Essays in Asset Pricing

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This dissertation examines a series of asset pricing "anomalies" and investigates links to fundamentals. In the first chapter I investigate the gross yield effect. Gross yield, defined as gross interest expense divided by liabilities, has power comparable to book- to-market and firm size in predicting the cross-section of returns. Firms with low gross yield are found to earn higher returns than firms with high gross yield. This effect is significantly more pronounced when controlling for book-to-market since gross yield and book-to-market are positively correlated but predict returns with the opposite sign. The gross yield effect is difficult to reconcile with explanations of the value premium because high gross yield firms are more prone to distress and also tend to have high book-to-market ratios. This effect is robust to various factors related to distress and other characteristics known to have power in the cross-section. Gross yield survives controls for book-to-market, size, momentum, profitability, and a host of proxies for distress. Investors can significantly reduce the risk of value strategies by taking on exposure to gross yield.

In the second chapter we examine the link between average returns and cash-flow risk. This paper investigates cashflow risk and its relationship to average returns. We find that stocks with earnings that co-vary strongly with market-wide earnings also earn a high return. The cashflow beta (or earnings beta) of value stocks is found to be much higher than that of growth stocks, and small stocks have higher cashflow betas than large stocks. Thus, cashflow betas can explain a significant part of the Fama and French factors. This provides evidence for a risk-based explanation of anomaly returns because stocks earning a higher return also tend to have riskier cashflows.

In the third and final chapter I analyze an anomaly in the cross-section of FX volatility. This paper studies the cross-section of foreign exchange volatility returns. Statistically and economically significant returns are produced by a zero-cost trading strategy that is long (short) volatility swaps on currencies with high (low) historical volatility relative to implied volatility. The spread portfolio has a Sharpe ratio in excess of 1.7, results are robust to different market conditions and time periods, and it remains highly profitable after transaction costs. Standard risk adjustments do not significantly diminish profitability because the strategy is only weakly correlated with the equity market, the carry trade, and the Fama-French risk factors. Moreover, the historical-minus- implied volatility (HMI) factor also predicts excess-returns of the underlying currencies. Currencies that have high historical volatility relative to their implied volatility have much higher returns.

The Gross Yield Effect

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ABSTRACT

Gross yield, defined as gross interest expense divided by liabilities, has power comparable to book-to-market and firm size in predicting the cross-section of returns. Firms with low gross yield are found to earn higher returns than firms with high gross yield. This effect is significantly more pronounced when controlling for book-to-market since gross yield and book-to-market are positively correlated but predict returns with the opposite sign. The gross yield effect is difficult to reconcile with explanations of the value premium because high gross yield firms are more prone to distress and also tend to have high book-to-market ratios. This effect is robust to various factors related to distress and other characteristics known to have power in the cross-section. Gross yield survives controls for book-to-market, size, momentum, profitability, and a host of proxies for distress. Investors can significantly reduce the risk of value strategies by taking on exposure to gross yield.

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I. Introduction

Gross yield, defined as gross interest expense divided by liabilities, has power comparable to book-to-market in predicting the cross-section of returns. Previous research extensively documents a positive relationship between many proxies for value and expected equity returns. In stark contrast, gross yield is negatively correlated with future equity returns. To my knowledge this is the first study to document a negative relationship between gross yield on firm liabilities and expected equity returns.

A positive relationship between several proxies for value and returns has been widely documented. It is well known that the earnings-to-price ratio is positively related to returns. More recently Novy-Marx (2013) documents that gross profits-to-assets predicts returns, and the book-to-market effect is widely documented both when considering the equity portion alone as well as when considering enterprise-wide book-to-market (Nissim and Penman (2003)). What I find is in stark contrast to earlier research: a negative relationship between yield and subsequent returns. Empirically, returns to my gross yield strategy are strongly correlated with the Fama and French (1992) factors HML and SMB as well as an earnings-to-price factor. Thus, these returns are puzzling when examined through the lens of the Fama and French (1992) three factor model. Also, gross yield correlates strongly with measures of distress and negatively forecasts earnings growth.

The empirical association between measures of yield and expected returns on the same asset has been extensively documented. Hansen and Hodrick (2007); Fama (1984) show that currencies with higher interest rates have higher returns than currencies with low yield interest rates. Gorton, Hayashi, and Rouwenhorst (2013) document a forward discount bias for commodity futures, and Campbell and Shiller (1988) show that dividend price ratios forecast equity index returns.

Gross yield focuses solely on accounting liabilities in the denominator and thus differs from traditional proxies for value which typically involve scaling by price. Gross yield is strongly related to the yield on long-term debt: high correlation of gross yield with earnings-to-price, and theoretical models based on the intuition that debt and equity are merely differently structured claims on the same underlying asset suggest that the required return on debt and equity be positively correlated. Empirical studies on the relationship between equity and debt returns have found that they are positively correlated (Kwan (1996); Blume, Keim, and Patel (1991)). It is necessary to test if

returns of my gross yield strategy are due to indirectly sorting on characteristics which could drive yield spreads. Indeed, the gross yield effect persists when controlling for the characteristics that determine the relationship between equity and debt returns of the same firm. While these factors do not explain the effect, the negative association of gross yield with future returns is more pronounced among both low volatility and low leverage firms. Collin-Dufresne, Goldstein, and Martin (2001) find that equity returns and yield spread changes are less correlated in practice than might be expected. They find that only a small portion of credit spreads can be explained by firm-level variables, which suggests a disconnect between debt and equity markets. In any case, a contingent claim analysis might only be partially relevant to the gross yield anomaly because not all liabilities are traded and the denominator of gross yield includes operating liabilities as well as financial liabilities.

Previous research argues that the profitability of value strategies is mechanical, since firms that require a higher rate of return have lower prices. For example Berk (1998) and Ball (1978) argue that accounting ratios involving price pick up on higher expected returns because they identify firms with depressed prices. Berk (1998) argues that the low price is justified because of risk. Behavioral explanations also suggest that accounting variables scaled by price identify low priced stocks (Lakonishok, Shleifer, and Vishny (1994)). However, they argue that high expected returns of these stocks are due to mispricing due to behavioral biases of investors. When either argument is applied to the gross yield effect, a positive relationship between gross yield and average returns would be expected: high gross yield indicates high expected returns. Contrary to this intuition, firms with higher gross yield produce markedly lower returns than firms with lower gross yield. They do so despite having higher book-to-market ratios and smaller size. Double sorts on gross yield and book-to-market suggest that gross yield effectively helps identify "bad" value: high book-to-market stocks that also have high gross yield have much less impressive returns than high book-to-market stocks with low gross yield.

Double sorts on size and gross yield suggest that the gross yield effect is present in all size quintiles. This suggests that the gross yield effect is also economically relevant and not only present amongst small or micro capitalization stocks. Moreover, the anomaly is unlikely to be explained by transaction costs, since gross yield is a highly persistent metric, with results being only slightly weaker if gross yield is lagged an additional year.

II. Yield and the cross-section of expected returns

Gross yield is distinct form the yield on debt claims since it scales interest by total liabilities. However, yield on debt and gross yield are strongly correlated. Structural models like Merton (1974) and related models such as Longstaff and Schwartz (1995); Black and Cox (1976); Leland (1994) and Collin-Dufresne et al. (2001) suggest that debt and equity returns on the same firm should be positively correlated under most circumstances. In Merton's model the debt claim is essentially a combination of a risk-free debt claim and a short position in a put option on the firm at the value of the risk-free claim. The model specifies a firm value process and assumes that default is triggered at the maturity date if the face value of debt is larger than firm value. In the case of default, debt holders receive the residual firm value instead of face value. If the probability of default is zero, the put option is worthless and the debt claim issued by the firm behaves like a risk-free bond. As the probability of default increases the debt claim is largely composed of the short put option. If a default event is very likely, and the expected residual firm value is low, then debt should be more equity-like. If the probability of default is low and residual firm value high, debt should behave more like a risk-free bond.

Chen, Collin-Dufresne, and Goldstein (2009) suggest that credit spreads are defined by firm value, the risk-free rate, and several "other state variables" related to expected default. To the present analysis firm-level state variables are the most relevant since they might explain cross-sectional differences in gross yield. Macro-variables like the level of interest rates are less important to this analysis since they affect all securities. The most important firm-level variables from the literature that determine the probability of default are:

1. Leverage: higher leverage increases the probability of default. Therefore it should be expected that debt of high-leverage firms is more equity-like. In order to control for leverage I control for of debt/(debt + market value of equity).
2. Profitability: higher profitability decreases the probability of default. Firms earning higher returns on their assets can afford to pay higher interest rates on their debt. Therefore it should be expected that debt of high-profitability firms is less equity-like. In order to control for profitability I control for the ratio of gross profits to gross assets.
3. Asset Volatility: higher volatility also increases the probability of default. Higher volatility

increases the value of the put option and therefore the debt of highly volatile firms should behave more like equity. In order to control for volatility I use the 250-day standard deviation of equity returns.

4. Probability of downward jumps: the higher the probability of a downward jump, the less residual value bond holders are expected to recover in the event of default. Unfortunately the probability of downward jumps is not easily observable without a cross-section of option prices for each firm. Only a small number of firms have reliable data on implied volatility smirks. Therefore, I rely on skewness of returns measured over the past 250 trading days.
5. Past returns: firms facing default typically experienced poor past returns. I aim to control for this by controlling for past 12 month returns. I would expect gross yield to be more informative about expected stock returns for firms with poor recent returns.

A. Fama-MacBeth regressions

Table I presents time-series averages of Spearman rank correlations and shows that gross yield is positively correlated with book-to-market. Table II shows results of Fama and MacBeth regressions of firm gross yield controlling for book-to-market, size and past performance over twelve months. I use Compustat data from the inclusion of the American Stock Exchange (Amex) in 1962 and assume all accounting data is available in June of the following calendar year. Thus, tests cover the sample period from 1962 to 2010. Table III also presents results for gross yield when the variable is demeaned by median industry values. For industry definitions I use the Fama and French (1997) 49 industry portfolios.

The first specification in Table II shows that gross yield has power comparable to the Fama and French factors book-to-market and size in predicting the cross-section of returns. The second specification replaces gross yield with yield on long-term debt. Yield on long-term debt has virtually no power in predicting returns. In the third specification, I include earnings-to-price which can be interpreted as the equity counterpart to gross yield. The slope on gross yield remains virtually unaffected while earnings-to-price has the expected positive sign. The fourth specifications adds 12-month momentum, which also does not diminish the significance of gross yield. The fifth specification includes leverage, to ensure the power of gross yield is not due to implicitly sorting on this variable. Finally, the sixth specification includes all controls and gross yield maintains a

highly significant T-statistic of -4.27 in this case.

Even though leverage is closely related to gross yield, specifications 5 and 6 show that controlling for this characteristic does not eliminate the performance of gross yield. Also, volatility and jump risk do not appear to be responsible for predictive power of gross yield. In the context of the Merton (1974) model, 12-month momentum is also expected to be related to gross yield as distressed firms with high gross yield can be expected to have much poorer returns than firms with low gross yield. Since momentum predicts returns, it is reassuring that the inclusion of the momentum variable does not eliminate the power of gross yield.

It is known that industry-adjusted characteristics often perform better (see e.g.: Asness, Porter, and Stevens (2000)). Table III repeats the previous analysis with industry-adjusted analysis. As expected, the T-statistic for book-to-market increases. Gross yield, however, does not perform better: for all specifications the raw yield metric is a more successful predictor. For completeness Table IV repeats the analysis with industry-wide metrics. While book-to-market becomes almost insignificant, gross yield has power comparable to the industry-adjusted metric, suggesting that both industry-wide and industry-adjusted variation in gross yield are valuable for predicting returns.

B. Sorts on gross yield

The Fama and MacBeth regressions of Table II allow a glimpse at the predictive power of gross yield. However, they weight small caps and micro caps very heavily. Also, they are very sensitive to outliers and rely on a parametric model that might well be misspecified, which makes the results difficult to judge. In this section I examine equal-weighted and value-weighted portfolios sorted on gross yield providing a non-parametric test of the pricing power of gross yield in the cross-section.

Table V shows results for univariate sorts on gross yield. Gross yield and book-to-market are highly correlated and therefore high gross yield firms should outperform low yield firms since they are value stocks. Portfolios are formed using a quintile sort based on New York Stock Exchange (NYSE) breakpoints. The table reports average excess returns, as well as alphas and factor loadings obtained from regressing portfolio returns on the Fama and French factors. Moreover, time-series averages of gross yield (GY), book-to-market (BM), and market capitalization (ME) are reported. The sample includes financial firms and I verify, in unreported results, that results change little if these firms are excluded. Table V shows that returns are generally decreasing in gross yield, with

the highest yield portfolio earning 0.08 percent per month lower average returns than the portfolio with the lowest gross yield firms. The high-low spread portfolio has a monthly Fama and French alpha of -0.36 percent and a highly significant T-statistic of -4.12. The Fama and French alpha has a higher T-statistic than the slope for gross yield in cross-sectional regressions. It appears that returns of the gross yield strategy are more correlated with HML and SMB factor returns, than the gross yield characteristic is correlated with book-to-market and firm size. However, this difference partially arises because cross-sectional regressions do not control for the market factor. High gross yield firms are value stocks, meaning that they have high book-to-market ratios, while low gross yield firms are growth stocks in the sense that they have low book-to-market ratios. Despite high gross yield firms returns behaving like value stocks as well as having similar characteristics, they have lower expected returns. This leads to the Fama and French alphas of the spread portfolio being much higher than the raw returns.

C. Yield and size

Value-weighted returns presented in Table V already suggest that the strategy is economically significant and not exclusive to small caps and micro caps. In this section I further show that results are robust to firm size by performing double portfolio sorts on gross yield and market capitalization. Portfolios are formed by independently sorting on size and gross yield, using NYSE breakpoints. The sample covers from 1963 to 2010.

Table VI also reports the characteristics of size portfolios which show modest variation in gross yield with larger stocks having slightly less gross yield. Table VI also reports characteristics of gross yield portfolios.

Table VI reports returns for double-sorted portfolios on size and gross yield. The gross yield effect is present across all size quintiles and is almost as strong amongst the largest stocks as it is for the smallest stocks. Table VI also reports intercepts and their T-statistics from regressions of these returns on the Fama and French factors. The difference in returns and Fama and French alphas is present amongst all size quintiles. This shows that the gross yield effect is economically relevant even amongst the largest firms.

III. Yield and value

Table I shows that the correlation coefficient between gross yield and book-to-market is positive. Since gross yield predicts returns in the opposite direction, the two characteristics should complement each other. Table VII presents results which suggest that traditional value strategies can be improved by controlling for gross yield. Value strategies are far more profitable if they exclude stocks that have very high gross yields and instead focus on firms that have low-to-moderate gross yield. Similarly, a univariate gross yield strategy can be improved by incorporating book-to-market: firms with low gross yield are much more profitable if they also have high book-to-market ratios.

A. Double sorts on gross yield and book-to-market

This section examines these conjectures by analyzing the performance of portfolios double-sorted on book-to-market and gross yield. Portfolios are formed by independently sorting on these two variables, again using NYSE break points. The sample ranges from 1963 to 2010. Table VII presents average returns as well as Fama and French alphas and factor loadings for high-minus-low portfolios. Moreover, the table shows the average number of stocks in each portfolio as well as average firm size.

Low gross yield firms outperform high gross yield firms across all book-to-market quintiles. As expected, book-to-market does not explain gross yield returns, and each book-to-market and yield strategies are stronger when controlling for the other. The results confirm the hypothesis that controlling for gross yield significantly improves the performance of the book-to-market strategy. The average value spread across gross yield quintiles is much larger than the univariate spread portfolio for book-to-market.

B. Large cap gross yield and value

Results from Table VI indicate that gross yield has power even amongst the largest stocks. In this section I restrict the sample to the 500 largest stocks as measured by market capitalization at the end of December each year. Table XII shows results from cross-sectional Fama and MacBeth regressions on this sample. The predictive power of all variables is greatly diminished albeit gross yield, book-to-market and size still predict returns with the same sign.

Table XIII shows results for univariate sorts on gross yield. Gross yield and book-to-market are highly correlated and therefore high gross yield firms should outperform low gross yield firms since they are value stocks. Portfolios are formed using a quintile sort. This table reports average excess returns, as well as alphas and factor loadings obtained from regressing portfolio returns on the Fama and French factors. Moreover, time-series averages of gross yield (GY), book-to-market (BM), and market capitalization (ME) are reported. The sample includes financial firms. I verify in unreported results that results change little if financial firms are excluded.

The spread portfolio still has negative average returns and the Fama and French alpha is -0.34 percent per month and highly significant with a T-statistic of -4.17. Increases in gross yield are associated with higher loadings in particular on HML, but also SMB, again suggesting that high gross yield firms behave like value stocks in covariances. Also characteristics support this, with high gross yield firms being significantly less profitable and having much higher book-to-market ratios than low gross yield firms.

Table XIV presents double sorts for book-to-market and gross yield focusing exclusively on the 500 largest stocks. Value and gross yield strategies amongst the largest stocks are highly negatively correlated. Therefore, it is not surprising that Fama and French alphas are negative across all book-to-market quintiles.

C. Large cap yield and value strategy

The high negative Fama and French alphas already suggest the complementary relationship between gross yield and book-to-market. Firms with high book-to-market and low gross yield tend to be "good" value stocks, with much higher performance than high book-to-market and high gross yield. Table XIV presents a gross yield strategy that is long in low gross yield stocks and short in high yield stocks. An investor combining the value and gross yield strategies can significantly reduce the risk of a pure book-to-market strategy because returns of the gross yield strategy are negatively correlated with a book-to-market strategy. As a result the combined strategy has a T-statistic of 5 and a Sharpe ratio of 0.72 which is well above the Sharpe ratio for the market portfolio over the sample period despite only trading the largest stocks.

Figure 1 shows the performance of the combined yield and book-to-market strategy. The figure presents the three year rolling Sharpe ratio over the preceding three years at the end of each month

from 1963 to 2010 (represented by the dashed line). The figure also shows the trailing Sharpe ratio for a book-to-market strategy and a 50/50 mixed strategy. The mixed strategy has a much higher T-statistic (x)and Sharpe ratio than the value and gross yield strategy each have individually.

While both the value and gross yield strategies did have solid performance over the sample period, both suffered significantly for long periods of time. The mixed strategy has much more consistent performance and did not have a losing year.

IV. Portfolio sorts

In this section I control for several other characteristics that have power in the cross-section. Also, I examine robustness to characteristics that determine relative expected returns of debt and equity. The Merton (1974) model suggests that several factors related to the probability of default, and expected recovery rates in the event of default, should determine the extent to which debt and equity are correlated. Moreover, these factors also are expected to determine the magnitude of yield spreads: we would expect gross yield to be more correlated with equity returns for firms that have riskier debt. Analyzing gross yield and factors related to firm risk jointly provides a way to test if this can be observed. Moreover, I need to ensure that the returns on gross yield portfolios are not achieved by implicitly ranking on these theoretical drivers of yield spreads.

A. Double sorts on gross yield and leverage

Table V shows that high gross yield portfolios also have higher leverage. This is not surprising since other things equal, increasing leverage makes debt more risky and thus increases gross yield. In Table VIII, I examine how controlling for leverage affects the pricing power of gross yield. With the exception of the highest leverage quintile, high-minus-low portfolios formed on gross yield have negative alphas. While a closer relationship between required returns for debt and equity are expected for risky stocks, it remains unclear why gross yield and expected equity might be negatively related in the lower four leverage quintiles.

