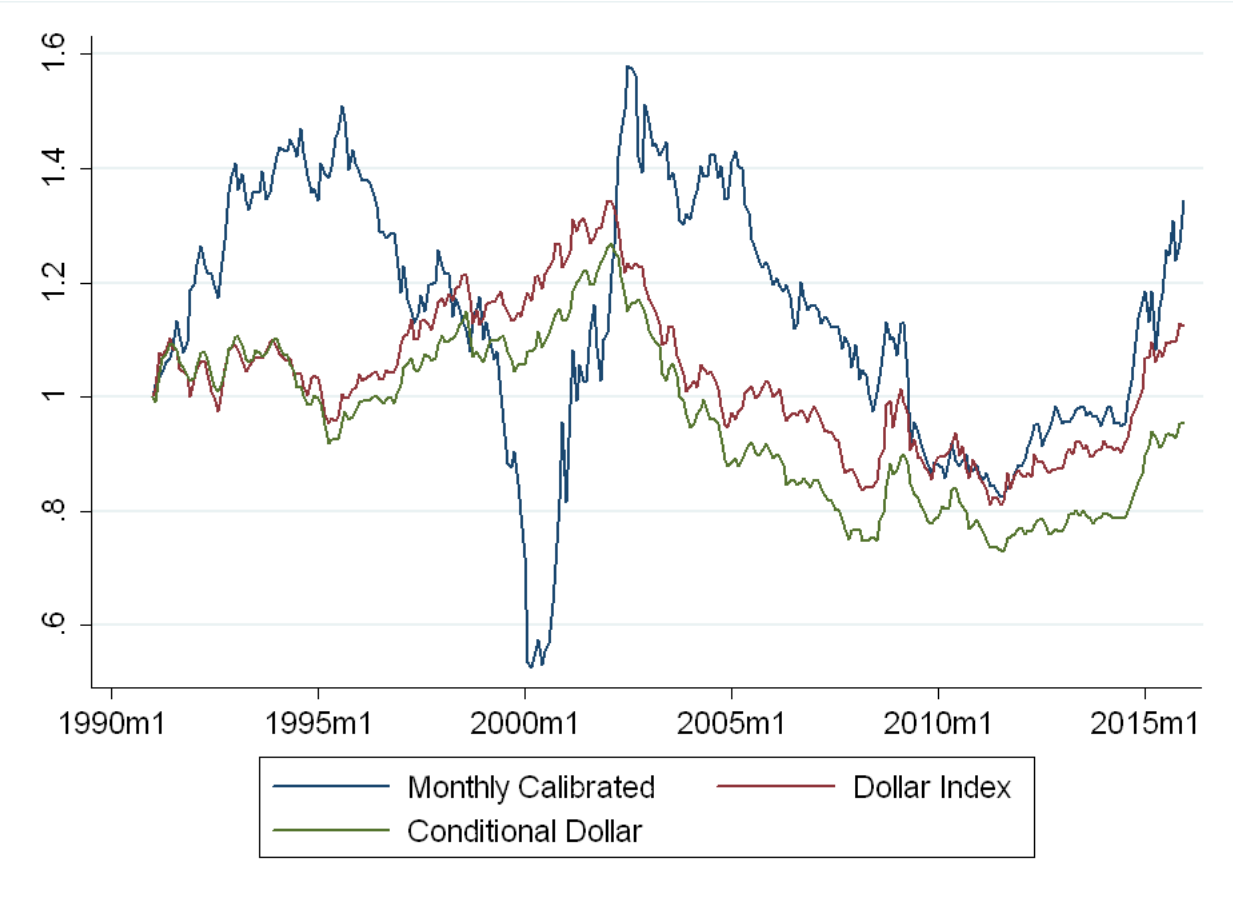
Represents annual foreign exchange income (loss) in millions of dollars

Figure 19: Value of $1 Invested in January 1991



Correlation (for percent changes) between monthly and daily is 16.9%, monthly and dollar index is 19.1 % and between daily and dollar index is 26.0%.