Interestingly returns increase in leverage when controlling for gross yield. However, since the leverage metric includes price, this is perhaps not too surprising. Results from Table II suggest that once we control for book-to-market, leverage provides no further valuable information in

predicting returns. Since Fama and French alphas of the high-minus-low portfolios are negative and significant for four leverage quintiles and insignificant for the highest leverage quintile, the results appear robust.

B. Double sorts on gross yield and idiosyncratic volatility

For firms at risk of default, expected returns on debt could be closely related to expected equity returns. Hence I would expect gross yield to be more highly correlated with equity returns amongst high volatility firms. Table IX reports returns for double-sorted portfolios on gross yield and volatility. Indeed the Fama and French alpha for the spread portfolio formed on gross yield is insignificant for the most volatile quintile. However, alphas are negative within all volatility quintiles and are significant within the other four. Similarly, returns are also negative for all quintiles except the most volatile. These results suggest that expected returns on debt and equity might be more closely related amongst firms with high volatility, however, the gross yield effect is robust to controls for idiosyncratic volatility.

C. Double sorts on gross yield and skewness

Similarly, firms with lower skewness might have a closer relationship between debt and equity returns because, historically, they were at risk for large downward jumps. However, historical skewness has not always been a good predictor of future skewness. Table X reports results from double sorts on skewness and gross yield. The gross yield-based spread portfolios are negative for all five skew quintiles and returns for double-sorted portfolios on skewness and gross yield. Skewness is defined as the 250-day rolling skewness of returns updated each month. The gross yield effect is present across all skewness quintiles. Fama and French alphas are negative and mostly significant with no discernible systematic variation based on skew. The gross yield effect does appear robust to controls for historical skewness.

D. Double sorts on gross yield and profitability

Finally, I examine interaction of profitability and gross yield. Profitability is defined as gross profit (Compustat REVT-COGS) divided by total assets (Compustat item AT). Since more profitable firms can afford higher interest payments, their debt should be less risky. Moreover, prof-

itability is a powerful predictor in the cross-section. Table XI reports results from double sorts on profitability and gross yield. Fama and French alphas are negative for all but the most profitable stocks. Surprisingly, the gross yield effect is strongest among the least profitable firms.

The gross yield effect remains a puzzle and does not appear to be explained by factors related to distress. Even though Fama and French alphas are less significant among high volatility and leverage stocks, they are more significantly negative for low-profitability firms and unrelated to historical skewness even though these stocks might very well be at higher risk of default.

V. Conclusion

The negative association between gross yield and returns is puzzling considering the empirically established notion that measures of value are positively associated with expected returns. Firms with high gross yield have lower returns despite having much higher book-to-market ratios and smaller size than low gross yield firms. Therefore, the results cannot be explained by the Fama and French three factor model and are difficult to explain with the Berk (1998) critique since gross yield can reasonably be expected to signal higher required return. Also, behavioral explanations relating anomalies to over-reaction do not explain the returns, since high gross yield firms exhibit continuation of low returns rather than mean-reverting. Importantly, the gross yield effect is almost as pronounced among the very largest stocks. The fact that results are almost as strong when restricting the universe to the largest 500 equities by market capitalization suggests the anomaly has economic implications rather than being merely an interesting statistical pattern confined to small and hard-to-trade stocks. Empirically, gross yield adds significant information to traditional value. A strategy that is long low gross yield firms and short high gross yield firms is a growth strategy both in characteristics and covariances. Since the gross yield and value strategies are negatively correlated, they complement each other very well. Investors can significantly reduce the risk of value strategies by taking on exposure to the gross yield strategy. Value investors should therefore incorporate information about gross yield since this can dramatically decrease their risk. Moreover, the gross yield effect is robust to various factors related to distress and other characteristics known to have power in the cross-section. Gross yield survives controls for book-to-market, size, momentum, profitability, and a host of proxies for distress.

VI. Appendix

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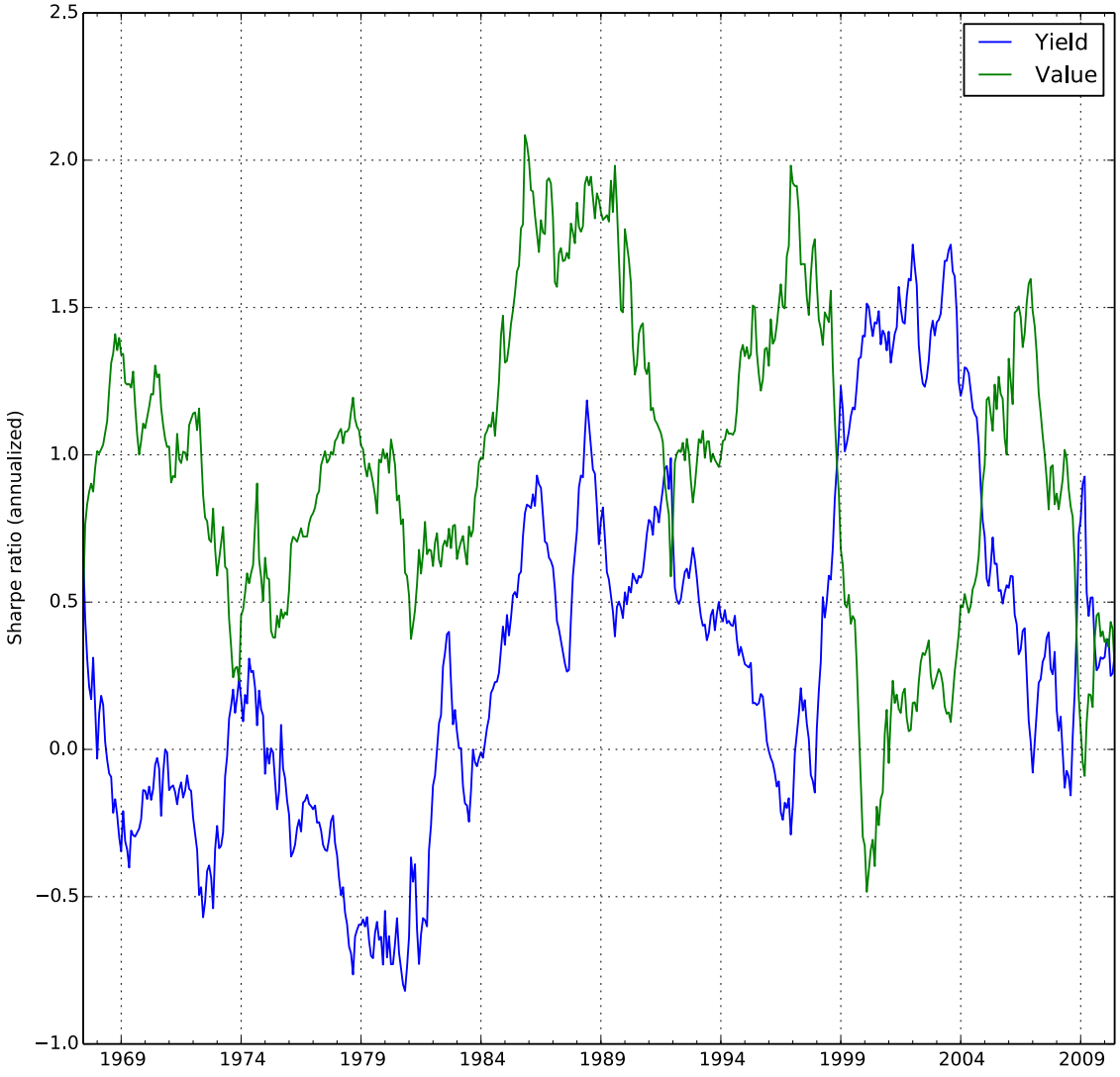

Figure 1. Rolling Sharpe Ratios Performance over time of gross yield and value strategies. The figure shows the trailing five-year Sharpe ratios of gross yield and value strategies (blue and green lines, respectively) and a 50/50 mix of the two (red dashed line). The strategies are long/short extreme value-weighted quintiles from sorts on gross profits-to-assets and book-to-market, respectively, and correspond to the strategies considered in Table VII. The sample covers June 1963 to December 2010. Shaded areas are NBER recessions.

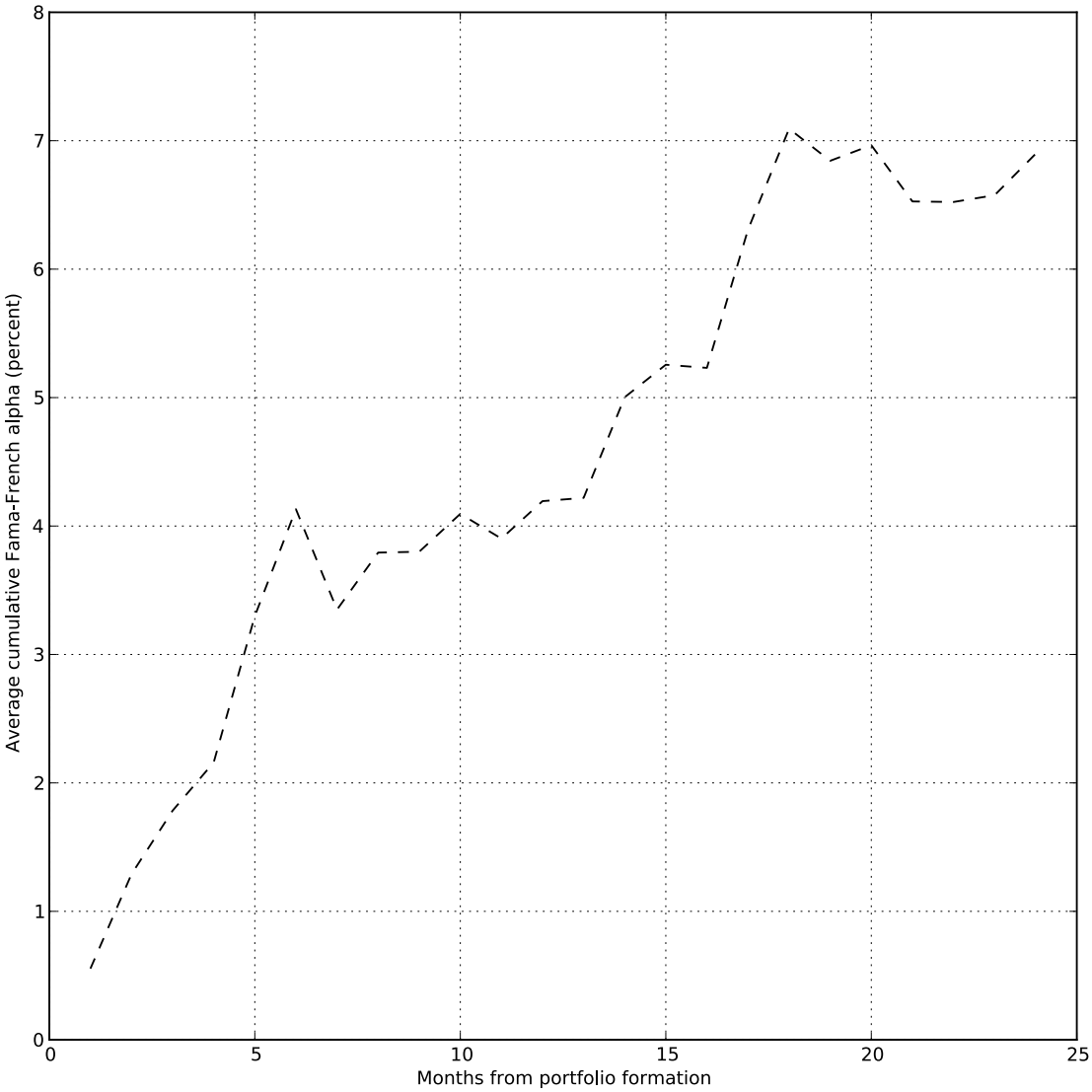

Figure 2. Cumulative Alpha per month after portfolio formation Persistence of yield strategy performance. This figure shows the average cumulative returns to the gross yield strategy considered in Table A6 from one to 25 months after portfolio formation. The sample covers January 1972 to December 2010

Table I

Spearman rank correlations between independent variables. This table reports the time-series averages of the cross section Spearman rank correlations between the independent variables employed in the Fama and MacBeth regressions of Table 1: profitability [(REVT - COGS)/A], book-to-market, market equity, and past performance measured over 12 months. The sample covers from 1963 to 2010.

	YIELD	BM	MV	EP	LEVER	MOM12	SKEW250	VOL250
YIELD	1.00	0.12	-0.07	0.01	0.31	-0.05	0.02	0.05
BM	0.12	1.00	-0.24	0.14	0.42	-0.13	0.03	0.01
MV	-0.07	-0.24	1.00	0.17	-0.06	0.07	-0.25	-0.47
EP	0.01	0.14	0.17	1.00	0.15	0.05	-0.12	-0.27
LEVER	0.31	0.42	-0.06	0.15	1.00	-0.09	-0.02	-0.06
MOM12	-0.05	-0.13	0.07	0.05	-0.09	1.00	0.15	-0.03
SKEW250	0.02	0.03	-0.25	-0.12	-0.02	0.15	1.00	0.23
VOL250	0.05	0.01	-0.47	-0.27	-0.06	-0.03	0.23	1.00

Table II

Fama and MacBeth regressions of returns on measures of gross yield. This table reports results from Fama and MacBeth regressions of returns on gross yield (gross interest expense XINT scaled by liabilities LT). Regressions include controls for book-to-market [BM], size [MV], yield on long-term debt [YIELDLT], leverage [LEVER], earnings-to-price [EP] and past performance measured over 12 months [MOM12] and covers July 1963 to December 2010.

	(1)	(2)	(3)	(4)	(5)	(6)
BM	0.28	0.18	0.23	0.23	0.34	0.23
	[5.68]	[2.96]	[5.39]	[5.55]	[7.37]	[6.61]
EP			0.16	0.15		0.16
			[3.01]	[3.07]		[3.31]
MOM12				0.10		0.10
				[2.22]		[2.25]
MV	-0.17	-0.09	-0.19	-0.19		-0.19
	[-2.20]	[-1.07]	[-2.70]	[-2.80]		[-2.82]
YIELDLT		0.04				
		[0.74]				
YIELD	-0.09		-0.09	-0.09	-0.09	-0.09
	[-3.49]		[-3.51]	[-3.92]	[-3.77]	[-4.27]
LEVER					0.03	-0.01
					[0.68]	[-0.37]
INTERCEPT	0.79	0.63	0.80	0.81	0.80	0.81
	[3.30]	[3.25]	[3.35]	[3.39]	[3.34]	[3.40]

Table III

Fama and MacBeth regressions of returns on measures of gross yield demeaned by industry. This table reports results from Fama and MacBeth regressions of returns on gross yield (gross interest expense XINT scaled by liabilities LT). Regressions include controls for book-to-market [BM], size [MV], yield on long-term debt [YIELDLT], leverage [LEVER], earnings-to-price [EP] and past performance measured over 12 months [MOM12] and covers July 1963 to December 2010.

	(1)	(2)	(3)	(4)	(5)	(6)
BM	0.27	0.22	0.24	0.24	0.28	0.21
	[7.79]	[4.35]	[7.13]	[7.43]	[7.70]	[7.43]
EP			0.16	0.16		0.16
			[4.37]	[4.56]		[4.66]
MOM12				0.08		0.08
				[2.36]		[2.58]
MV	-0.16	-0.06	-0.18	-0.18		-0.18
	[-2.59]	[-1.03]	[-3.15]	[-3.23]		[-3.22]
YIELDLT		-0.01				
		[-0.17]				
YIELD	-0.05		-0.04	-0.04	-0.06	-0.07
	[-2.25]		[-2.04]	[-2.33]	[-3.07]	[-3.86]
LEVER					0.12	0.08
					[3.78]	[2.92]
INTERCEPT	0.78	0.62	0.78	0.79	0.78	0.79
	[3.26]	[3.31]	[3.24]	[3.30]	[3.27]	[3.31]

Table IV

Fama and MacBeth regressions of returns on industry-level measures of gross yield. This table reports results from Fama and MacBeth regressions of returns on gross yield (gross interest expense XINT scaled by liabilities LT). Regressions include controls for book-to-market [BM], size [MV], yield on long-term debt [YIELDLT], leverage [LEVER], earnings-to-price [EP] and past performance measured over 12 months [MOM12] and covers July 1963 to December 2010.

	(1)	(2)	(3)	(4)	(5)	(6)
BM	0.06	-0.02	0.07	0.09	0.08	0.06
	[1.32]	[-0.26]	[1.66]	[2.15]	[1.65]	[1.35]
EP			-0.05	-0.05		-0.05
			[-1.11]	[-0.99]		[-1.03]
MOM12				0.06		0.06
				[1.49]		[1.44]
MV	-0.09	-0.04	-0.08	-0.09		-0.10
	[-1.95]	[-0.63]	[-1.78]	[-2.14]		[-2.46]
YIELDLT		-0.01				
		[-0.14]				
YIELD	-0.08		-0.08	-0.08	-0.06	-0.07
	[-2.05]		[-2.18]	[-2.26]	[-1.45]	[-2.02]
LEVER					-0.05	0.01
					[-1.36]	[0.16]
INTERCEPT	0.75	0.69	0.75	0.76	0.74	0.75
	[3.12]	[3.33]	[3.15]	[3.21]	[3.11]	[3.21]

Table V

Excess returns to portfolios sorted on gross yield. This table shows monthly value-weighted average excess returns to portfolios sorted on gross yield [gross interest expense (XINT) scaled by liabilities (LT)] employing NYSE breakpoints, and results of time-series regressions of these portfolio returns on the Fama and French factors [the market factor (MKT), the size factor small-minus-large (SMB), and the value factor high-minus-low (HML)], with T-statistics (in square brackets). It also shows time-series average portfolio characteristics [portfolio gross profits-to-assets (GP/A), leverage, average firm size (ME, in millions of dollars), and number of firms (n)]. The sample covers July 1963 to December 2010.

	r	α	MKT	SMB	HML	GP/A	BM	Leverage	Market Value
Low	0.83	0.27	0.95	0.82	-0.04	0.35	-0.67	0.28	1040029
	[3.29]	[3.08]	[45.71]	[28.31]	[-1.24]				
2	0.76	0.09	1.02	0.70	0.23	0.36	-0.55	0.38	3036227
	[3.22]	[1.34]	[67.12]	[32.98]	[10.04]				
3	0.77	0.08	0.99	0.59	0.36	0.31	-0.42	0.47	2098331
	[3.52]	[1.21]	[66.83]	[28.43]	[16.16]				
4	0.64	-0.07	0.99	0.62	0.38	0.28	-0.37	0.51	1375298
	[2.86]	[-1.02]	[59.78]	[26.95]	[15.18]				
High	0.75	-0.09	1.04	1.01	0.41	0.27	-0.37	0.54	406517
	[2.68]	[-0.74]	[37.59]	[26.10]	[9.77]				
H-L	-0.08	-0.36	0.09	0.19	0.45				
	[-0.81]	[-4.13]	[4.52]	[6.63]	[14.50]				

Table VI

Double sorts on gross yield and market equity. This table shows the value-weighted average excess returns to portfolios double-sorted, using NYSE breakpoints, on gross yield and market equity, and results of time-series regressions of high-minus-low portfolio returns on the Fama and French factors [the market, size and value factors MKT, SMB (small-minus-large), and HML (high-minus-low)]. T-statistics are given in square brackets. The sample covers July 1963 to December 2010.