Figure 20: Effect of Conditioning on Changes in Interest Rates



We first run a regression of $r_{DI,t} = \alpha + \beta_{3M}\Delta_{3M} + \beta_{TED}\Delta_{TED} + \epsilon_t$, and save the residuals. We then use the residuals to reconstruct a conditional dollar strength index.

List of Tables

Table 1: Summary Statistics for 2×3 Sort

	Annualized		Average Within Portfolios		
Portfolio	Mean	Standard Dev	$Beta_M$	Mkt. Cap. ($M)	t-Stat $\beta_{i,DI}$
1	14.45%	21.67%	1.08	274	-1.35
2	14.79%	18.41%	0.99	273	-0.21
3	14.72%	17.43%	0.81	278	0.90
4	10.37%	16.34%	1.15	14,000	-1.61
5	11.03%	14.18%	1.09	11,700	-0.44
6	12.46%	13.58%	0.92	10,000	0.71
HML	1.18%	9.03%			

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 returns on the CRSP value-weighted index 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 2: Summary Statistics for 10 Sort

	Annualized		Average Within Portfolios		
Portfolio	Mean	Standard Dev	$Beta_M$	Mkt. Cap. ($M)	t-Stat $\beta_{i,DI}$
1	10.88%	18.27%	1.12	4,796	-2.05
2	10.87%	16.78%	1.10	4,041	-1.31
3	11.25%	15.98%	1.07	3,622	-0.93
4	12.91%	15.02%	1.04	3,127	-0.64
5	9.64%	14.65%	1.04	3,037	-0.38
6	11.87%	14.97%	1.00	2,875	-0.14
7	12.84%	14.79%	0.97	2,593	0.11
8	11.03%	14.24%	0.92	2,529	0.40
9	11.91%	14.30%	0.86	2,432	0.75
10	13.23%	15.12%	0.74	2,237	1.46
HML	2.35%	14.80%			

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 returns on the CRSP value-weighted index 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 3: 2×3 q-Factor Model Regressions

Size	DI Exposure	Alpha	Mkt.	ME	IA	ROE
Small	Low	0.02	1.05	0.71	0.18	-0.38
		(1.84)	(37.82)	(20.97)	(3.36)	(8.74)
Small	Med	0.01	0.98	0.70	0.30	-0.09
		(1.41)	(47.09)	(27.64)	(7.34)	(2.72)
Small	High	0.01	0.94	0.69	0.39	0.01
		(0.77)	(39.42)	(23.92)	(8.39)	(0.14)
Big	Low	0.02	1.00	-0.12	-0.13	-0.16
		(1.77)	(51.90)	(4.93)	(3.53)	(5.51)
Big	Med	-0.01	1.02	-0.13	0.27	0.19
		(1.49)	(64.52)	(6.80)	(8.70)	(7.83)
Big	High	-0.01	0.96	-0.09	0.40	0.33
		(0.59)	(40.45)	(3.11)	(8.70)	(9.08)
	HML	-0.02	-0.08	0.00	0.37	0.44
		(1.32)	(2.53)	(0.08)	(6.22)	(9.29)

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 4: 2×3 Augmented Fama-French Model Regressions

Size	DI Exposure	Alpha	Mkt.	SMB	HML	MOM	BAB	QMJ
Small	Low	0.03	1.05	0.90	0.21	-0.23	-0.07	-0.02
		(2.41)	(41.70)	(29.57)	(6.78)	(12.64)	(2.56)	(0.53)
Small	Med	0.00	1.04	0.86	0.25	-0.11	0.04	0.16
		(0.33)	(64.77)	(44.59)	(12.76)	(9.54)	(2.14)	(5.98)
Small	High	-0.01	1.01	0.85	0.27	-0.11	0.12	0.22
		(0.87)	(50.95)	(35.67)	(10.94)	(7.89)	(5.88)	(6.46)
Big	Low	0.02	0.98	-0.09	-0.02	-0.03	-0.11	-0.09
		(1.90)	(42.67)	(3.16)	(0.86)	(1.81)	(4.62)	(2.23)
Big	Med	-0.01	1.04	-0.09	0.14	-0.04	0.05	0.20
		(1.85)	(62.13)	(4.72)	(6.89)	(3.28)	(2.73)	(7.05)
Big	High	-0.02	1.02	-0.06	0.20	0.03	0.13	0.30
		(1.64)	(39.80)	(2.06)	(6.41)	(1.44)	(4.87)	(6.82)
	HML	-0.03	0.00	-0.01	0.14	0.09	0.21	0.31
		(2.34)	(0.13)	(0.31)	(3.28)	(3.46)	(5.90)	(5.26)

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 5: 10-Portfolio q-Factor Model Regressions

DI Exposure	Alpha	Mkt.	ME	IA	ROE
Low	0.04	0.96	-0.09	-0.28	-0.39
	(2.75)	(30.53)	(2.46)	(4.54)	(7.98)
2	0.00	1.07	-0.06	0.03	0.01
	(0.12)	(40.62)	(1.86)	(0.53)	(0.23)
3	0.00	1.05	-0.07	0.16	0.03
	(0.12)	(42.73)	(2.21)	(3.42)	(0.76)
4	0.03	0.98	-0.17	0.05	0.09
	(2.05)	(37.72)	(5.33)	(0.91)	(2.15)
5	-0.03	1.00	-0.06	0.30	0.18
	(2.38)	(41.65)	(2.02)	(6.40)	(4.75)
6	-0.02	1.04	-0.06	0.46	0.29
	(1.42)	(37.08)	(1.66)	(8.49)	(6.59)
7	0.00	1.00	-0.05	0.38	0.23
	(0.04)	(34.03)	(1.42)	(6.76)	(5.09)
8	-0.02	0.96	-0.09	0.37	0.26
	(1.10)	(32.12)	(2.47)	(6.47)	(5.64)
9	-0.02	0.95	0.01	0.45	0.34
	(1.08)	(28.84)	(0.34)	(7.11)	(6.74)
High	-0.02	1.02	0.04	0.54	0.38
	(1.00)	(31.12)	(1.10)	(8.53)	(7.50)
HML	-0.06	0.06	0.14	0.82	0.77
	(2.29)	(1.10)	(2.18)	(8.10)	(9.52)

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: 10-Portfolio Augmented Fama-French Model Regressions

DI Exposure	Alpha	Mkt.	SMB	HML	MOM	BAB	QMJ
Low	0.05	0.91	-0.05	-0.13	-0.12	-0.12	-0.26
	(2.83)	(23.87)	(1.11)	(2.70)	(4.12)	(2.96)	(3.90)
2	-0.01	1.10	-0.01	0.09	0.02	-0.10	0.11
	(0.42)	(36.48)	(0.24)	(2.41)	(0.85)	(3.15)	(2.14)
3	0.01	1.00	-0.08	0.06	-0.05	0.00	-0.04
	(0.86)	(35.14)	(2.41)	(1.57)	(2.40)	(0.11)	(0.75)
4	0.01	1.03	-0.07	0.01	-0.08	0.02	0.24
	(1.01)	(35.78)	(1.95)	(0.24)	(3.77)	(0.82)	(4.95)
5	-0.03	1.03	-0.01	0.22	-0.03	0.03	0.19
	(2.52)	(38.18)	(0.39)	(6.75)	(1.43)	(0.91)	(4.05)
6	-0.02	1.08	-0.01	0.26	-0.04	0.09	0.30
	(1.81)	(34.88)	(0.20)	(6.82)	(1.67)	(2.91)	(5.75)
7	-0.01	1.05	-0.01	0.19	0.03	0.03	0.29
	(0.50)	(31.68)	(0.18)	(4.69)	(1.35)	(0.84)	(5.03)
8	-0.03	1.00	-0.07	0.14	-0.01	0.19	0.21
	(2.15)	(31.05)	(1.79)	(3.59)	(0.46)	(5.86)	(3.86)
9	-0.03	1.01	0.06	0.21	-0.01	0.18	0.32
	(1.90)	(27.33)	(1.26)	(4.63)	(0.25)	(4.69)	(5.03)
High	-0.02	1.11	0.15	0.37	-0.01	0.05	0.48
	(1.64)	(31.09)	(3.54)	(8.44)	(0.56)	(1.25)	(7.91)
HML	-0.07	0.19	0.20	0.50	0.10	0.16	0.74
	(2.66)	(3.10)	(2.70)	(6.45)	(2.21)	(2.53)	(6.89)