	Low	2	3	4	High	H-L	α	MKT	HML	SMB
Low	1.65	1.46	1.37	1.11	1.30	-0.36	-0.50	0.09	0.25	-0.00
	[4.80]	[4.36]	[4.25]	[3.55]	[3.81]	[-2.37]	[-3.30]	[2.44]	[4.60]	[-0.01]
2	0.64	0.84	0.97	0.62	0.55	-0.10	-0.41	0.17	0.47	0.17
	[2.36]	[2.86]	[3.43]	[2.32]	[1.78]	[-0.68]	[-3.05]	[5.36]	[9.73]	[3.96]
3	0.76	0.59	0.69	0.69	0.44	-0.32	-0.57	0.14	0.45	-0.03
	[2.80]	[2.20]	[2.73]	[2.60]	[1.55]	[-2.29]	[-4.25]	[4.49]	[9.38]	[-0.66]
4	0.69	0.69	0.58	0.46	0.40	-0.29	-0.51	0.12	0.44	-0.07
	[2.72]	[2.84]	[2.59]	[2.14]	[1.52]	[-2.23]	[-4.17]	[4.03]	[9.94]	[-1.77]
High	0.50	0.49	0.50	0.48	0.30	-0.19	-0.40	0.05	0.36	0.11
	[2.20]	[2.42]	[2.58]	[2.53]	[1.26]	[-1.57]	[-3.31]	[1.87]	[8.35]	[2.72]

Table VII

Double sorts on gross yield and book-to-market. This table shows the value-weighted average excess returns to portfolios double-sorted, using NYSE breakpoints, on gross yield and book-to-market, and results of time-series regressions of high-minus-low portfolios returns on the Fama and French factors [the market, size and value factors MKT, SMB (small-minus-large), and HML (high-minus-low)]. T-statistics are given in square brackets. The sample covers July 1963 to December 2010.

	Low	2	3	4	High	H-L	α	MKT	HML	SMB
Low	0.36	0.24	0.20	0.07	0.32	-0.05	-0.36	0.09	0.44	0.36
	[1.28]	[0.91]	[0.75]	[0.26]	[0.96]	[-0.29]	[-2.27]	[2.37]	[7.81]	[6.91]
2	0.74	0.61	0.50	0.43	0.43	-0.31	-0.44	0.03	0.20	0.13
	[2.85]	[2.58]	[2.21]	[1.93]	[1.55]	[-2.25]	[-3.18]	[0.97]	[4.14]	[2.84]
3	1.02	0.82	0.71	0.55	0.46	-0.56	-0.75	0.10	0.35	-0.01
	[3.99]	[3.45]	[3.34]	[2.56]	[1.72]	[-4.17]	[-5.70]	[3.33]	[7.37]	[-0.12]
4	1.06	1.05	1.13	0.89	0.88	-0.17	-0.35	0.13	0.26	0.03
	[4.12]	[4.08]	[4.78]	[3.78]	[3.14]	[-1.22]	[-2.45]	[3.92]	[5.13]	[0.60]
High	1.56	1.39	1.45	1.21	1.39	-0.17	-0.41	0.15	0.30	0.22
	[5.43]	[4.86]	[5.16]	[4.31]	[4.37]	[-1.13]	[-2.78]	[4.32]	[5.69]	[4.59]

Table VIII

Double sorts on gross yield and leverage. This table shows the value-weighted average excess returns to portfolios double-sorted, using NYSE breakpoints, on gross yield and leverage [book value of debt/(market value of equity+book value of debt)], and results of time-series regressions of high-minus-low portfolios returns on the Fama and French factors [the market, size and value factors MKT, SMB (small-minus-large), and HML (high-minus-low)]. T-statistics are given in square brackets. The sample covers July 1963 to December 2010.

	Low	2	3	4	High	H-L	α	MKT	HML	SMB
Low	0.62	0.34	0.27	0.16	0.21	-0.41	-0.40	-0.04	-0.11	0.28
	[2.26]	[1.28]	[0.89]	[0.48]	[0.61]	[-2.28]	[-2.26]	[-0.87]	[-1.66]	[4.72]
2	1.13	0.79	0.74	0.59	0.73	-0.40	-0.48	0.04	0.05	0.18
	[4.24]	[3.35]	[3.17]	[2.40]	[2.46]	[-2.59]	[-3.08]	[1.02]	[0.83]	[3.59]
3	1.17	0.91	0.72	0.68	0.65	-0.52	-0.65	0.14	0.17	-0.00
	[4.31]	[3.84]	[3.41]	[3.00]	[2.42]	[-3.26]	[-4.03]	[3.74]	[2.90]	[-0.06]
4	1.01	0.97	0.92	0.65	0.79	-0.22	-0.36	0.07	0.11	0.26
	[3.72]	[3.68]	[4.10]	[2.99]	[2.89]	[-1.21]	[-1.94]	[1.68]	[1.70]	[4.24]
High	0.98	0.98	1.33	0.87	1.13	0.14	0.02	0.02	0.08	0.37
	[3.21]	[2.71]	[3.79]	[2.71]	[3.21]	[0.60]	[0.06]	[0.41]	[0.88]	[4.69]

Table IX

Double sorts on gross yield and return volatility. This table shows the value-weighted average excess returns to portfolios double-sorted, using NYSE breakpoints, on gross yield and volatility [standard deviation of past 250 trading day returns], and results of time-series regressions of high-minus-low portfolios returns on the Fama and French factors [the market, size and value factors MKT, SMB (small-minus-large), and HML (high-minus-low)]. T-statistics are given in square brackets. The sample covers July 1963 to December 2010.

	Low	2	3	4	High	H-L	α	MKT	HML	SMB
Low	0.67	0.70	0.63	0.51	0.39	-0.28	-0.32	-0.08	0.13	0.06
	[3.95]	[4.03]	[3.80]	[3.15]	[2.27]	[-2.86]	[-3.23]	[-3.29]	[3.63]	[1.89]
2	0.76	0.68	0.79	0.72	0.73	-0.03	-0.24	0.14	0.29	0.14
	[3.72]	[3.07]	[3.44]	[3.17]	[2.92]	[-0.24]	[-2.01]	[5.16]	[6.86]	[3.56]
3	0.87	0.63	0.84	0.77	0.82	-0.05	-0.35	0.14	0.54	0.11
	[3.35]	[2.37]	[3.03]	[2.77]	[2.82]	[-0.38]	[-2.70]	[4.46]	[11.62]	[2.56]
4	0.95	0.92	0.68	0.75	0.74	-0.22	-0.49	0.06	0.60	0.05
	[2.79]	[2.59]	[2.10]	[2.29]	[2.20]	[-1.29]	[-3.12]	[1.55]	[10.71]	[0.92]
High	1.06	1.19	1.16	0.62	1.10	0.04	-0.16	0.00	0.40	0.15
	[2.51]	[2.58]	[2.63]	[1.52]	[2.58]	[0.20]	[-0.78]	[0.09]	[5.51]	[2.31]

Table X

Double sorts on gross yield and return skewness. This table shows the value-weighted average excess returns to portfolios double-sorted, using NYSE breakpoints, on gross yield and return skewness [measured over the past 250 trading day returns], and results of time-series regressions of high-minus-low portfolios returns on the Fama and French factors [the market, size and value factors MKT, SMB (small-minus-large), and HML (high-minus-low)]. T-statistics are given in square brackets. The sample covers July 1963 to December 2010.

	Low	2	3	4	High	H-L	α	MKT	HML	SMB
Low	0.72	0.58	0.67	0.48	0.56	-0.17	-0.46	0.06	0.54	0.20
	[2.94]	[2.53]	[3.22]	[2.22]	[2.00]	[-1.06]	[-3.12]	[1.79]	[10.30]	[4.11]
2	0.78	0.74	0.69	0.63	0.65	-0.13	-0.37	0.06	0.42	0.18
	[3.15]	[3.09]	[3.15]	[2.88]	[2.36]	[-0.93]	[-2.76]	[1.96]	[8.77]	[4.21]
3	0.78	0.66	0.83	0.69	0.79	0.01	-0.25	0.09	0.42	0.23
	[3.00]	[2.53]	[3.37]	[2.83]	[2.68]	[0.08]	[-1.91]	[2.99]	[8.92]	[5.32]
4	0.91	0.84	0.84	0.73	0.88	-0.03	-0.38	0.20	0.55	0.18
	[3.14]	[3.03]	[3.11]	[2.61]	[2.61]	[-0.19]	[-2.52]	[5.55]	[10.31]	[3.78]
High	1.11	1.15	0.93	0.82	0.85	-0.26	-0.46	0.06	0.35	0.14
	[3.46]	[3.66]	[3.08]	[2.85]	[2.48]	[-1.45]	[-2.57]	[1.35]	[5.56]	[2.35]

Table XI

Double sorts on gross yield and profitability. This table shows the value-weighted average excess returns to portfolios double-sorted, using NYSE breakpoints, on gross yield and gross profitability [(REVT-GOGS)/AT], and results of time-series regressions of high-minus-low portfolios returns on the Fama and French factors [the market, size and value factors MKT, SMB (small-minus-large), and HML (high-minus-low)]. T-statistics are given in square brackets. The sample covers July 1963 to December 2010.

	Low	2	3	4	High	H-L	α	MKT	HML	SMB
Low	0.78	0.83	0.83	0.50	0.53	-0.25	-0.52	0.14	0.49	0.00
	[2.11]	[2.24]	[2.33]	[1.42]	[1.44]	[-1.57]	[-3.39]	[3.93]	[8.90]	[0.02]
2	0.96	0.82	0.76	0.68	0.77	-0.19	-0.42	0.14	0.45	-0.04
	[3.55]	[3.16]	[3.01]	[2.72]	[2.77]	[-1.26]	[-2.99]	[4.06]	[8.86]	[-0.96]
3	0.73	0.62	0.74	0.65	0.85	0.12	-0.03	0.03	0.29	0.08
	[3.24]	[2.82]	[3.60]	[3.20]	[3.48]	[1.03]	[-0.25]	[1.12]	[6.68]	[1.94]
4	0.80	0.75	0.70	0.64	0.93	0.13	-0.09	0.07	0.39	0.11
	[3.61]	[3.44]	[3.53]	[3.29]	[3.86]	[1.07]	[-0.76]	[2.38]	[9.26]	[2.84]
High	0.91	0.84	0.96	0.90	1.22	0.31	0.01	0.09	0.45	0.26
	[3.88]	[3.63]	[4.12]	[3.88]	[4.48]	[2.23]	[0.10]	[3.03]	[9.70]	[6.21]

Table XII

Fama and MacBeth regressions of returns on measures of gross yield for the 500 largest stocks. This table reports results from Fama and MacBeth regressions of returns on gross yield (gross interest expense XINT scaled by liabilities LT). Regressions include controls for book-to-market [BM], size [MV], yield on long-term debt [YIELDLT], leverage [LEVER], earnings-to-price [EP] and past performance measured over 12 months [MOM12] and covers July 1963 to December 2010.

	(1)	(2)	(3)	(4)	(5)	(6)
BM	0.19	0.08	0.13	0.13	0.22	0.14
	[3.99]	[1.76]	[3.22]	[3.72]	[5.52]	[4.74]
EP			0.18	0.17		0.17
			[4.06]	[4.10]		[4.46]
MOM12				0.12		0.12
				[2.72]		[2.69]
MV	-0.06	-0.06	-0.07	-0.08		-0.08
	[-1.22]	[-1.43]	[-1.48]	[-1.73]		[-1.74]
YIELDLT		0.04				
		[1.48]				
YIELD	-0.06		-0.07	-0.07	-0.05	-0.06
	[-2.35]		[-2.67]	[-2.88]	[-2.32]	[-2.53]
LEVER					-0.00	-0.04
					[-0.00]	[-1.14]
INTERCEPT	0.62	0.52	0.62	0.61	0.62	0.61
	[2.87]	[2.81]	[2.86]	[2.78]	[2.87]	[2.79]

Table XIII

Excess returns to portfolios sorted on gross yield for the 500 largest stocks. This table shows monthly value-weighted average excess returns to portfolios sorted on gross yield [gross interest expense (XINT) scaled by liabilities (LT)] employing NYSE breakpoints, and results of time-series regressions of these portfolios returns on the Fama and French factors [the market factor (MKT), the size factor small-minus-large (SMB), and the value factor high-minus-low (HML)], with T-statistics (in square brackets). It also shows time-series average portfolio characteristics [portfolio gross profits-to-assets (GP/A), leverage, average firm size (ME, in millions of dollars), and number of firms (n)]. The sample covers July 1963 to December 2010.

	r	α	MKT	SMB	HML	GP/A	BM	Leverage	Market Value
Low	0.65	0.11	1.03	0.49	0.03	0.39	-0.76	0.33	2551563
	[2.85]	[1.81]	[71.38]	[24.35]	[1.17]				
2	0.62	0.00	1.05	0.38	0.24	0.36	-0.63	0.41	5099580
	[2.86]	[0.08]	[78.04]	[20.02]	[11.44]				
3	0.66	-0.03	1.03	0.31	0.45	0.30	-0.50	0.52	3450264
	[3.18]	[-0.45]	[71.44]	[15.48]	[20.45]				
4	0.59	-0.11	1.01	0.30	0.51	0.26	-0.43	0.56	2637188
	[2.93]	[-1.70]	[67.49]	[14.19]	[22.52]				
High	0.57	-0.23	1.15	0.60	0.45	0.25	-0.47	0.55	1488787
	[2.28]	[-2.92]	[62.18]	[23.22]	[15.92]				
H-L	-0.08	-0.34	0.12	0.11	0.42				
	[-0.88]	[-4.17]	[6.28]	[4.08]	[14.48]				

Table XIV

Double sorts on gross yield and book-to-market for the 500 largest stocks. This table shows the value-weighted average excess returns to portfolios double-sorted, using NYSE breakpoints, on gross yield and book-to-market, and results of time-series regressions of high-minus-low portfolios returns on the Fama and French factors [the market, size and value factors MKT, SMB (small-minus-large), and HML (high-minus-low)]. T-statistics are given in square brackets. The sample covers July 1963 to December 2010.

	Low	2	3	4	High	H-L	α	MKT	HML	SMB
Low	0.48	0.30	0.43	0.16	0.47	-0.01	-0.24	0.11	0.37	0.10
	[1.71]	[1.24]	[1.74]	[0.62]	[1.58]	[-0.08]	[-1.51]	[2.93]	[6.49]	[1.83]
2	0.52	0.53	0.30	0.37	0.20	-0.31	-0.45	0.09	0.25	-0.04
	[2.11]	[2.38]	[1.34]	[1.69]	[0.81]	[-2.38]	[-3.43]	[2.95]	[5.42]	[-1.00]
3	0.79	0.58	0.61	0.47	0.34	-0.45	-0.58	0.04	0.19	0.12
	[3.38]	[2.60]	[2.98]	[2.33]	[1.35]	[-3.42]	[-4.36]	[1.35]	[4.03]	[2.67]
4	0.80	0.86	0.85	0.83	0.67	-0.13	-0.30	0.12	0.19	0.13
	[3.56]	[3.94]	[4.00]	[4.06]	[2.66]	[-0.92]	[-2.13]	[3.66]	[3.91]	[2.85]
High	1.01	0.96	1.08	1.01	1.06	0.04	-0.15	0.17	0.15	0.25
	[4.19]	[3.67]	[4.31]	[4.16]	[3.73]	[0.30]	[-1.03]	[5.19]	[3.01]	[5.42]

Table XV
Summary Statistics of large cap strategy across five GDP growth regimes. Regime 1 indicates recession and 5 expansion

	count	mean	std	min	25%	50%	75%	max
Recession	113	0.42	3.32	-19.12	-0.81	0.51	1.78	9.93
2	112	0.25	2.10	-4.71	-1.00	0.20	1.32	9.19
3	113	-0.33	1.84	-7.34	-1.26	-0.25	0.95	3.21
4	113	-0.10	1.57	-4.03	-1.34	-0.18	1.20	4.23
Expansion	111	0.17	1.93	-5.83	-1.02	0.29	1.07	6.00

Can Cashflow Risk Explain the Value Spread?

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ABSTRACT

This paper investigates cashflow risk and its relationship to average returns. We find that stocks with earnings that co-vary strongly with market-wide earnings also earn a high return. The cashflow beta (or earnings beta) of value stocks is found to be much higher than that of growth stocks, and small stocks have higher cashflow betas than large stocks. Thus, cashflow betas can explain a significant part of the Fama and French factors. This provides evidence for a risk-based explanation of anomaly returns because stocks earning a higher return also tend to have riskier cashflows.

JEL classification: .

*Rasekhschaffe is with USI, Reggiani is with Bocconi. We thank Giovanni Barone-Adesi, Francesco Franzoni, Eric Nowak and Stephen H. Penman. We are grateful to Scott Richardson and Rebecca Tekula.

I. Introduction

It is widely known that the classical capital asset pricing model (CAPM) has failed to explain a broad range of anomalies in the closely studied period after 1962. Among the most notable anomalies are the Fama and French (1992) factors, namely size and book-to-market. Adrian and Franzoni (2009) suggest that the beta of value stocks has decreased over time: while the CAPM was able to explain a significant part of the value spread in the beginning of the 20th century, beta becomes negative for the value spread during the latter part of the 20th century. In recent research Frazzini and Pedersen (2010) show that beta not only fails to explain the book-to-market anomaly, but that a spread portfolio formed on beta has a negative expected return. This result calls into question the foundational assumption that riskier assets earn a higher return. From an empirical perspective this also undermines the ability of beta to explain anomalies consistent with theory: Since beta does not have a positive price of risk in the cross-section, it might lack credibility explaining anomalies even if betas are aligned with returns of test assets.

Time-varying aggregate cashflows lead to changes in the investment opportunity set and directly affect current-period wealth. Since listed firms are intertwined with the economy it is not surprising that cashflow shocks correlate positively with changes in gross domestic product (GDP) and consumption. Also, cashflow innovations vary with common indicators of distress such as the default spread and the term-spread. Arbitrage pricing theory suggests that aggregate cashflow (or earnings) risk needs to be priced in the cross-section in order to be a systematic risk factor: stocks whose cashflows are highly sensitive to market-wide cashflow innovations should have high expected returns.

We think that cashflow beta is a very suitable candidate for a risk factor since it inherits much of the theoretical underpinnings of the traditional CAPM. The dividend model of Campbell and Shiller (1988) relates returns to cashflows and therefore firms with riskier cashflows might also be more risky investments. Regardless of whether markets are entirely efficient, it is a widely held belief that riskier assets have higher expected returns. While previous studies (see e.g. Cohen, Polk, and Vuolteenaho (2009); Da and Warachka (2009)) have looked to different cashflow measures explaining anomalies ex-post, surprisingly little attention has been paid to cashflow beta as a risk factor.