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

Variable	Correlation with HML_{10-1}
3-Month Treasury	-0.0971
1-Year Treasury	-0.0598
5-Year Treasury	-0.0559
10-Year Treasury	-0.0672
aaa Corprate Yield	-0.0733
baa Corporate Yield	-0.0286

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

Table 8: Explaining Variation in Momentum Portfolios using HML_{10-1} Factor

	FF 3-Factor	Add HML_{10-1}		Add HML_{10-1} and ROE	
MOM Portfolio	R^2	t on HML_{10-1}	R^2	t on HML_{10-1}	R^2
1	0.62	-6.58	0.67	-2.46	0.73
2	0.70	-4.54	0.72	-1.15	0.76
3	0.72	-1.68	0.73	0.70	0.74
4	0.79	0.28	0.79	1.77	0.80
5	0.84	2.66	0.84	3.08	0.84
6	0.84	1.66	0.84	0.72	0.85
7	0.81	4.17	0.82	2.51	0.83
8	0.83	6.25	0.85	2.50	0.87
9	0.79	5.71	0.81	1.11	0.86
10	0.73	1.42	0.73	-2.43	0.78

These are the 10 momentum portfolios from Jegadeesh and Titman [1993]. The second column is the R^2 from $r_{i,t} = \alpha + \beta_{i,m} mkt_t + \beta_{i,smb} smb_t + \beta_{i,hml} hml_t + \epsilon_{i,t}$. The second column adds $HML_{10-1,t}$ to the regression, and the third column adds both $HML_{10-1,t}$ and ROE_t.

Table 9: Explaining Variation in MOM and ROE Factors using HML_{10-1}

Regressand	Alpha	Beta on HML_{10-1}	R^2
MOM Factor	0.01	0.23	0.04
OLS	(1.81)	(3.42)	
Newey-West	(1.60)	(1.19)	
ROE Factor	0.00	0.34	0.27
OLS	(2.89)	(10.44)	
Newey-West	(2.79)	(8.02)	

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 10: Differences in Momentum Strategies Across the US, UK and EU

Countries	t-Stat on HML_{10-1}	Correlation
$US^{MOM} - UK^{MOM}$	-2.51	-0.1543
$US^{MOM} - EU^{MOM}$	-2.34	-0.1434

Using the data from Asness et al. [2013], we construct winner minus loser (WML) factors for all 3 countries. US-UK is the difference between WML_t^{US} and WML_t^{UK} and US-EU is 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.