We aim to answer the question: do fundamentally more risky firms earn a higher return. To this end we measure risk by examining the underlying cashflows of firms. Unlike return betas we do not expect cashflow betas to be affected by transitory mispricing. To achieve this we study the cashflow betas of firms and document that cashflow beta-sorted portfolios provide a spread portfolio with positive expected return. To estimate cashflow betas we strictly limit ourselves to information available to investors at any point in time. Each year betas are re-estimated for all stocks and investors learn about cashflow betas only as financial statements become available, which is in contrast to the common approach to estimate betas over the full sample. Estimating betas over the full sample can be especially mis-leading when estimation risk is high which is the case in the present analysis because of the small sample of observations.

The first goal of this paper is to investigate if cashflow beta is priced in the cross-section. To this end we estimate the price of risk of cashflow beta using individual stocks as the test assets. In contrast with traditional beta, we are able to show that cashflow beta has a positive and significant price of risk. To ensure that our estimated price of risk corresponds to an investible strategy, we estimate cashflow betas at all points in time for all stocks. Next, we form portfolios based on the loadings on aggregate cashflow innovations. If the price of cashflow risk is positive, we expect portfolios of assets with high loadings to have high average returns.

We find that cashflow beta carries a significant price of risk. The decile with the highest loading outperforms the decile with the lowest loading by approximately 3.5% per annum. We find this to be consistent with economic theory: low cashflow beta assets effectively provide a hedge against aggregate cashflow shocks and therefore should have a lower price of risk than highly cyclical assets. Furthermore, the dividend model of Campbell and Shiller (1988) shows that cashflows equal returns in the long run. This effectively links cashflow risk to return risk and suggests that high cashflow beta stocks might have high demand and low expected returns because their future returns are expected to be more risky.

The second goal of this paper is to see if returns to book-to-market, size, and long-term mean-reversion portfolios are related to cashflow risk. Since our cashflow risk factor has theoretical underpinnings and has been shown empirically to have a positive price of risk, we now will analyze the cashflow risk of anomaly portfolios. There are reasons to believe that beta-contamination described in Brainard, Shapiro, and Shoven (1990) might be especially problematic for valuation-

based anomalies like the book-to-market effect, since these are likely to pick up transitory mispricing. Hence cashflow betas are particularly useful in this case since they remain largely unaffected by temporary inefficiencies. Although cashflow risk of anomaly portfolios has been an area of active research, our measure differentiates itself by having considerable pricing power in the cross-section of stocks and not just anomaly test assets: portfolios of stocks with high ex-ante cashflow loadings have high average returns. Moreover, firm earnings are directly observable and therefore cashflow betas can be directly estimated. Since the beta is not a residual like in the Campbell and Shiller (1988) decomposition, no assumptions about state variables are necessary.

We find that cashflow betas for size and book-to-market portfolios do vary significantly explaining a large portion of their returns. High book-to-market portfolios have much higher cashflow betas than low book-to-market portfolios. In fact the spread in cashflow betas between high book-to-market stocks and low book-to-market stocks is almost as large as for cashflow beta sorted portfolios. Also, portfolios with small stocks have higher cash-flow betas than portfolios with large stocks.

Measure

In our analysis we deliberately focus on the simplest cashflow measure possible, year-on-year return on equity innovations, since more complex approaches frequently require assumptions about state variables or make real time estimation impossible. Return on equity innovations are easy to observe, do not require additional assumptions for computation, and we know exactly when the information becomes available. Even though we would like to measure changes in expected cashflows going forward, we limit ourselves to using past cashflow changes in order to provide an empirically sufficient proxy and avoid either relying excessively on specific assumptions of a model or depending on analyst forecasts that are known to be biased. Since we use essentially a backward looking measure we test if sorting on cashflow betas continues to provide a large spread in cashflow-risk loading after portfolio formation. This is particularly important since cashflow beta estimates are not reliable in a statistical sense due to annual data frequency resulting in few data points. We demonstrate that sorting on ex-ante cashflow loadings also produces a large spread in cashflow betas after portfolio formation. Furthermore, book-to-market sorted portfolios and size-sorted portfolios have cashflow betas that are aligned with returns: test assets with higher returns tend to have

riskier cashflows. Provided that cashflow beta is also a priced factor in the cross-section of returns this plausibly suggests that at least some of the observed anomaly returns are due to fundamental risk. Finally, cashflows of book-to-market sorted portfolios are correlated with macroeconomic risk proxies that forecast aggregate returns.

While shareholders ultimately care about the cashflows they receive, earnings are arguably better than net dividends as a proxy for cashflows since dividend payout ratios are driven by many considerations including taxation apart from earnings. Beginning with Ball and Brown (1968) and Beaver (1968), a stream of papers documents that realized stock returns are related to realized earnings, consistent with the casual observation that stock prices move when earnings differ from expectation. More recently, Andrew and Johannes (2006) estimate that a disproportionate amount of anticipated stock price volatility is associated with uncertainty resolution around earnings announcements. Thus it appears that expected earnings are at risk; investors "buy" earnings and the return outcome depends on the difference between actual and expected earnings. Also, the large return volatility associated with earnings announcements suggests that investors view current earnings as indicative of future earnings. We measure risk as the cashflow beta coefficient and find that these betas vary systematically with market cashflows and the risk premium.

Literature

It is well known that high book-to-market stocks earn higher returns than low book-to-market stocks. Several studies of dynamic trading strategies suggest that the excess returns of high book-to-market stocks cannot be explained by risk because returns are not explained by the CAPM. Lakonishok, Shleifer, and Vishny (1994) argue that conditional risk models are unlikely to result in a plausible explanation because high book-to-market stocks exhibit a lower beta when returns are negative. They argue that the value premium must be due to overreaction or other behavioral biases. A group of studies endeavours to explain the failure of the unconditional CAPM by introducing conditioning information. Lettau and Ludvigson (2001); Santos and Veronesi (2004); Lustig and Van Nieuwerburgh (2007); Jagannathan and Wang (1996) and Zhang (2005) suggest that betas of book-to-market and size-sorted stocks vary over the business cycle in ways that explain positive unconditional alphas. Petkova and Zhang (2005) find that betas of book-to-market sorted portfolios vary with the price of risk, but not enough to explain the value spread. Lewellen and Nagel (2006)

argue that the conditional CAPM does not explain the value spread because cross-sectional tests fail to account for restrictions imposed by theory. Beaver, Kettler, and Scholes (1970) suggest that accounting-based risk measures are impounded in market-price-based risk measures. However, recent evidence indicates that accounting-based risk measures may be more successful in explaining the cross section of returns and in particular the value spread. This may result from cashflow betas linking returns to risk, even if some mispricing obscures the link between beta and returns. Risky assets (high book-to-market stocks in most studies) might be underpriced and result in low betas. Brainard et al. (1990) argue that even slight mispricing might contaminate both returns and higher moments. Cohen et al. (2009) show that cashflow betas explain most of the price difference between high and low book-to-market stocks. Nekrasov and Shroff (2009) also show that cashflow betas reasonably explain the cross section of average returns. In related research Campbell and Vuolteenaho (2004) decompose beta into a cashflow and discount rate component and show that high book-to-market stocks have relatively high cashflow betas and low discount-rate betas. They argue that cashflow betas should carry a higher risk premium. Cohen et al. (2009) conclude that return betas approach cashflow risk as the holding period increases. Da and Warachka (2009) show that systemic earnings forecast revisions are a useful predictor of cross-sectional anomalies.

Since many characteristics may align with anomaly portfolio returns (Lewellen and Nagel (2006)), it is important that proposed risk factors have power not only in the cross section of anomaly portfolios, but also individual equities. Thus our study adds to previous research like Cohen et al. (2009) and Da and Warachka (2009) because it does not merely focus on cashflow risk after portfolio formation without linking the cashflow measure to the cross-section of anomaly factor returns.

II. Methodology

Cashflow risk motivation

Since stock prices equal the discounted sum of future cashflows, stock returns are naturally driven by earnings realizations. Campbell and Shiller (1988) decompose stock returns in a cashflow component ($N_{CF,t+1}$) and a discount rate component ($N_{DR,t+1}$):

$$r_{t+1} - E_t[r_{t+1}] = N_{CF,t+1} - N_{DR,t+1} \tag{1}$$

where the discount rate component equals

$$N_{DR,t+1} = (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+j+1} \tag{2}$$

and the cashflow component equals

$$N_{CF,t+1} = (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j d_{t+j+1} \tag{3}$$

where Δd_{t+j+1} and r_{t+j+1} denote, respectively, the log stock cashflow growth and the log stock return over a future time period $[t+j, t+j+1)$ with ρ being the log-linearization constant (commonly set to 0.95 with annual frequency). Cashflows from Equation (3) do not equal changes in expected earnings since cashflows represent outflows from the firm to the investor. Earnings represent an inflow of funds. Earnings and cashflows from Equation (3) are related through the clean surplus accounting identity:

$$B_{t+1} = B_t + X_{t+1} - D_{t+1} \tag{4}$$

where B_{t+1} is book equity, X_{t+1} is earnings, and D_{t+1} is cashflows. d_{t+j+1} from Equation (3) is the log of D_{t+j+1}. The log return on book equity is:

$$e_{t+j+1} = log(1 + \left(\frac{X_{t+j+1}}{B_{t+j}}\right)) \tag{5}$$

Campbell and Vuolteenaho (2004) and Cohen et al. (2009) log-linearize the clean surplus identity and replace cashflows Δd_{t+j+1} in Equation (3) with log returns on book equity. Thus the cashflow component becomes:

$$N_{CF,t+1} = (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j e_{t+j+1} \tag{6}$$

Equation (6) suggests that cashflow shocks and earnings shocks contain similar information since

cashflows to shareholders eventually need to be financed by earnings.

For our purposes it is more natural to examine earnings rather than cashflows since dividends are known to be smoothed and dividend policy is also impacted by many considerations apart from expected cashflow shocks (i.e. tax treatment). Since cashflows eventually need to be paid from earnings, current earnings shocks might be a better proxy than current cashflow shocks for future cashflow shocks.

Cashflow risk measure

Equation (6) suggests that the cashflow component of stock prices requires the knowledge of cashflow shocks across all horizons. However, in our analysis we rely on past cashflow shocks since future expected shocks are not directly observable. Several papers from the accounting literature (see e.g.: Ball and Brown (1968) and Beaver (1968),) document that price changes correlate highly with earnings changes. In a more recent study Andrew and Johannes (2006) estimate that a disproportionate amount of anticipated stock price volatility is associated with uncertainty resolution around earnings announcements, which suggests that current earnings shocks inform investors about future earnings shocks.

Specifically, our cashflow proxy for Equation (3) is defined as follows:

$$N_{CF,t} = \frac{\Delta e_t}{B_{t-1}} \tag{7}$$

To construct market-wide earnings innovations we take the cross-sectional sum of Δe_t for each year and divide it by the cross-sections mean of B_t each year where Δe_t are earnings innovations at time t and B_{t-1} is book value at time $t-1$.

Pre-formation regressions

Our goal is to to test whether stocks with different sensitivities to market-wide earnings innovations have different average returns. To measure the sensitivity to market-wide earnings innovations we first compute expanding window regressions for each stock with sufficient observations:

$$N_{CF,t-1} = \alpha^i_{CF} + \beta^i_{CF,t-1} N^M_{CF,t-1} + \varepsilon^i_{t-1} \tag{8}$$

where i and M superscripts denote portfolios and the market respectively. The cashflow beta $\beta^i_{CF,t-1}$ denotes the co-variance between changes in portfolio earning and changes in market-wide earnings at time $t-1$. We re-estimate $\beta^i_{CF,t-1}$ each year in order ensure all information is in the investor's information set.

We construct a set of test assets that are diverse in their cashflow beta by sorting firms into portfolios each calendar year based on their latest $\beta^i_{CF,t-1}$. We use all stocks from AMEX, NASDAQ and NYSE that have a minimum of ten observations in order to make estimates reasonably precise. We then hold the portfolios constant and measure their returns from June in year t to June in year $t+1$ to ensure the inputs for Equation (8) were known to investors.

Estimation of cashflow betas of test assets

For our estimation of cashflow betas of anomaly portfolios, we aggregate firm-level earnings innovations from Equation (7), and regress portfolio earnings innovations on market earnings innovations.

$$N_{CF,t} = \alpha^i_{CF} + \beta^i_{CF,t} N^M_{CF,t} + \varepsilon^i_t \tag{9}$$

Cross-sectional regressions

Our cross-sectional regressions involving individual stocks and the 20 size and book-to-market portfolios confirm the economic intuition that cashflow betas should be a priced risk factor. We take the regression coefficients $\beta^i_{CF,t-1}$ from Equation (8) and estimate the following cross-sectional regression:

$$r^i_{t+\delta} - rf_t = \lambda_0 + \lambda_1 \beta^i_{CF,t-1} + \varepsilon^i_{t+\delta} \tag{10}$$

where the dependent variable $r^i_{t+\delta}$ represents the returns to portfolio i, and rf_t represents the risk-free rate over the same horizon.

III. Empirical results

Data

Our data is from the Compustat annual file and the Center for Research in Security Prices database (CRSP), and covers the 1962-2010 period. All firms are listed in the United States, and we exclude all firms that do not have their fiscal-year-end in December to ensure contemporaneous cashflows. We use book value of common equity and earnings before extraordinary items from Compustat. Stock prices and returns are from CRSP. Price per share is taken at fiscal-year-end and book value and earnings are assumed to be known six months after. Book value is computed as Compustat common equity (CEQ) plus preferred treasury stock (TSTKP), less preferred dividends in arrears (DVPA). Earnings is defined as earnings before extraordinary items (IB), less special items (SPI), adjusted for taxes.

Firm-year observations with negative book value, missing earnings, or share price less than 20 cents are excluded from the analysis. Also, firms missing shares outstanding are excluded. Other missing data items are set to zero. The variables used to fit the expected risk premium are defined as follows: the dividend yield is the sum of dividends accruing to the CRSP value-weighted index of the trailing twelve months divided by the level of the index. The default spread is the yield spread between Moody's Baa and Aaa corporate bonds. The term premium is the spread between the ten-year and the one-year treasury bond. Default yields are from the monthly database of the Federal Reserve Bank of St. Louis. Government bond yields are from the Ibbotson database, and the short rate is the one month treasury bill rate from CRSP.

Summary statistics

There are 68,716 firm-years in the investigation over our 44 year period, with an average of 1,561 firms per year. Panel A of Table I gives the distribution of monthly returns from the 12 months over which they are observed and distributions of the estimated book-to-market (B/M) and return on common equity (ROCE). The table description explains the trimming of variables for the means and standard deviations. The table reports that the distributions of returns and B/M in the sample are quite similar to those for all firms on CRSP and Compustat. The relationship between B/M and other variables is highlighted in Panel B of Table I where characteristics of five

portfolios formed from ranking firms on B/M are reported. As in Fama and French (1992) among others B/M is positively correlated with returns over the subsequent 12 months, suggesting that high B/M stocks require a higher return. Note that B/M is negatively correlated with ROCE, and high B/M firms have lower profitability and are identified with higher risk in asset pricing models.

[Place Table I about here]

Cashflow beta sorted portfolios: Post-formation factor loadings

In the penultimate row of Table II, we present the post-formation factor loadings of the cashflow beta sorted portfolios. We computed them as follows: After forming portfolios by sorting on cashflow beta estimates available at time t, we sum all earnings innovations and book values in the following year $t+1$ for each portfolio and compute the portfolio cashflow beta by regressing on market cashflow innovations as described with Equation (9).

The penultimate row in Table II indicates that portfolios formed on past β^i_{CF} show a significant spread in β^i_{CF} over the subsequent year.

Cashflow beta sorted portfolios: Post-formation returns

The first row of Table II presents portfolio returns. Returns increase from 0.89 percent per month for the decile with the smallest loadings to 1.18 percent for the decile with the highest loadings. While the difference between decile 10 and decile 1 is not quite significant ($t =$)for the period under examination, the spread portfolio does have a Sharpe ratio comparable to the market portfolio.

Anomaly Portfolios

In this section we examine returns of book-to-market portfolios and size portfolios and study their relationship with cashflow beta. The first row of Table III reports returns for book-to-market deciles. Consistent with prior evidence, returns increase almost monotonically in book-to-market. As is common, the relationship is stronger for equal-weighted portfolios because the book-to-price effect is more pronounced among smaller stocks. The second row shows the augmented DickeyFuller (ADF) test statistic for the cashflow innovations. The critical value at the 1% level is -3.63. Hence

a unit root for the portfolio cashflow innovations is rejected. The fourth row presents the average cashflow beta from Equation (9), and the penultimate and final rows give betas estimated over the entire sample and their T-statistics respectively.

Both the average learning beta and the full sample beta are strongly increasing in book-to-market. This indicates that cashflow betas might provide an "explanation" for the book-to-market anomaly. The difference in average cashflow betas observed by investors between the extreme value and growth portfolios is 1.56: a spread almost as large as for cashflow beta sorted portfolios.

Row 1 of Table IV presents returns for size-sorted deciles. As expected, small stocks outperform large stocks by a significant margin and the small firm effect in our sample remains strong even when considering value-weighted portfolios. Again, the ADF test statistic for cashflow innovations (in the third row) allows us to reject a unit root for all portfolios. Similar to the book-to-market portfolios, all measures of cashflow risk go in the correct direction to "explain" returns. The difference in cashflow betas for the smallest and largest decile is 0.47.

Cross-sectional price of risk

This section formalizes the observation that cashflow betas are aligned with returns for the B/M and size portfolios. Specifically, we use the twenty portfolios as test assets and run cross-sectional regressions to estimate the price of beta risk. We estimate Fama and MacBeth regressions of the portfolio returns of the test assets on their cashflow betas. We adjust the standard errors with the Newey and West (1987) procedure for autocorrelation up to ten lags. Table IX presents estimates for the price of risk of our cashflow beta and the risk-free rate. The coefficient for cashflow beta, λ_1, is positive and highly significant. The adjusted R-Squared indicates that the cashflow beta factor explains approximately 50% of the return variation of book-to-market and size-sorted portfolios, suggesting that approximately half the variation in book-to-market and size-sorted portfolio returns is attributable to cashflow risk.

[Place Table IX about here]

We compute robust T-statistics with the generalized method of moments (GMM) to account for estimation error in the cashflow beta estimates. The covariance matrix for the moment conditions

is computed with the Newey and West (1987) autocorrelation adjustment with 10 lags, therefore the T-statistics account for both cross-sectional and time-series estimation errors.

These empirical findings suggest that cashflow risk is an important cross-sectional risk factor for the Fama and French (1992) factors. Large growth stocks justifiably earn lower returns than small value stocks because their earnings are significantly less risky. It is well known that cross-sectional asset pricing models can spuriously explain book-to-market and size returns because their factor structure lowers the hurdle significantly (Lewellen and Nagel (2006)). Giving credence to the results, cashflow beta has a solid theoretical foundation and explains the cross-section of individual stocks and not only the cross-section of the test assets.

IV. Conclusion

We aim to answer the question: Is fundamental risk compensated with higher returns. This question is particularly important since value stocks have lower CAPM betas than growth stocks in recent decades. Differing from earlier research that only examines cashflow risk of anomaly portfolios, we show that fundamental risk measured as covariances of cashflows, does have significant power in the cross-section of individual equities. This provides an important empirical foundation for our cashflow beta. A risk factor which is not associated with positive expected returns lacks credibility.

Further, high book-to-market portfolios have much higher cashflow betas than low book-to-market stocks and small stock portfolios have much higher cashflow betas than large stocks, suggesting that some of their return variation is compensation for fundamental risk. This contrasts with return betas: High book-to-market portfolios have lower betas than low book-to-market stocks. Also, we find that cashflow betas lead return betas: over time high cashflow beta stocks also have riskier returns.

Stock returns are partially driven by changes in earnings. We find that beyond the well-known contemporaneous relationship with returns, earnings shocks also have significant explanatory power in the cross-section of both stocks and anomaly portfolios. A significant amount of the Fama and French (1992) factor returns can be explained by our cashflow beta. Cashflow betas are higher for both value stocks and small stocks, partially explaining their high returns. Our findings suggests

that fundamentally risky firms earn higher returns. Value stocks are fundamentally more risky than growth stocks and small stocks are fundamentally more risky than large stocks. Shortly after portfolio formation their returns appear less risky, perhaps because these stocks are indeed mispriced. In the intermediate term CAPM betas increases for these stocks and better reflect their fundamental risk.

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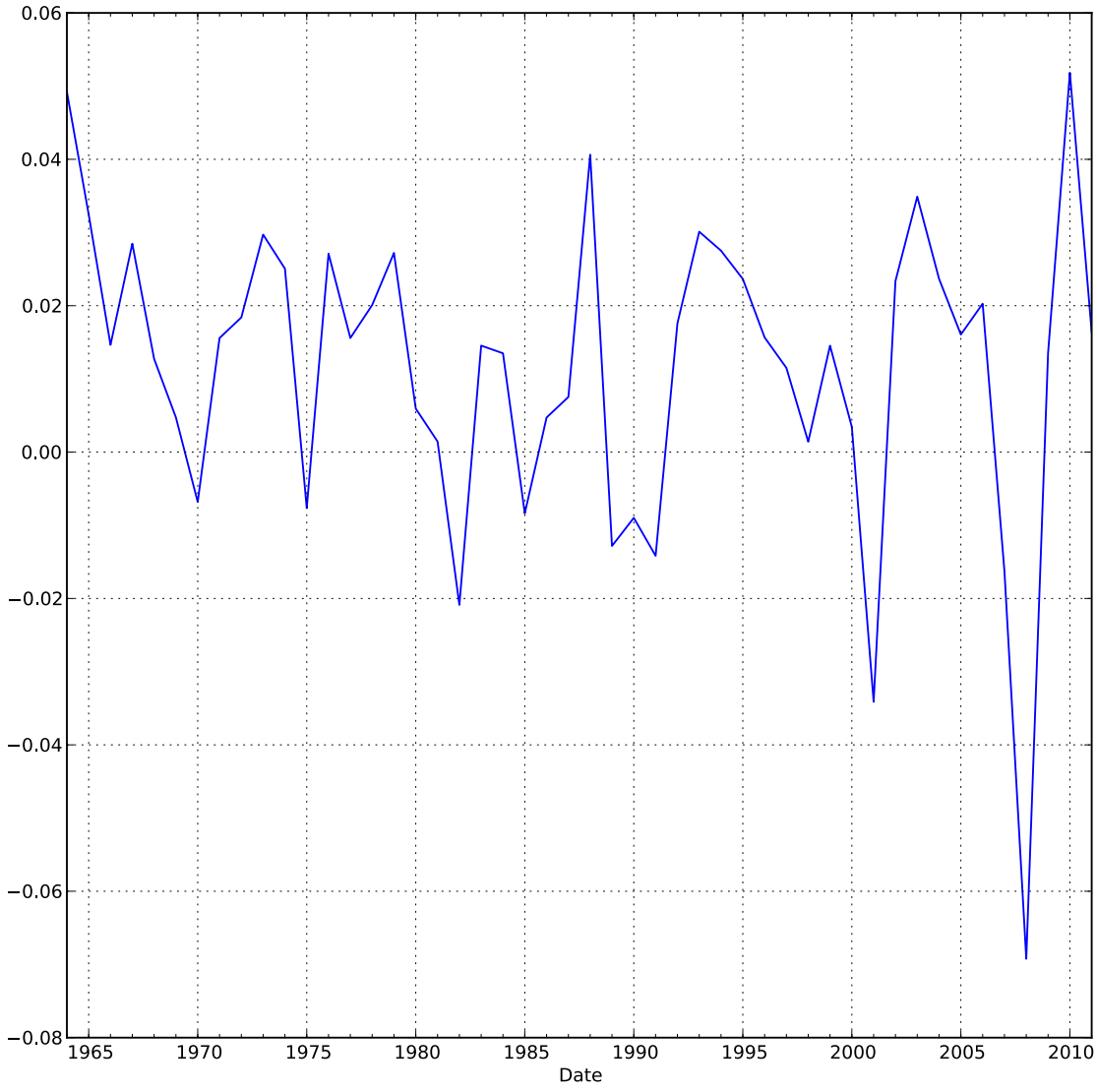

Figure 1. Aggregate cashflow innovation

This figure shows the time series of aggregate earnings innovations $N_{CF,t} = \frac{\Delta e_t}{B_{t-1}}$.

Figure 2. Cumulative return to the cashflow beta spread portfolio

This figure shows the time series cumulative returns of a zero-investment portfolio that is long high cashflow beta assets and short low cashflow beta assets.

This figure presents earnings innovations for the year after portfolio formation. The plots compare market-wide cashflow innovations with book-to-market, size, and cashflow beta sorted portfolios.

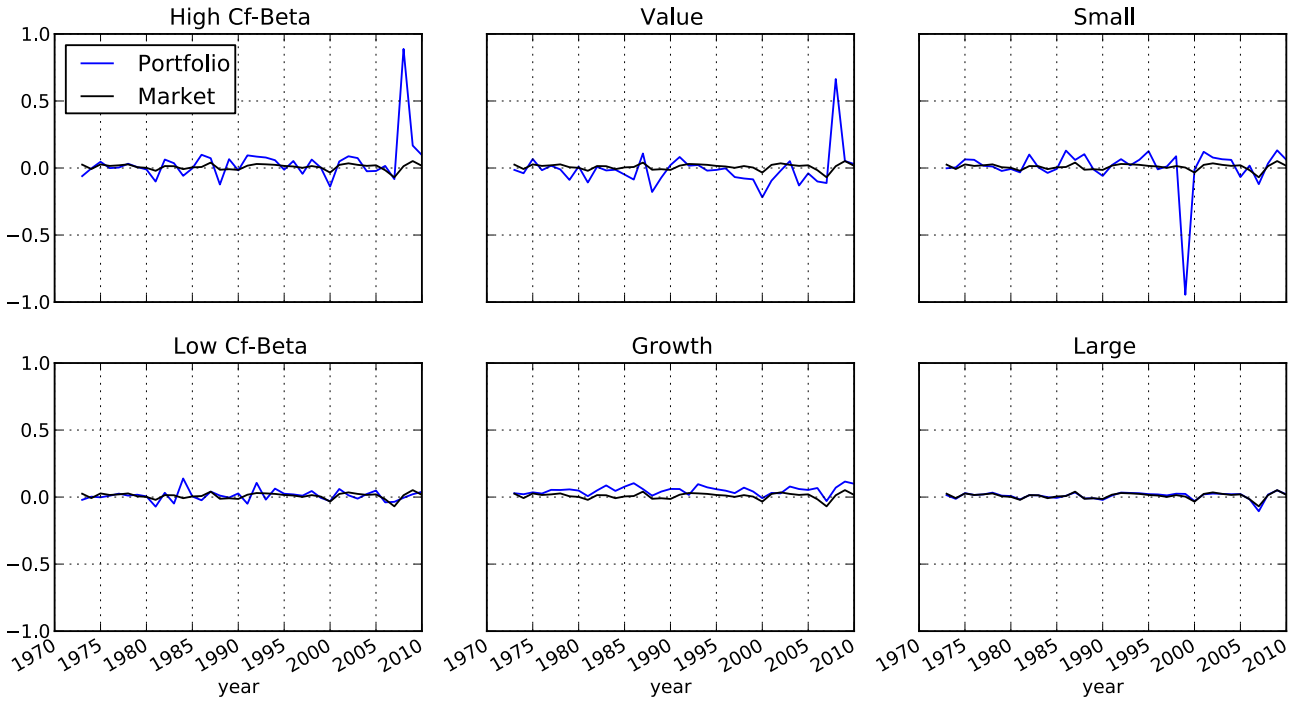

Figure 3. Cashflows of portfolios and the market portfolio

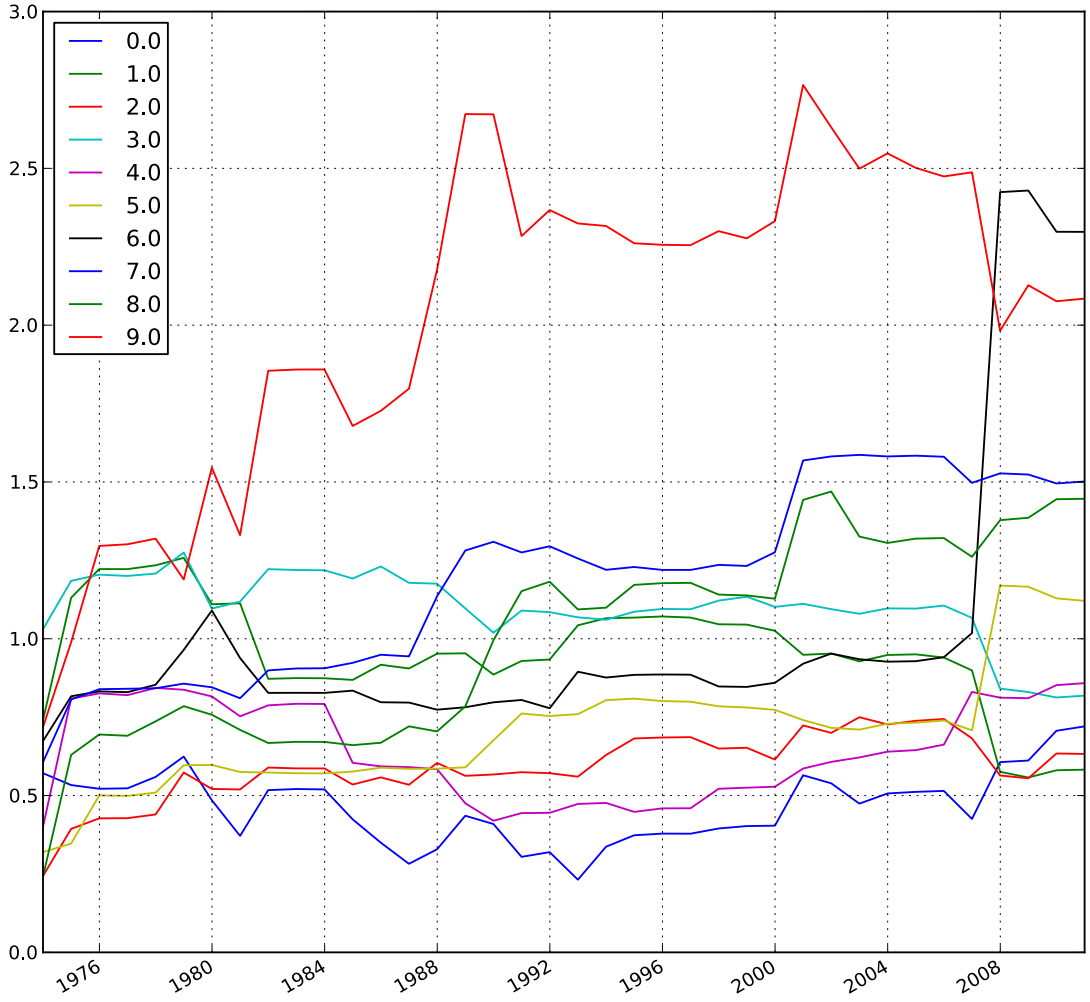

Figure 4. Cashflow beta evolution of book-to-market sorted portfolios

This figure presents cashflow beta estimates for ten book-to-market portfolios estimated with expanding window regressions.

Table I

Summary statistics.

This table presents summary statistics broken down by calendar year. Columns NYSE, AMEX, and NASDAQ present the percentage of stocks that are included in our sample from each of these exchanges. Column BP is the median book-to-market value in each calendar year. ROCE is the median return on common equity for each calendar year, and MV reports the median market value in millions USD for each calendar year. The BOOK-TO-MARKET column reports the aggregate book-to-market ratio for each year. The COUNT column reports the total number of stocks in our sample for each year.

YEAR	NYSE	AMEX	NASDAQ	BP	ROCE	MV	BOOK-TO-MARKET	COUNT
1965	28%	6%	0%	0.47	0.02	336	0.43	398
1966	33%	8%	0%	0.65	0.01	157	0.51	480
1967	51%	22%	0%	0.53	0.00	127	0.47	809
1968	52%	22%	0%	0.46	0.01	148	0.46	852
1969	53%	24%	0%	0.68	0.01	105	0.56	913
1970	55%	25%	0%	0.77	-0.00	90	0.59	1004
1971	57%	29%	100%	0.75	0.01	92	0.57	1128
1972	57%	31%	0%	0.79	0.02	91	0.53	1175
1973	59%	34%	0%	1.28	0.02	60	0.69	1214
1974	63%	41%	26%	1.88	0.01	27	1.05	1894
1975	63%	41%	30%	1.41	0.01	39	0.86	2023
1976	63%	41%	30%	1.10	0.03	56	0.76	1996
1977	63%	41%	29%	1.10	0.02	63	0.90	1971
1978	63%	41%	28%	1.16	0.02	64	0.95	1905
1979	63%	39%	27%	1.13	0.02	75	0.91	1890
1980	63%	39%	23%	1.03	0.01	86	0.79	1907
1981	63%	39%	23%	1.08	0.01	86	0.94	1868
1982	63%	41%	21%	0.95	-0.01	93	0.87	1919
1983	61%	42%	21%	0.76	0.02	115	0.76	1989
1984	60%	41%	21%	0.86	0.02	104	0.79	1952
1985	59%	38%	22%	0.70	0.00	118	0.65	2018
1986	57%	35%	21%	0.67	0.01	111	0.61	2003
1987	58%	35%	21%	0.79	0.02	93	0.66	1965
1988	59%	40%	24%	0.71	0.02	103	0.62	2054
1989	59%	42%	27%	0.67	0.01	118	0.53	2138
1990	57%	42%	27%	0.86	0.00	90	0.61	2140
1991	56%	43%	26%	0.66	0.01	128	0.49	2165
1992	54%	44%	24%	0.59	0.02	157	0.45	2186
1993	54%	43%	24%	0.55	0.02	181	0.42	2296
1994	55%	42%	32%	0.65	0.02	125	0.47	2754
1995	56%	41%	33%	0.56	0.02	148	0.39	3011
1996	55%	41%	34%	0.52	0.02	170	0.36	3155
1997	55%	40%	37%	0.44	0.02	195	0.30	3184
1998	57%	43%	39%	0.53	0.01	176	0.27	3236
1999	60%	43%	40%	0.56	0.01	193	0.27	3168
2000	62%	43%	46%	0.66	0.01	142	0.30	3073
2001	64%	42%	52%	0.58	-0.00	216	0.33	2993
2002	65%	43%	58%	0.66	0.02	180	0.42	3007
2003	65%	43%	56%	0.47	0.02	335	0.38	2893
2004	64%	41%	55%	0.44	0.02	410	0.39	2803
2005	62%	42%	53%	0.47	0.02	424	0.40	2708
2006	62%	40%	54%	0.46	0.01	487	0.40	2703
2007	65%	41%	57%	0.54	0.00	425	0.41	2661
2008	65%	49%	59%	0.86	-0.03	270	0.59	2583
2009	66%	54%	61%	0.66	-0.00	367	0.55	2564
2010	65%	51%	61%	0.59	0.03	517	0.52	2451

Table II

CF-betas for CF factor

This table reports characteristics of cashflow beta sorted portfolios. The RET row shows average monthly returns for the year after portfolio formation. ADF presents the augmented Dickey-Fuller test for earnings innovations $N_{CF,t} = \frac{\Delta e_t}{B_{t-1}}$. ROCEbetaavg reports the average beta as observed by investors in real time. The row fullsamplebeta shows betas estimated over the full period with corresponding T-statistics.

index	1	2	3	4	5	6	7	8	9	10
RET	0.88	1.02	0.90	1.06	0.87	1.03	1.02	1.05	1.02	1.19
ADF	-8.64	-4.07	-4.66	-5.29	-2.04	-4.89	-5.10	-5.06	-5.59	-5.70
ROCEbetatvlast	0.60	0.35	0.93	0.46	1.28	1.75	0.70	1.68	1.55	2.32
ROCEbetaavg	0.41	0.17	0.49	0.62	0.86	1.32	1.15	1.78	1.72	2.20
fullsamplebeta	0.64	0.37	0.95	0.47	1.29	1.76	0.67	1.67	1.57	2.44
tstats	2.20	2.37	5.09	3.99	5.40	8.84	4.59	10.39	9.70	2.18

Table III

CF-betas for book-to-market sorted portfolios

This table reports characteristics of book-to-market sorted portfolios. The RET row shows average monthly returns for the year after portfolio formation. ADF presents the augmented Dickey-Fuller test for earnings innovations $N_{CF,t} = \frac{\Delta e_t}{B_{t-1}}$. ROCEbetaavg reports the average beta as observed by investors in real time. The row fullsamplebeta shows betas estimated over the full period with corresponding T-statistics.

index	1	2	3	4	5	6	7	8	9	10
RET	0.69	0.85	0.96	0.99	1.09	1.16	1.26	1.37	1.44	1.71
VWRET	0.70	0.89	0.77	0.86	0.98	0.95	0.94	1.18	1.27	1.43
ADF	-4.56	-6.60	-5.01	-5.88	-5.20	-3.89	-5.57	-4.61	-5.74	-5.78
ROCEbetatvlast	0.72	0.58	0.63	0.82	0.86	1.12	2.30	1.50	1.45	2.08
ROCEbetaavg	0.46	0.96	0.59	1.10	0.64	0.70	1.01	1.18	1.00	2.03
fullsamplebeta	0.83	0.60	0.70	0.84	0.93	1.21	2.46	1.56	1.56	2.20
tstats	4.39	3.47	5.09	5.32	6.43	8.58	7.22	11.62	7.70	2.31

Table IV

CF-betas for size-sorted portfolios

This table reports characteristics of size-sorted portfolios. The RET row shows average monthly returns for the year after portfolio formation. ADF presents the augmented Dickey-Fuller test for earnings innovations $N_{CF,t} = \frac{\Delta e_t}{B_{t-1}}$. ROCEbetaavg reports the average beta as observed by investors in real time. The row fullsamplebeta shows betas estimated over the full period with corresponding T-statistics.

index	1	2	3	4	5	6	7	8	9	10
RET	1.63	1.23	1.20	1.19	1.15	1.20	1.09	1.19	1.09	1.03
VWRET	1.35	1.26	1.24	1.21	1.15	1.16	1.06	0.96	0.91	0.80
ADF	-5.98	-5.78	-5.43	-5.59	-5.33	-4.74	-4.68	-4.99	-4.96	-5.07
ROCEbetatvlast	1.87	1.10	1.17	1.37	1.17	1.24	0.98	0.91	0.94	1.08
ROCEbetaavg	1.33	0.82	1.09	1.03	1.11	0.96	0.99	0.70	0.91	0.87
fullsamplebeta	1.95	1.22	1.21	1.40	1.19	1.31	1.02	0.97	0.98	1.14
tstats	1.55	4.25	6.09	5.16	6.83	7.80	8.78	10.34	12.42	18.37