Table 11: Sorting into 10 Portfolios, Calibrating on Daily Data

	Sort on Daily Data			Sorted on Monthly Data		
Portfolio	Mean	Standard Dev	t-Stat on $\beta_{i,DI}$	Mean	Standard Dev	t-Stat on $\beta_{i,DI}$
1	13.08%	17.11%	-3.37	10.88%	18.27%	-2.05
2	12.04%	16.45%	-2.09	10.87%	16.78%	-1.31
3	9.90%	15.43%	-1.53	11.25%	15.98%	-0.93
4	12.42%	15.31%	-1.10	12.91%	15.02%	-0.64
5	13.51%	15.34%	-0.72	9.64%	14.65%	-0.38
6	12.04%	15.19%	-0.35	11.87%	14.97%	-0.14
7	11.05%	14.67%	0.04	12.84%	14.79%	0.11
8	11.75%	15.51%	0.50	11.03%	14.24%	0.40
9	11.91%	15.45%	1.05	11.91%	14.30%	0.75
10	11.23%	15.45%	2.03	13.23%	15.12%	1.46
HML	-1.85%	15.69%		2.35%	14.80%	

Require 1000 non-missing daily observations over previous 5 years to be included, maximum possible observations is around 1,200. Means and standard deviations are annualized.

Table 12: Sorting into 2 × 3 Portfolios, Calibrating on Daily Data

	Sorted on Daily Data			Sorted on Monthly Data		
Portfolio	Mean	Standard Dev	t-Stat on $\beta_{i,DI}$	Mean	Standard Dev	t-Stat on $\beta_{i,DI}$
1	15.46%	20.86%	-2.09	14.45%	21.67%	-1.35
2	14.58%	18.58%	-0.44	14.79%	18.41%	-0.21
3	14.31%	18.27%	1.13	14.72%	17.43%	0.90
4	11.02%	15.53%	-2.73	10.37%	16.34%	-1.61
5	10.78%	14.70%	-0.73	11.03%	14.18%	-0.44
6	11.24%	14.46%	0.94	12.46%	13.58%	0.71
HML	-0.46%	8.90%		1.18%	9.03%	

Require 1000 non-missing daily observations over previous 5 years to be included, maximum possible observations is around 1,200. Means and standard deviations are annualized.

Table 13: Alphas for HML_{10-1} and $HML_{2\times3}$ Portfolios Using Daily Data

Sort	Alpha	Market	SMB	HML	MOM	BAB	QMJ
10	-0.01	0.09	-0.27	-0.05	-0.10	-0.26	0.13
	(0.31)	(1.13)	(3.04)	(0.57)	(1.93)	(3.55)	(1.03)
2x3	0.00	-0.01	-0.02	0.00	-0.02	-0.19	0.16
	(0.15)	(0.19)	(0.35)	(0.05)	(0.69)	(4.18)	(2.05)
Sort	Alpha	Market	ME	IA	ROE		
10	-0.02	0.06	-0.37	0.05	-0.26		
	(0.58)	(0.99)	(4.79)	(0.43)	(2.58)		
2x3	0.00	-0.06	-0.10	0.01	-0.12		
	(0.13)	(1.43)	(2.12)	(0.10)	(2.02)		

Require 1000 non-missing daily observations over previous 5 years to be included, maximum possible observations is around 1,200. See Tables 5 and 6 for descriptions of the regressors.

Table 14: Sorting into 2×3 Portfolios using 3 Years of Calibration Data

	3-Year Calibration			5-Year Calibration		
Portfolio	Mean	Standard Dev	t-Stat $\beta_{i,DI}$	Mean	Standard Dev	t-Stat $\beta_{i,DI}$
1	15.11%	21.48%	-1.28	14.45%	21.67%	-1.35
2	14.67%	18.64%	-0.14	14.79%	18.41%	-0.21
3	14.06%	17.61%	0.98	14.72%	17.43%	0.90
4	11.23%	15.80%	-1.45	10.37%	16.34%	-1.61
5	10.69%	14.51%	-0.30	11.03%	14.18%	-0.44
6	11.08%	14.09%	0.82	12.46%	13.58%	0.71
HML	-0.60%	9.50%		1.18%	9.03%	

Means and standard deviations are annualized. t-Statistics are equal weighted averages within portfolios.