Table V

CF-betas for long-term return-sorted portfolios

This table reports characteristics of long-term return sorted portfolios (three-year historical return). The RET row shows average monthly returns for the year after portfolio formation. ADF presents the augmented Dickey-Fuller test for earnings innovations $N_{CF,t} = \frac{\Delta e_t}{B_{t-1}}$. ROCEbetaavg reports the average beta as observed by investors in real time. The row fullsamplebeta shows betas estimated over the full period with corresponding T-statistics.

index	1	2	3	4	5	6	7	8	9	10
RET	1.81	1.31	1.22	1.15	1.13	1.15	1.06	1.03	0.95	0.90
VWRET	0.97	0.99	1.03	1.06	0.94	0.96	0.82	0.92	1.00	0.95
ADF	-6.10	-6.18	-4.60	-4.18	-3.99	-4.23	-5.62	-4.33	-5.49	-4.78
ROCEbetatvlast	1.63	2.85	0.66	1.67	1.06	0.77	0.90	0.73	1.04	1.44
ROCEbetaavg	1.21	1.27	0.59	0.94	1.16	0.83	0.96	0.90	1.08	1.42
fullsamplebeta	1.76	3.02	0.74	1.75	1.08	0.79	0.95	0.76	1.09	1.47
tstats	2.15	6.98	3.86	9.49	9.61	6.75	8.12	3.97	4.51	4.89

Table VI

Time-evolution of loadings

This table reports betas and Fama-French factor loadings for Cf-beta sorted portfolios for three years after portfolio formation

Lag	Factor	1	2	3	4	5	6	7	8	9	10	h-l
First Year	Mkt-RF	1.02	0.86	0.84	0.90	0.95	1.04	0.98	1.09	1.20	1.26	0.24
	SMB	-0.07	-0.25	-0.38	-0.35	-0.35	-0.15	-0.23	-0.10	0.05	0.32	0.38
	HML	0.01	0.23	0.22	0.24	0.19	0.41	0.25	0.23	0.20	0.14	0.13
Second Year	Mkt-RF	0.99	0.89	0.88	0.96	1.01	1.06	1.17	1.05	1.24	1.38	0.39
	SMB	-0.07	-0.31	-0.37	-0.33	-0.47	-0.12	-0.24	-0.11	0.08	0.29	0.37
	HML	0.01	0.27	0.31	0.27	0.07	0.53	0.40	0.13	0.20	0.17	0.16
Third Year	Mkt-RF	1.01	0.86	0.97	0.93	1.15	1.13	1.22	1.11	1.30	1.50	0.49
	SMB	-0.06	-0.30	-0.32	-0.41	-0.44	-0.17	-0.24	-0.08	0.03	0.25	0.32
	HML	0.05	0.30	0.38	0.26	0.20	0.51	0.36	0.18	0.19	0.25	0.20
Fourth Year	Mkt-RF	1.00	0.89	1.04	0.97	1.22	1.18	1.34	1.15	1.37	1.56	0.56
	SMB	-0.02	-0.34	-0.37	-0.38	-0.49	-0.22	-0.27	-0.04	-0.06	0.32	0.35
	HML	0.12	0.30	0.48	0.24	0.27	0.47	0.43	0.25	0.19	0.21	0.08

Table VII

Correlation of cashflow innovations with proxies for expected risk premium

This table reports correlations of the earnings innovations of book-to-market sorted portfolios with proxies of the expected risk-premium. DEF is the default spread, TERM is the term spread, DY the dividend yield and RFyield is the risk-free rate.

BMrank	DEF	TERM	DY	RF_yield
1	-0.00	0.01	0.00	-0.00
2	-0.00	-0.03	-0.00	-0.00
3	-0.00	-0.00	-0.00	-0.00
4	-0.00	-0.01	-0.00	-0.00
5	-0.00	-0.00	0.00	-0.00
6	-0.00	0.02	0.00	-0.00
7	-0.00	0.02	0.00	-0.00
8	0.00	-0.01	0.00	-0.00
9	-0.00	0.03	0.00	-0.00
10	0.01	0.29	0.00	-0.02

Table VIII

Correlation with economic fundamentals

This table reports on the correlation of cashflows of book-to-market sorted portfolios with macro variables. GDP represents changes in GDP, CPI changes in the inflation rate, and UNRATE change in the unemployment rate.

BMrank	GDP	CPI	UNRATE
1	-0.03	-0.19	-0.00
2	0.00	-0.09	-0.00
3	0.01	-0.16	-0.00
4	0.00	-0.07	-0.00
5	-0.01	-0.14	-0.00
6	0.01	-0.09	-0.00
7	-0.00	-0.11	-0.00
8	-0.01	-0.13	0.00
9	-0.03	-0.24	0.00
10	-0.05	-0.18	0.00

Table IX

Cross-sectional price of risk

This table reports estimates for the risk premium for the cashflow beta λ_1 from cross-sectional regressions using 20 size and book-to-market portfolios as test assets.

	λ_0	λ_1
Estimate	0.008	0.004
T-Stat	3.302	4.383

The Cross-Section of Currency Volatility

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June 13, 2013

ABSTRACT

This paper studies the cross-section of foreign exchange volatility returns. Statistically and economically significant returns are produced by a zero-cost trading strategy that is long (short) volatility swaps on currencies with high (low) historical volatility relative to implied volatility. The spread portfolio has a Sharpe ratio in excess of 1.7, results are robust to different market conditions and time periods, and it remains highly profitable after transaction costs. Standard risk adjustments do not significantly diminish profitability because the strategy is only weakly correlated with the equity market, the carry trade, and the Fama-French risk factors. Moreover, the historical-minus-implied volatility (HMI) factor also predicts excess-returns of the underlying currencies. Currencies that have high historical volatility relative to their implied volatility have much higher returns.

JEL classification: F31; F37;G10;G11.

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I. Introduction

Returns from volatility trading are determined by implied volatility and realized volatility. It is generally accepted that volatility varies considerably over time and tends to revert to a long run mean. Hence it is intuitive to ask if large deviations of implied volatility from long-run historical volatility are indicative of expected returns. In this paper I test if excess returns can be earned by trading volatility based on historical-minus-implied volatility (HMI).

Long-term mean reversion has been documented extensively across multiple asset classes including the foreign exchange (FX) market (see for example Jorda and Taylor (2012); Asness, Moskowitz, and Pedersen (2009)). While there has been some research into predictability of FX returns based on signals from the options market (see for example Malz (1997)), relatively little research exists on the predictability of option returns. A notable exception is della Corte, Sarno, and Tsiakas (2010) who study the forward bias in FX volatility. One of the first studies to focus on trading volatility directly (Goyal and Saretto (2009)) has found a strategy premised on long-term mean-reversion to be highly profitable in the equity options market.

The first goal of this paper is to verify if HMI predicts the cross-section of excess option returns. The FX market is ideally suited to this purpose since options on the most active currencies are more liquid than options on individual equities, and data from the over-the-counter (OTC) market is highly accurate and reliable.

In contrast to examining volatility returns through time, focusing on the cross-section of volatility returns allows me to control for various known anomalies in the FX market such as interest rate differentials, momentum, and reversion to purchasing power parity (Jorda and Taylor (2012); Menkhoff, Sarno, and Schmeling (2012)). In addition I use several risk factors from equity markets, including Fama and French (1992), as benchmarks to calculate risk-adjusted returns.

My second goal is to investigate if the HMI factor is also a priced risk factor in the cross-section of underlying currency returns. To this end I form portfolios based on HMI factor betas of currencies and find that it does not have a significant price of risk in the cross-section of FX returns in a standard linear asset pricing framework.

In stark contrast, ranking currencies on the HMI characteristic results in a significantly profitable strategy. This strategy has economically large and statistically significant risk-adjusted and

raw returns, and exhibits a negative correlation with the carry trade and several other risk factors, resulting in highly significant risk-adjusted returns.

I document that on average volatility swaps on currencies have negative expected returns, which is in line with previous studies on volatility and volatility risk premia (see for example, Coval and Shumway (2001), Bakshi, Kapadia, and Madan (2003), Hodrick, Xing, Ang, and Zhang (2006) Carr and Wu (2009) and Christoffersen, Heston, and Jacobs (2010)). However, an investor that sells volatility swaps is exposed to risks that are positively correlated with proxies of distress such as the Chicago Board Options Exchange Volatility Index, VIX, and faces highly negatively-skewed returns as is common with strategies that sell volatility. In contrast, the proposed factor is by construction approximately market-neutral. By engaging in a strategy exploiting cross-sectional differences in expected volatility returns, the investor holds both long and short positions, thus immunizing against direct volatility exposure.

In many ways this paper is related to the literature on "value" and long-term mean-reversion, which studies assets that have a low price relative to fundamentals. Extant literature documents a positive association between numerous proxies for value and subsequent returns (see for example Thaler and De Bondt (1984); Fama and French (1992)), and various studies have shown that value effects are not confined to the equity market, but are pervasive among asset classes (Asness et al. (2009)). There are varying views about attribution to risk or mispricing, both sides argue that assets that appear cheap should be expected to have higher returns (see e.g: Berk (1998)). Much literature about the fundamental equilibrium exchange rate is related to the broader topic of value and long-term mean reversion (see for example Jorda and Taylor (2012) for a recent treatment).

My analysis employs implied volatility data on the most liquidly traded currencies from OTC options provided by JP Morgan Chase. Jiang and Tian (2007) show that model-free implied volatility exactly equals the no-arbitrage price of a volatility swap and also suggest a straightforward methodology of deriving it from a cross-section of implied volatilities. I compute the model-free implied volatility from a range of strike prices as in Jiang and Tian (2005) and Carr and Wu (2009) and use this as the strike price of a volatility swap. A volatility swap can be synthesized from plain vanilla put and call options. By using the synthetic volatility swap rate instead of at-the-money implied volatility, it is possible to compute payoffs as the difference between realized and implied volatility. This is because the return of the volatility swap only depends on realizations of volatility

after entering the contract: changes in implied volatility affect the daily mark-to-market, however at expiration realized volatility is the sole variable determining the return. Hence, volatility swaps make it possible to engage in volatility speculation while eliminating exposure to other factors.

The results provide strong evidence that HMI predicts the cross-section of FX volatility swap payoffs. Returns cannot be explained by standard risk models like the Fama and French (1992) three factor model, the international capital asset pricing model (CAPM), a momentum factor, or a short-term mean reversion factor. Since volatility and option returns are highly non-linear, the common approach to adjust returns with a linear factor model might be inappropriate. Therefore, I examine returns to the strategy conditional on different market states by sorting equity market returns and carry trade returns into quartiles and analyze how returns to the strategy vary across these different environments. While it is beyond the scope of this study to determine whether returns to the strategy are compatible with the efficient market hypothesis, evidence suggests that it cannot be fully explained by standard risk factors.

Further, I verify if HMI has explanatory power in the cross-section of underlying currency returns. If the HMI factor were a systemic risk factor, arbitrage pricing theory would suggest that the factor may also be priced in the cross-section of FX spot returns: currencies with different sensitivities to factor returns should also have different expected returns. Since average factor returns are positive, currencies with a high loading on the factor should also have higher returns. Empirically, currencies that load highly on the factor do not perform significantly better than currencies with a low loading. In contrast, the HMI characteristic predicts returns of underlying currencies. A market neutral FX spot strategy sorted on HMI has an attractive Sharpe ratio of 0.58 in the sample and exhibits significantly negative correlation with the carry trade. These finding are provocative because they run counter to evidence from recent empirical studies (Bollerslev (2007); Bollerslev, Tauchen, and Zhou (2009)) regarding the relationship between future equity index returns and volatility risk premia. In the FX market, expected returns are higher for currencies that have high historical-minus-implied volatility.

Finally, I analyze the robustness of results with respect to different transaction cost assumptions. Since bid-ask spreads for OTC volatility swaps are not available, I use typical bid-ask spreads for the options used to synthesize the swap. Following Goyal and Saretto (2009), I consider transaction costs in the range of 50 percent to 100 percent of the quoted spread.

II. Model-Free Implied Volatility and Volatility Risk Premia

In this section I examine the patterns in realized and implied volatility. For most currencies, implied volatility (as described below in section II.A) is higher than realized volatility during the sample period. However, in agreement with Mueller, Stathopoulos, and Vedolin (2012), I find that the volatility risk premium varies significantly over time and is slightly negative for the Australian Dollar (AUD) and the Canadian Dollar (CAD) during the sample. Since a large part of this period is characterized by the financial crisis, it is possible that the volatility risk premium is lower than expected because of large losses during the sample period. Empirically, Sharpe ratios for a short volatility position are much higher in the earlier part of the sample before 2007.

It is also noteworthy that model-free implied volatilities are higher than at-the-money (ATM) implied volatilities for all currency pairs, which is consistent with stylized facts on a positive volatility smile. For instance, the Japanese Yen (JPY), a "safe haven" currency, has on average an ATM volatility that is almost 100 basis points lower than the model-free volatility. In contrast, the Australian Dollar ATM implied volatility is only about 30 basis points lower than the corresponding model-free implied volatility of the same duration.

[Place Table II about here]

Table II presents mean values grouped by currency in Panel A and summary statistics for key metrics in Panel B.

Table V shows that implied volatility is highly correlated amongst currencies. Furthermore, implied volatilities for currencies are highly correlated with the VIX. I derive an FX implied volatility index in order to have a benchmark for systematic volatility innovations. I also construct the index FXVIX by taking the cross-sectional average of all implied volatility innovations of the sample currencies. I use the one-month maturity for FXVIX since it is the targeted average maturity of the VIX. The maturity of OTC options being constant, it is straightforward to compute the cross-sectional averages in implied volatility.

[Place Figure A about here]

Figure A shows both the VIX and the FX counterpart.

A. *Variance and Volatility Swaps*

A variance swap is a forward contract on realized variance; a volatility swap is a forward contract on realized volatility. Contrary to option straddles these instruments provide exposure to volatility alone and are not affected by the assumptions underlying the Black-Scholes model.

The payoff of a currency variance swap at expiration is equal to

$$[RV_{t,T} - SW_{t,T}]L \tag{1}$$

where RV is the realized annualized variance between time t and T; SW denotes the fixed variance swap rate that is determined at time t and is paid at time T and L denotes the notional dollar amount. Therefore, no arbitrage dictates that the variance swap rate be equal to the risk-neutral expected value of realized variance:

$$SW_{t,T} = \mathbb{E}^{\mathbb{Q}}[\mathrm{RV_{t,T}}] \tag{2}$$

where $\mathbb{E}[\bullet]$ denotes the time t conditional expectation operator under some risk-neutral measure. Given that the replicating portfolio contains options of all strikes at the correct weights, the portfolio will exactly capture realized variance.

The swap rate or "strike price" is usually set to ensure the variance swap has zero value at entry. The "strike" price of a variance swap is directly related to the concept of model-free variance and volatility. Britten Jones and Neuberger (2002) derive a model-free implied variance fully specified by a set of traded options. In an important extension, Jiang and Tian (2005) show that when calculating the model-free variance from a limited set of strikes, the approximation error is small and the relationship remains valid when the underlying asset exhibits jumps. Jiang and Tian (2009) show that the strike price $SW_{t,T}$ of a variance swap is equal to the model-free implied variance of Britten Jones and Neuberger (2002). Following Britten Jones and Neuberger (2002) and Demeterfi, Derman, Kamal, and Zou (1999), I calculate the model-free implied variance thusly:

$$E_t^{\mathbb{Q}}(\int_t^T \sigma_u^2 du) = 2re^{rt}(\int_0^{S_t} \frac{1}{K^2} P(K,T)\, dK + \int_{S_t}^{\infty} \frac{1}{K^2} C(K,T)\, dK) \tag{3}$$

where S_t is the underlying exchange rate and $P(K,T)$ and $C(K,T)$ are the put and call prices with

maturity T and strike K.

Throughout this paper I work with implied volatility rather than variances, as it is the more commonly used metric. As shown by Carr and Wu (2002), a volatility swap can be replicated by a log contract which in turn can be replicated by a static portfolio of vanilla options and a position in a forward contract.[1]

In reality, options are only available at discrete strike prices and only for an interval around the underlying spot price. Therefore, errors arise due to the discretization of strike prices, thus assumptions must be made about implied volatility for strikes beyond the available interval. Following Jiang and Tian (2005), I interpolate implied volatility between the available strike prices by fitting a cubic spline, and set implied volatility less than 10 delta and more than 90 delta equal to the implied volatility for these options. Conventions for OTC FX options greatly facilitate computation of model-free implied volatility since quoting by sticky delta already contains all relevant information regarding moneyness. In agreement with Mueller et al. (2012), I find that potential errors for FX options are extremely small under reasonable assumptions.

Metrics and Factor Construction

I calculate the metrics with the model-free implied volatility of section II.A and historical volatility measured over various durations ranging from 60 days to 400 days:

$$HMI = log(RV_{t-L,t}) - log(IV_t) \tag{4}$$

At month t I compute HMI with RV_L measured over an L day period from $t-L$ to t and construct equal-weighted FX volatility portfolios with duration of n months and hold the portfolio for N months. I focus on one-month duration and holding periods, but also examine different parameter values for robustness in a later section. For a holding period of one month, I keep the portfolio to expiry in order to minimize transaction costs. In addition, I implement a more robust version by combining returns from all parameter values for L from 60 days to 400 days. Averaging returns of all strategies for all parameters L, rather than averaging parameters and trading with the average parameter, benefits from diversification without sacrificing robustness.

In the main analysis I use non-overlapping monthly returns, since overlapping daily trading

strategies require special assumptions when marking-to-market the portfolios. Results tend to be stronger using overlapping daily returns which I present in complimentary analysis. HMI portfolios are constructed by sorting into three equal-weighted portfolios each month. The spread portfolio, which is the main focus of my subsequent analysis, is constructed by taking the difference between the top tertile and the bottom tertile.

Underlying Portfolios

Analogous to the volatility returns, I form portfolios of the underlying currency pairs by ranking on HMI with RV_L measured over a L day period from $t-L$ to t, and holding for n months from t to $t+n$. In addition to equal-weighted portfolios, I also consider equal volatility weighting portfolios since they are commonly used in the asset management industry (see for example: Asness, Frazzini, and Pedersen (2012)).

III. Data Description

Currency Options

The data used in this paper are over the counter traded FX options from JP Morgan Chase for the most liquid currency pairs with the US Dollar: The Australian Dollar (AUD), the Canadian Dollar (CAD) the Euro (EUR), the Swiss Franc (CHF), the Danish Krone (DKK), the British Pound (GBP), the Japanese Yen (JPY), and the Norwegian Krone (NOK). The data frequency is daily and the sample covers from January 1996 through October 2010. Over-the-counter options have several attributes that make them preferable to exchange traded FX options. The OTC options market is many times more liquid than the FX options traded on the Chicago Mercantile Exchange (CME), which is the most liquid exchange for FX options. As a result, transaction costs due to bid-ask spread and market impact are much lower and prices are more accurate. Specifically, the quotes are firm for at least 10 million USD. In contrast to exchange-traded options, the data provide a time-series of options of constant maturity. For example, daily implied volatilities are available for one month options. In contrast, the maturity of exchange traded options declines every day. Also, these options trade in terms of implied volatility at sticky deltas, which is very convenient. As is industry standard the implied volatility quotes are available at five deltas: 10

delta call, 25 delta call, at the money forward (ATM), 25 delta put and 10 delta put. Maturities of the data set range from 1 month to 60 months.

FX Spot Data

All spot FX data is for cross rates with the US Dollar: AUD, CAD, EUR, CHF, DKK, GBP, JPY, and NOK. All data on exchange rates comes from the FRED database provided by the St. Louis Federal Reserve Bank. The data are New York noon buying rates.

For complementary analysis I use estimates of realized volatility based on high-frequency returns provided by the Oxford-Man Institute of Quantitative Finance. The data is available for the following currencies: CHF, EUR, GBP and JPY.

[Place Figure 1 about here]

Equity Index, Government Bond, Commodity and Volatility Data

I construct liquid international benchmarks for several asset classes from futures which would have been tradable in large size. My aim is to provide additional perspective to typical benchmarks that often are not directly tradable or are very illiquid, such as the CRSP market factor .

My benchmark for *international equity* risk is the equal-weighted average of the most liquid equity index futures returns: DAX, CAC40, Dow Jones, HangSeng, Nikkei, S&P500, NASDAQ, Russell, SPI200, TSX60, KOSPI, IBEX35, EUROSTOXX 50, and the FTSE100.

Similarly, I create an excess *long-term bond* benchmark composed of the most liquid government bond futures with 10-year maturity or more. Included as they become available, are futures for the Bund, Japanese Government Bond, Long Gilt, US Treasury 10-Year, US Treasury 30-Year, Canadian Government Bond, and Australian Government Bond. A *short-term bond* benchmark is constructed from futures for the US Treasury 2-Year, US Treasury 5-Year, Australian 3 Year, Korean T-Bond, Schatz, and Bobl . A *short-term interest rate* benchmark is constructed of the following futures: Canadian Banker's Acceptance, Eurodollar, Euribor, Euroyen, Short Sterling, Euroswiss, and Australian Babl.

I provide contracts used for a *commodity benchmark* with all contracts specified in Appendix A. The data are derived from Commodity Systems Inc., a provider of reliable daily futures data. I

appropriately adjust for the roll yield, ensuring that excess returns incorporate both dividends and financing costs.[2] The benchmarks would have been tradable in large size and in real time.

I use the VIX index as a benchmark for implied volatility in equity markets. For robustness, I use the old VIX which is available for the entire sample period as well as the new VIX which is available from January 2004. Also I construct an FX volatility index.

Macroeconomic and Liquidity Data

As a liquidity proxy I use the TED spread (Libor minus the three month t-bill rate) for major economies provided by the FRED database from St. Louis Federal Reserve.

Data for Fama and French equity risk factors HML and SMB as well as a short-term reversal factor and a momentum factor are provided by Ken French on his website.

IV. Empirical Analysis

In this section I analyze the volatility returns and characteristics of FX volatility swap portfolios sorted on the HMI metric from Equation (4) and analyze the relationship to an aggregate variance risk premium. For most currencies implied volatility is higher than realized volatility.

[Place Figure 2 about here]

A. Return Correlations

Table V presents pairwise correlations between payoffs to long positions in variance swaps ($RV - IV$) for individual currencies in Panel A and correlation of IV in Panel B. As would be expected, implied volatility is highly correlated across currency pairs. Remarkably, differences between ex-ante implied and realized volatility exhibit relatively low correlations. In particular, volatility returns for typical funding currencies of the carry trade, such as the Swiss Franc and the Japanese Yen, are negatively correlated with the Australian Dollar and the Mexican Peso.

[Place Table V about here]

V. The Cross-section of Option Returns

A. Sharpe Ratios

To determine if HMI predicts the cross-section of volatility returns I analyze returns of HMI-sorted portfolios (tertiles). Specifically, I construct an HMI factor which is the average volatility return of the top tertile minus the bottom tertile. Illustrating the magnitude of the risk-adjusted returns, Table VI presents Sharpe ratios of the HMI factor constructed with a variety of parameter choices L for the estimation period of historical standard deviation. Sharpe ratios are very high in comparison to known anomalies trading the underlying FX rates such as the carry trade (Pojarliev, Cesare, Jorda, and Taylor (2010)) and the momentum effect (Menkhoff et al. (2012)) which typically have Sharpe ratios below or close to one.

To focus on specific choices of the measurement period L (of historical volatility) would introduce subtle look-ahead bias since it is not clear if investors could have selected these parameters ex-ante. I therefore focus on a more robust strategy presented in Panel B of Table VI. This strategy consists of an equal-weighted portfolio of HMI strategies formed with the look-back parameter L selected over the interval $[30, 400]$ in steps of ten, which should include most reasonable parameter choices. This alleviates concerns that results are driven by parameter choices that could not have been made ex-ante.

[Place Table VI about here]

Table VI shows that the HMI strategy is profitable for all parameters of the look-back period L with historical volatility being estimated from the last 30 to 400 trading days. Most individual Sharpe ratios are greater than one, and the maximum Sharpe ratio (2.35) occurs when volatility is computed over the last 60 observations. Of course it would not be representative to focus only on the most profitable parameters as these would unduly bias the results. However, the combined strategy (Sharpe=1.77) that averages the returns of all individual sub-strategies is high, which is remarkable given that this aggregate strategy is robust by construction and largely circumvents in-sample over-fitting concerns. Partly, the combined strategy has a higher Sharpe ratio than the average Sharpe ratio of the sub strategies because they are less than perfectly correlated. Moreover, confining the sample size to the most liquid markets ensures that the strategy could be traded in

considerable size while buffering from market impact.

Overall, risk-adjusted results are comparable in magnitude to the findings of Goyal and Saretto (2009) for equity options and della Corte, Sarno, and Tsiakas (2011) for forward volatility agreements. Due to the fact that my sample is limited to maximum 13 currencies at any time, my profits per market are higher than that of Goyal and Saretto (2009) because their strategy trades thousands of optionable equities. Therefore, my results corroborate their findings since there is much less concern about liquidity and short-selling constraints in the FX market.

Cross-Sectional Regressions

In order to separate returns attributable to the HMI factor from returns due to common risk factors in FX, as presented in Table VII I employ Fama and MacBeth (1973) type cross-sectional regressions of volatility swap returns on (i) lagged measures of the HMI metric, (ii) lagged forward discounts, (iii) lagged currency excess returns over the last 150 days, (iv) lagged currency excess returns over the last 500 days, and (v) model-free implied volatility to account for carry, momentum long-term mean-reversion, and implied volatility respectively. Controlling for implied volatility is particularly important to ensure that results for HMI are not driven by implicitly sorting on implied volatility. Table VII shows that HMI is by far the strongest predictor of excess volatility returns.

$$rvol_t^i = \alpha_t + \beta_{HMI,t} HMI_{t-L,t-1}^i + \beta_{FD,t}(f_{t-1}^i - S_{t-1}^i) + \beta_{MOM,t} MOM_{t-150d,t-1}^i + \beta_{IV,t} IV_{t-1}^i \epsilon_t \quad (5)$$

Equation (5) results in a time-series of cross-sectional slopes. Table VII reports the averages and T-statistics based on Newey and West (1987) standard errors. Specification (I) shows results using only the HMI factor, and the T-statistic is highly significant. The intercept is significantly negative, which is consistent with a negative volatility risk premium. Specification (II) makes it clear that the carry factor cannot account for returns. Interestingly, specification (IV) shows that the slope of implied volatility is positive, albeit not significant. This suggests that implied volatility cannot explain the cross-section of volatility returns.

Risk-Adjusted Returns

I perform regressions on the spread portfolio, as well as the long and the short legs, with several specifications of a linear pricing model, where the risk factors F_t are: the Fama and French (1992) risk factors; the Carhart (1997) momentum factor; an investable international stock market factor constructed from liquid futures; the Chicago Board Options Exchange Volatility Index, VIX; a carry factor implemented for the sample currencies; and the liquid asset class benchmarks from section III. All factors are excess returns, and the intercept can therefore be interpreted as mispricing relative to the model.

$$R_{P,t} = \alpha_t + \beta_p^{'} F_t + \epsilon_{p,t} \tag{6}$$

Table IX reports parameter estimates for the model in Equation (6). Specification (I) regresses HMI returns on a market-neutral carry factor. The relationship is insignificant and the alpha remains highly significant. Specification (II) uses the Fama and French (1992) risk factors. In this specification only HML is significantly related to HMI even though it loads negatively on HML and the T-statistic of the alpha increases slightly. Specification (III) adds the Carhart (1997) momentum factor, however results are not materially affected and the T-statistic for alpha remains highly significant. Specification (V) uses the tradable asset class benchmarks, and here a few interesting relationships emerge. HMI appears not to be significantly related to commodity returns or equity index returns. However, the HMI portfolio loads positively on short-term interest rates and long-term bonds while loading negatively on short-term bonds.

[Place Table IX about here]

B. Is it Exposure to Aggregate Volatility Risk?

A possible explanation for HMI returns would be exposure to aggregate volatility risk. Even though the construction of the factor approximately immunizes it to direct exposure by offsetting short volatility positions with long positions, it is still possible that returns are negatively correlated with aggregate volatility risk which would explain the profitability of the factor. In order to control for this, I construct an equal-weighted aggregate volatility return index. For each month I calculate

the return to a long position in volatility swaps scaled by the historical 100-day volatility (the same approach to sizing positions is used for the HMI factor) for each of the sample currencies. Then, to create the index, I calculate the equal-weighted cross-sectional average of the volatility returns.

[Place Table X about here]

Table X reports summary statistics for aggregate volatility returns. As expected overall returns are negative (Sharpe=-1.17), however the strategy is very positively skewed and has high kurtosis. While the portfolio has a low average return of -8 percent per month, the maximum monthly return of 148 percent makes it clear that being short volatility is a risky proposition.

[Place Table XI about here]

Table XI reports alphas and betas of HMI returns with respect to the FX volatility benchmark. With some exceptions most sub-strategies load negatively on the FXVOL factor. However, alphas remain significant for almost all parameter choices and the T-statistic of the combined strategy remains high (4.21). While exposure to aggregate volatility risk explains some of the HMI returns, they are not eliminated.

VI. Robustness Checks

A. Sub-Sample Analysis

Table XII presents an investigation of robustness of HMI volatility returns in different economic regimes. Specifically, I divide the sample into NBER recessions and expansions, and low and high volatility regimes. Profitability of the strategy does appear to be related to the business cycle since Sharpe ratios are much lower during recessions than expansions. In line with this observation, HMI also has higher Sharpe ratios when the TED spread is low. Surprisingly, the strategy performs better when the FXVIX is high.

[Place Table XII about here]

Despite the relationship with business cycle variables, returns are positive during all sub-samples, and Sharpe ratios remain attractive even during recessions and liquidity constrained environments.

B. Transaction Costs

Table XIII reports the impact of transaction costs on the profitability of the HMI strategy. The typical bid-ask spread of a volatility swap on a liquid G10 currency pair such as EUR-USD is about 0.5 percent. It is well known that the quoted spread is larger than the effective spread. Quoted prices have not yet attracted trades and it is possible to achieve price improvement by posting a limit order inside the spread (see for example De Fontnouvelle, Fishe, and Harris (2003), Mayhew (2002)). Following Goyal and Saretto (2009) I analyze the impact of trading at various percentages of the quoted spread ranging from 50 percent to 100 percent.

[Place Table XIII about here]

Although transaction costs can have a significant impact, the strategy remains solidly profitable with a Sharpe ratio just below one, even when trading at the quoted spread. When assuming an effective spread of 75 percent of the quoted spread the Sharpe ratio is solidly above one (1.19).

Is HMI a Priced Risk Factor in the Cross-Section of Currency Returns?

In order to determine if HMI is a priced risk factor in the cross-section of currency returns, it is necessary to estimate the cross-sectional price of risk. In a first step I estimate rolling betas for each currency on HMI returns over the last 260 trading days (approximately one calendar year) to pick-up potential time-variation while providing enough data points to estimate betas reliably. In a second step, I perform cross-sectional Fama and MacBeth (1973) regressions to estimate the risk-premium.

[Place Table VIII about here]

Table VIII shows that the risk premium is insignificant and slightly negative, suggesting that HMI is not priced in the cross-section of currency returns. While it is possible that betas could not be estimated reliably because of the non-linearity of HMI returns, previous empirical research (see for example Hodrick et al. (2006)) has successfully estimated volatility-related risk factors in this way.

VII. Does the HMI Characteristic Predict Exchange Rate Returns?

Research on the relationship between volatility variables and returns of underlying markets has been very active and several studies have found a significant link. For instance Bollerslev et al. (2009) find a significant positive relationship between a factor closely related to HMI and subsequent equity index returns. Table XIV reports statistics for zero investment portfolios of currencies based on HMI sorted tertiles. The zero investment portfolio is computed by averaging returns for the top tertile minus the bottom tertile. Following the methodology of the volatility trading strategy in section V.A, I examine the evidence over a wide range of parameters for the estimation window L, over which historical volatility is measured. Returns are positive for almost all parameter choices and the highest Sharpe ratios occur when historical volatility is estimated over the last year. Again, I focus on an implementation that is the average of all the sub-strategies in order to minimize data snooping bias.

[Place Table XIV about here]

Interestingly, the strategy is negatively correlated with the carry trade. Figure 3 shows cumulative returns of underlying currencies ranked on HMI as well as cumulative returns to the carry trade. Returns are comparable in raw returns and Sharpe ratio.

[Place Figure 3 about here]

Table XVI reports results for adjusting returns in a linear asset pricing framework.

[Place Table XVI about here]

Table XVI reports parameter estimates and T-statistics for regressing various risk factors on underlying FX spot portfolios formed on HMI. As expected, HMI loads negatively on the carry factor. Specification (II) adjusts for the Fama and French (1992) factors. Alphas are not materially affected, and specification (III) shows that the factor also loads negatively on momentum. Specification (IV) shows that HMI loads negatively on a short-term reversal factor, which is often interpreted as a liquidity variable. In this setting, the T-statistic of the alpha increases to 2.95,

confirming that the returns cannot be explained away by common risk factors. Specification (V) uses the tradable asset class benchmarks as risk factors. The HMI spot portfolio does not load significantly on any of these factors, however, alphas are reduced and the T-statistic decreases to 1.9.

VIII. Conclusion

Previous empirical studies suggest that assets that appear underpriced compared to proxies of value tend to have high expected returns in several asset classes. Since returns to volatility speculation depend on implied and realized volatility, I investigate if historical-minus-implied volatility is indicative of expected returns. To test this conjecture I form portfolios on HMI and then measure the return of the spread portfolio to isolate returns from the aggregate volatility risk premium. I find that the spread portfolio is highly profitable and returns approximately ten percent per month. Further, risk-adjusted returns are also high, the Sharpe ratio in the sample period is 1.77, and covariance risk with standard risk factors does not explain the returns to the strategy. Returns remain positive during NBER recessions and expansions and equity bull and bear markets and returns are robust to realistic estimates of transaction costs.

My results complement the analysis of Goyal and Saretto (2009) who find similar results for equity options. Since OTC FX options are much more liquid than equity options, this paper adds credence to an exploitable value factor in the cross section of volatility.

I also examine whether the HMI predicts underlying currency returns. Indeed, currencies that have high historical-minus-implied volatility have high returns over the next month. Returns to a zero investments portfolio of currencies ranked on HMI are comparable in magnitude to the carry trade and cannot be explained by exposure to a forward discount factor, FX momentum, or the Fama and French (1992) risk factors. I find that the factor is independent of previously studied anomalies in the FX market.

Appendix A. Appendix

Table I
Futures Specifications

NAME	EXCHANGE	CONTRACT SIZE	CURRENCY	START DATE	TICK SIZE
Soybean Oil	CBT	60000 lb	USD	19500717	0.010000
Corn	CBT	5000 bu	USD	19470102	0.250000
Crude-Brent–IPE	ICE	1000 bbl	USD	19880623	0.010000
Crude Oil-Light	NYMEX	1000 bbl	USD	19830330	0.010000
Gold	COMEX	100 toz	USD	19750102	0.100000
CopperHG	COMEX	25000 lb	USD	19660103	0.050000
Heating Oil No2	NYMEX	42000 gal	USD	19781115	0.000100
Cattle-Live	CME	40000 lb	USD	19641130	0.025000
Gas Oil-IPE	ICE	100 tonnes	USD	19810406	0.050000
Hogs-Lean	CME	40000 lb	USD	19660228	0.025000
Natural Gas-Henry Hub	NYMEX	10000 mmBtu	USD	19900403	0.001000
Gasoline-Reformulated Blendstock	NYMEX	42000 gal	USD	19841203	0.000100
Soybeans	CBT	5000 bu	USD	19471231	0.250000
Silver	COMEX	5000 toz	USD	19630612	0.100000
Soybean Meal	CBT	100 short tons	USD	19510829	0.100000
Wheat	CBT	5000 bu	USD	19220103	0.250000
RapeseedCanola	WCE	20 tonnes	CAD	19691231	0.100000
CAC 40 Index-MATIF	EURONEXT	10 EUR x Index	EUR	19880818	0.500000
FTSE 100 Index LIFFE	EURONEXT	10 GBP x Index	GBP	19840402	0.500000
S&P Canada 60	ME	200 CAD x Index	CAD	19981231	0.050000
S&P 500 Index-E-mini	CME	50 USD x Index	USD	19500103	0.250000
SPI 200 Index	SFE	25 AUD x Index	AUD	19830216	1.000000
Nasdaq 100 Index-E-mini	CME	20 USD x Index	USD	19851001	0.250000
Dax Index	EUREX	25 EUR x Index	EUR	19901123	0.500000
Hang Seng Index–HKFE	HKEX	50 HKD x Index	HKD	19860506	1.000000
Nikkei 225 Index-	OSE	1000 JPY x Index	JPY	19880903	1.000000
KOSPI 200 Index	KSE	500000 KRW x Index	KRW	19980120	0.050000
IBEX 35 Index	MEFF	10 EUR x Index	EUR	19920420	0.500000
Dow Jones Euro Stoxx 50 Index	EUREX	10 EUR x Index	EUR	19980622	0.100000
TOPIX Index sessions	TSE	10000 JPY x Index	JPY	19900403	0.500000
MIB FTSE Index S&P-June09	MIF	5 EUR x Index	EUR	19930319	1.000000
DJIA Mini USD5 Index	CBT	5 USD x Index	USD	19920102	1.000000
Swiss Market Index	EUREX	10 CHF x Index	CHF	19901109	0.100000
Australian Govt Bond 6%3Yr	SFE	100000 AUD	AUD	19880517	0.005000
Australian Govt Bond 6%10Yr	SFE	100000 AUD	AUD	19841205	0.005000
Canada 10 Yr Govt Bond	ME	100000 CAD	CAD	19890915	0.010000
Euro German Bobl	EUREX	100000 EUR	EUR	19911004	0.005000
Euro German Bund	EUREX	100000 EUR	EUR	19901123	0.010000
Euro German Schatz	EUREX	100000 EUR	EUR	19970307	0.001000
Japanese 10yr Govt Bond-Floor Only	TSE	100000000 JPY	JPY	19900404	0.010000
Korean T-Bond3 Yr	KOFEX	100000000 KRW	KRW	19990929	0.010000
Gilt-Long8.75-13yr LIFFE	EURONEXT	100000 GBP	GBP	19821118	0.010000
T-Note-US 2 Yr -CBT	CME	200000 USD	USD	19900622	0.007812
T-Note-U.S. 5 Yr	CBT	100000 USD	USD	19880520	0.007812
T-Note-US 10 Yr w/Prj A-CBT	CME	100000 USD	USD	19820503	0.015625
T-Bond-US	CBT	100000 USD	USD	19770822	0.015625
Canadian Bankers' Acceptance-3Mth-24 hr	ME	1000000 CAD	CAD	19880422	0.005000
Eurodollar-3 Mth-Globex	CME	1000000 USD	USD	19811209	0.002500
EURIBOR-3 Mth LIFFE	EURONEXT	1000000 EUR	EUR	19890420	0.005000
Euroyen-3Mth-EveningFloor -TIFFE	TFX	100000000 JPY	JPY	19890630	0.005000
Sterling Rate-3Mth LIFFE	EURONEXT	500000 GBP	GBP	19821104	0.005000
Fed Fund Rate1Mth-CBT	CME	5000000 USD	USD	19881003	0.002500
Euro Swiss Franc LIFFE	EURONEXT	1000000 CHF	CHF	19910207	0.005000
Australian Bank Bills90 Day	SFE	1000000 AUD	AUD	19900111	0.010000