Table 15: Sorting into 10 Portfolios using 3 Years of Calibration Data

	3-Year Calibration			5-Year Calibration		
Portfolio	Mean	Standard Dev	t-Stat $\beta_{i,DI}$	Mean	Standard Dev	t-Stat $\beta_{i,DI}$
1	10.58%	18.62%	-1.95	10.88%	18.27%	-2.05
2	10.28%	15.85%	-1.21	10.87%	16.78%	-1.31
3	14.39%	15.62%	-0.84	11.25%	15.98%	-0.93
4	10.62%	15.77%	-0.55	12.91%	15.02%	-0.64
5	11.09%	14.80%	-0.30	9.64%	14.65%	-0.38
6	12.30%	15.67%	-0.06	11.87%	14.97%	-0.14
7	10.33%	15.32%	0.19	12.84%	14.79%	0.11
8	12.03%	14.83%	0.48	11.03%	14.24%	0.40
9	11.98%	14.72%	0.83	11.91%	14.30%	0.75
10	10.27%	14.78%	1.55	13.23%	15.12%	1.46
HML	-0.31%	15.67%		2.35%	14.80%	

Means and standard deviations are annualized. t-Statistics are equal weighted averages within portfolios.

Table 16: Relaxing the Restriction to 36 Non-Missing Observations, 10 Portfolios

	Require at least 36 Non-Missing			Require 60 Non-Missing		
Portfolio	Mean	Standard Dev	t-Stat $\beta_{i,DI}$	Mean	Standard Dev	t-Stat $\beta_{i,DI}$
1	10.83%	18.32%	-2.08	10.88%	18.27%	-2.05
2	10.75%	16.76%	-1.32	10.87%	16.78%	-1.31
3	11.38%	15.89%	-0.94	11.25%	15.98%	-0.93
4	12.74%	15.08%	-0.64	12.91%	15.02%	-0.64
5	9.28%	14.61%	-0.38	9.64%	14.65%	-0.38
6	12.26%	15.04%	-0.13	11.87%	14.97%	-0.14
7	12.62%	14.88%	0.13	12.84%	14.79%	0.11
8	10.90%	14.32%	0.41	11.03%	14.24%	0.40
9	11.87%	14.24%	0.78	11.91%	14.30%	0.75
10	13.31%	15.15%	1.50	13.23%	15.12%	1.46
HML	2.49%	14.88%		2.35%	14.80%	

Means and standard deviations are annualized. t-Statistics are equal weighted averages within portfolios. This is done using a 5-year calibration period, so requiring 60 non-missing returns is equivalent to allowing zero missing returns.

Table 17: Relaxing the Restriction to 36 Non-Missing Observations, 2×3 Portfolios

	Require at least 36 Non-Missing			Require 60 Non-Missing		
Portfolio	Mean	Standard Dev	t-Stat $\beta_{i,DI}$	Mean	Standard Dev	t-Stat $\beta_{i,DI}$
1	14.56%	21.79%	-1.37	14.45%	21.67%	-1.35
2	14.76%	18.45%	-0.21	14.79%	18.41%	-0.21
3	14.58%	17.47%	0.93	14.72%	17.43%	0.90
4	10.34%	16.34%	-1.62	10.37%	16.34%	-1.61
5	10.99%	14.17%	-0.43	11.03%	14.18%	-0.44
6	12.39%	13.57%	0.74	12.46%	13.58%	0.71
HML	1.03%	9.06%		1.18%	9.03%	

Means and standard deviations are annualized. t-Statistics are equal weighted averages within portfolios. This is done using a 5-year calibration period, so requiring 60 non-missing returns is equivalent to allowing zero missing returns.

Table 18: Sorting into 10 Portfolios on $\beta_{i,DI}$

	Sorted on $\beta_{i,DI}$		Sorted on t-Statistics	
Portfolio	Mean	Standard Dev	Mean	Standard Dev
1	11.58%	29.78%	10.88%	18.27%
2	13.23%	23.13%	10.87%	16.78%
3	10.93%	19.00%	11.25%	15.98%
4	10.35%	16.18%	12.91%	15.02%
5	12.55%	14.84%	9.64%	14.65%
6	11.48%	13.82%	11.87%	14.97%
7	12.34%	13.70%	12.84%	14.79%
8	12.06%	14.24%	11.03%	14.24%
9	12.47%	14.25%	11.91%	14.30%
10	12.01%	18.29%	13.23%	15.12%
HML	0.44%	24.16%	2.35%	14.80%

Means and standard deviations are annualized.

Table 19: Sorting into 2×3 Portfolios on $\beta_{i,DI}$

	Sorted on $\beta_{i,DI}$		Sorted on t-Statistics	
Portfolio	Mean	Standard Dev	Mean	Standard Dev
1	14.59%	25.22%	14.45%	21.67%
2	15.38%	16.95%	14.79%	18.41%
3	13.85%	18.03%	14.72%	17.43%
4	10.92%	19.61%	10.37%	16.34%
5	10.96%	13.50%	11.03%	14.18%
6	12.24%	13.66%	12.46%	13.58%
HML	0.29%	13.03%	1.18%	9.03%

Means and standard deviations are annualized.

Table 20: Comparing Equal Weights and Value Weights in a 2×3 Sort

	Equal Weights		Value Weights	
Portfolio	Mean	Standard Dev	Mean	Standard Dev
1	18.03%	22.03%	14.45%	21.67%
2	17.96%	19.76%	14.79%	18.41%
3	16.93%	18.01%	14.72%	17.43%
4	11.64%	18.15%	10.37%	16.34%
5	12.83%	15.59%	11.03%	14.18%
6	13.64%	14.53%	12.46%	13.58%
HML	0.45%	8.50%	1.18%	9.03%

Means and standard deviations are annualized.

Table 21: Comparing Equal Weights and Value Weights in a 10 Portfolio Sort

	Equal Weights		Value Weights	
Portfolio	Mean	Standard Dev	Mean	Standard Dev
1	15.75%	22.25%	10.88%	18.27%
2	16.28%	19.80%	10.87%	16.78%
3	16.98%	19.50%	11.25%	15.98%
4	16.83%	18.88%	12.91%	15.02%
5	16.82%	18.61%	9.64%	14.65%
6	17.09%	18.52%	11.87%	14.97%
7	16.90%	17.71%	12.84%	14.79%
8	17.02%	17.33%	11.03%	14.24%
9	16.04%	17.05%	11.91%	14.30%
10	15.75%	16.24%	13.23%	15.12%
HML	0.00%	12.25%	2.35%	14.80%

Means and standard deviations are annualized.

Table 22: Removing Smallest 20% of Firms Each Month

	Drop Bottom 20% of Market Cap each Month			Only Filter $< \$500,000$		
Portfolio	Mean	Standard Dev	t-Stat on $\beta_{i,DI}$	Mean	Standard Dev	t-Stat on $\beta_{i,DI}$
1	10.85%	18.29%	-2.08	10.88%	18.27%	-2.05
2	10.99%	16.65%	-1.33	10.87%	16.78%	-1.31
3	11.17%	16.29%	-0.95	11.25%	15.98%	-0.93
4	11.76%	15.03%	-0.65	12.91%	15.02%	-0.64
5	10.03%	14.56%	-0.39	9.64%	14.65%	-0.38
6	11.71%	14.94%	-0.14	11.87%	14.97%	-0.14
7	11.54%	15.16%	0.12	12.84%	14.79%	0.11
8	11.95%	13.93%	0.40	11.03%	14.24%	0.40
9	10.87%	14.14%	0.77	11.91%	14.30%	0.75
10	12.95%	15.10%	1.49	13.23%	15.12%	1.46
HML	2.10%	14.84%		2.35%	14.80%	

Means and standard deviations are annualized.