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Notes

[1]Jensen's inequality causes convexity bias, however it is empirically negligible for the analysis carried out

[2]futures returns are excess returns where the risk-free rate is the repo rate

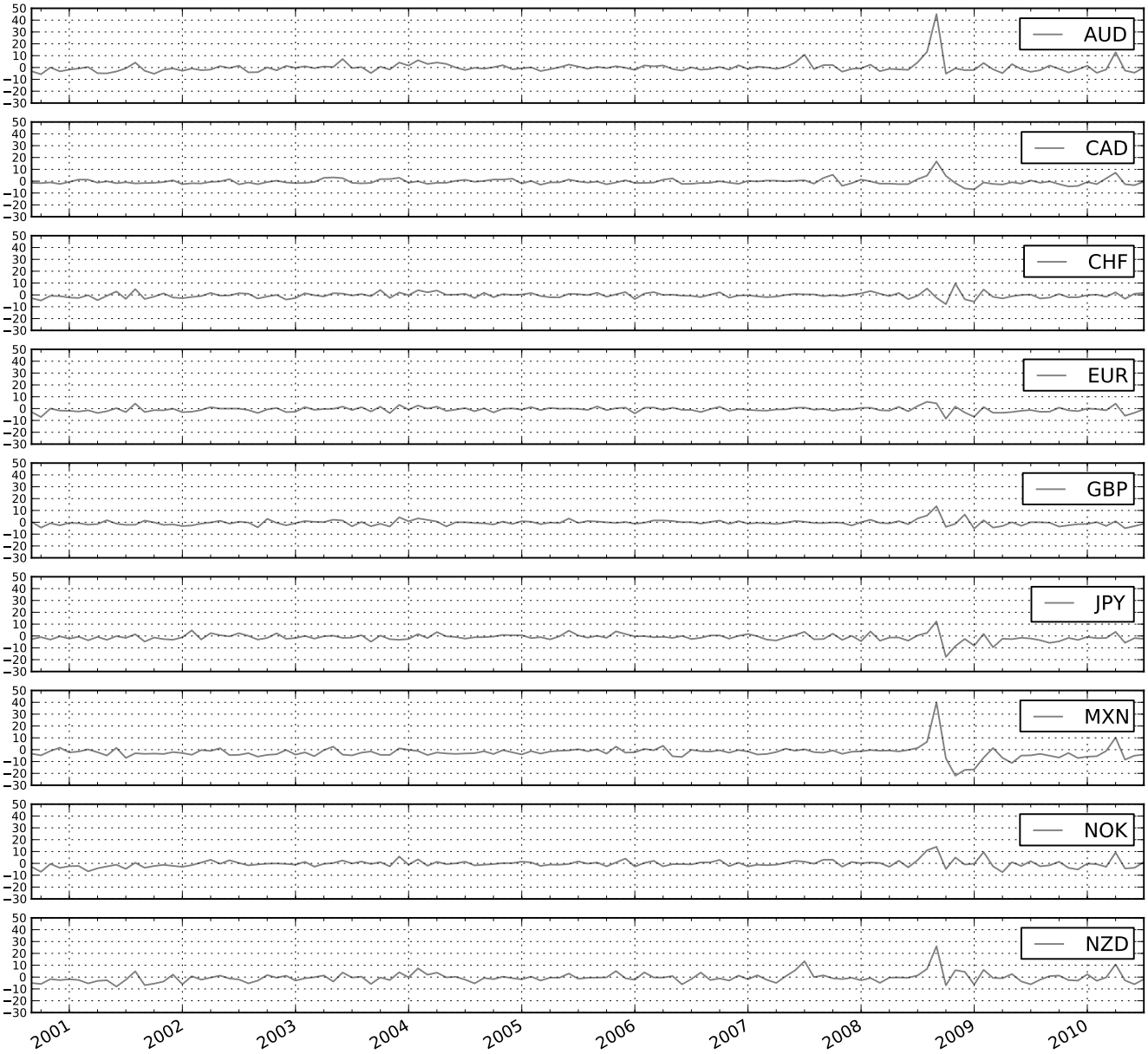

Figure 1. RV-IV This figure plots the monthly difference between realized and implied volatility.

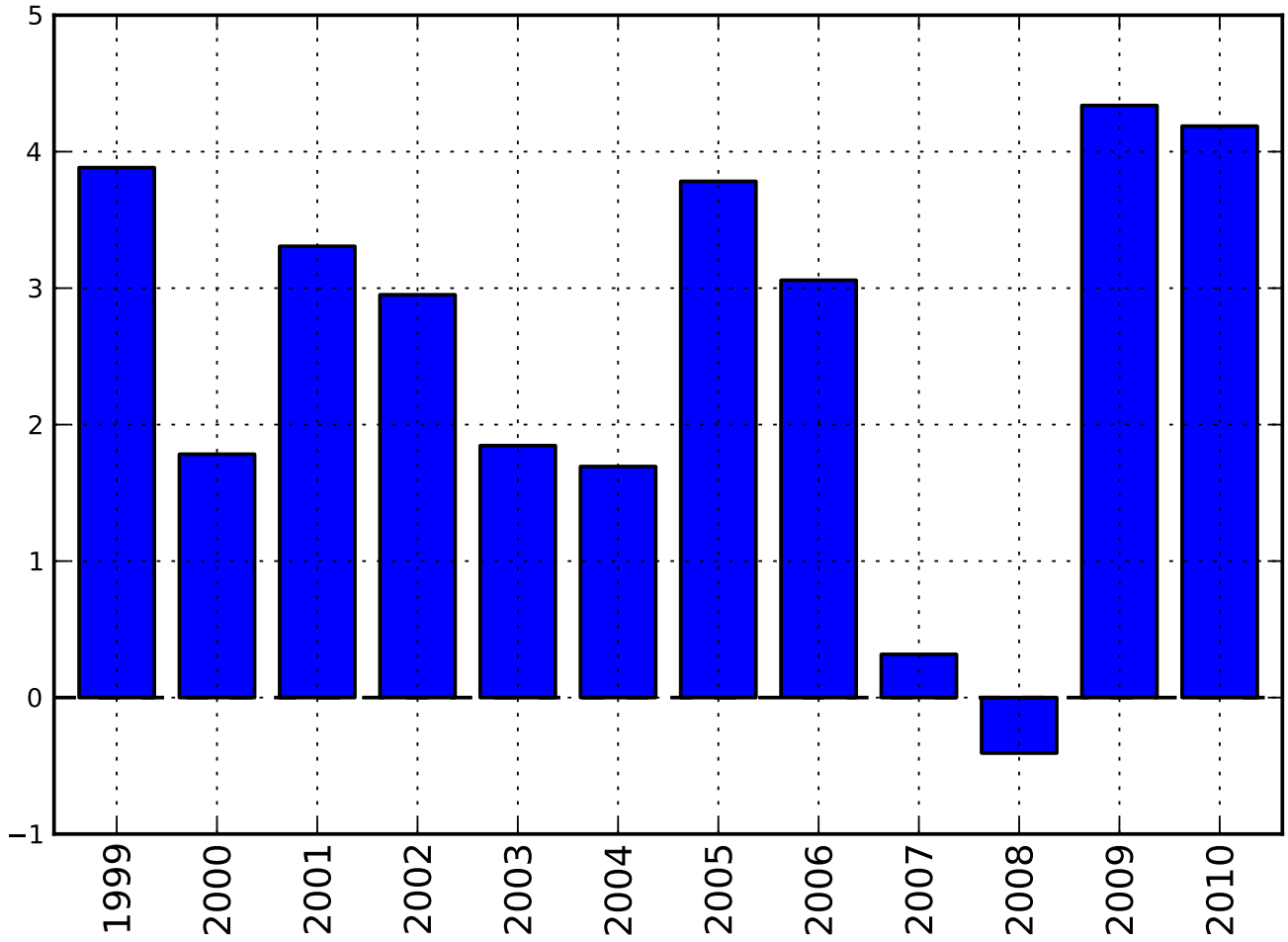

Figure 2. Annualized Sharpe ratios by Year This figure plots the Annualized Sharpe ratio realized by the HML factor before transaction costs for each calendar year of the sample period.

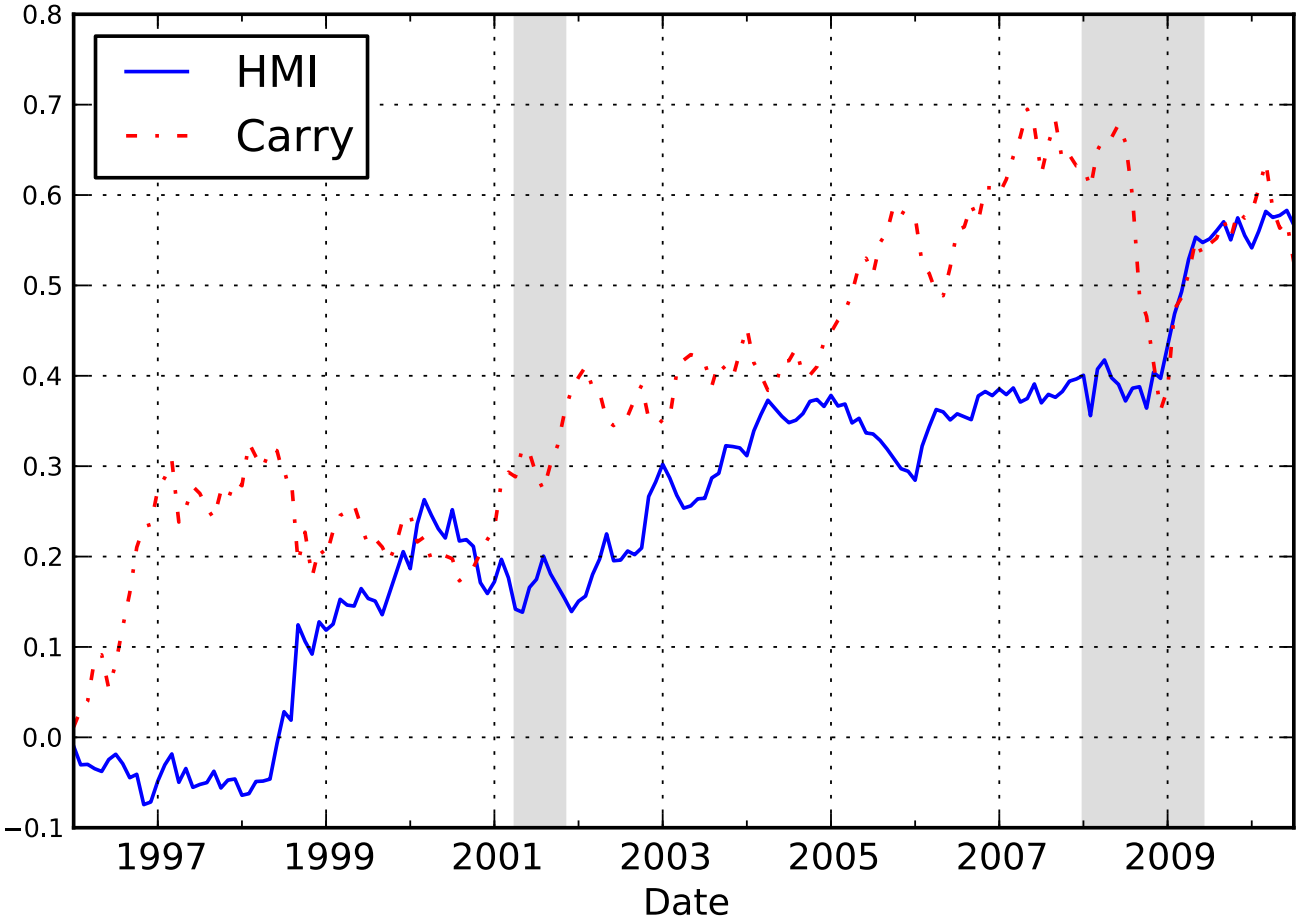

Figure 3. HMI Spot Currency Returns and the Carry Trade This figure plots the cumulative performance of the Carry Trade and a long/short Strategy based on the HMI factor. Shaded areas are NBER recessions.

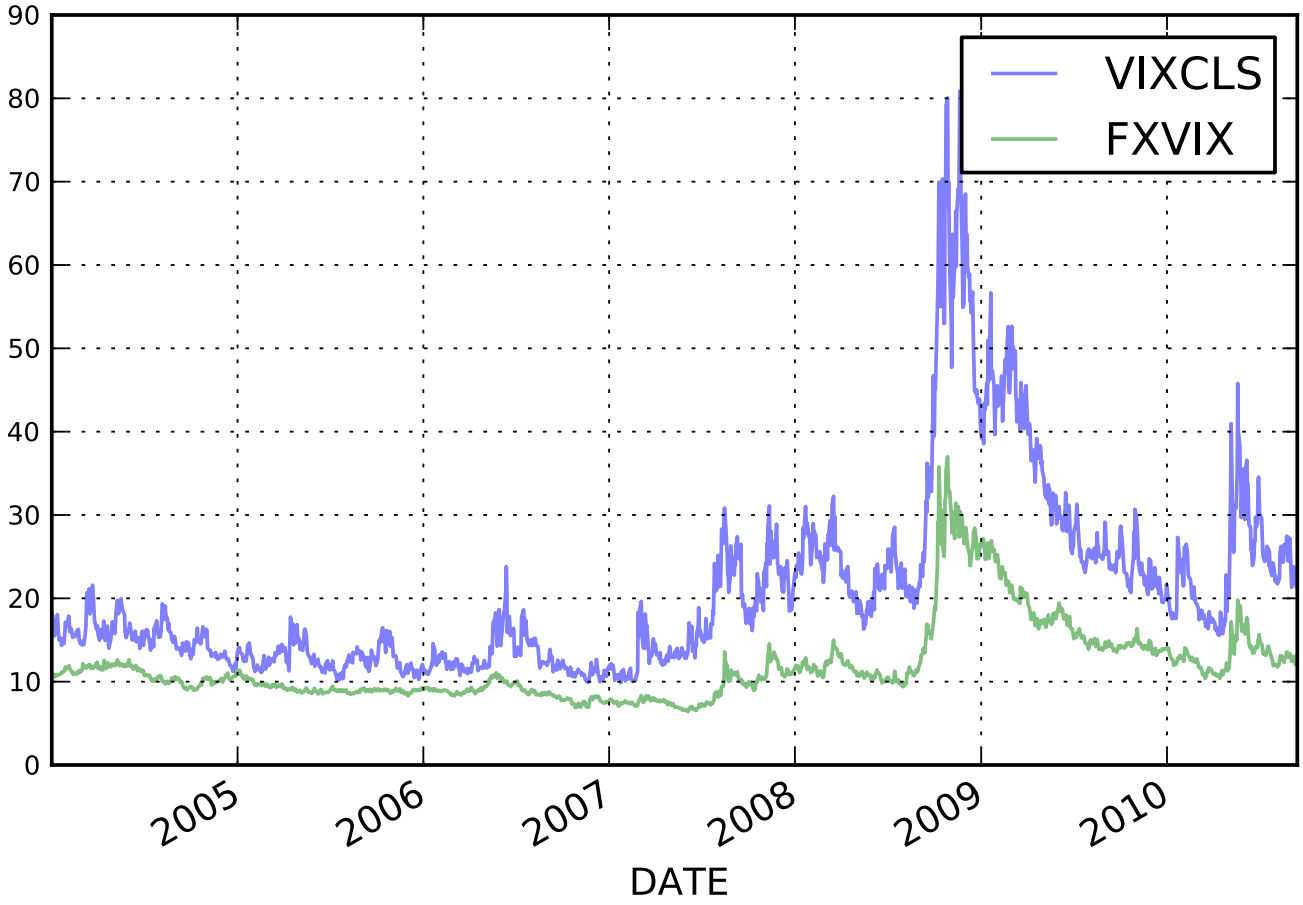

Figure 4. VIX and FXVIX This figure plots shows the VIX and the FXVIX for the period that the VIX is published

Table II

Summary Statistics

Panel A shows mean values for key measures broken down by currency from the month the currency enters the sample up to the last data point. ATM is at-the-money implied volatility, Mfree is Model-Free implied volatility which is equivalent to the volatlity swap rate. Realvol is the average of realized volatility computed each month to determine the return on the volatility swaps. HMI220 represents average the HMI metric with lookback parameter 220 days. Volret is the average volatility return, Carry is the average interest rate differential versus the US Dollar, and Return is the average return of the underlying currency during the sample period.

Panel A: Summary Statistics

	Start	End	Atm	Mfree	Realvol	HMI220	Volret	Carry	Return
AUDUSD	1999-01	2010-07	0.121	0.125	0.124	0.037	0.004	2.142	6.126
CADUSD	1999-01	2010-08	0.090	0.093	0.087	-0.066	-0.075	0.100	3.548
CHFUSD	1999-01	2010-08	0.108	0.112	0.107	-0.015	-0.045	-1.799	1.653
EURUSD	2000-09	2010-08	0.105	0.108	0.100	-0.044	-0.078	0.088	4.314
GBPUSD	1999-01	2010-08	0.093	0.097	0.091	-0.041	-0.055	1.168	0.973
JPYUSD	1999-01	2010-08	0.111	0.119	0.104	-0.056	-0.116	-2.915	0.338
MXNUSD	2000-09	2010-08	0.104	0.111	0.086	-0.181	-0.229	5.576	2.617
NOKUSD	1999-01	2010-08	0.120	0.124	0.117	-0.035	-0.064	1.413	3.565
NZDUSD	1999-01	2010-08	0.133	0.137	0.133	0.009	-0.023	3.565	7.079

Panel B: Aggregate Summary Statistics

	Atm	Mfree	Realvol	HMI220	Volret	Carry	Return
count	1219.000	1219.000	1210.000	1219.000	1210.000	1166.000	1157.000
mean	0.110	0.114	0.106	-0.041	-0.073	0.860	3.181
std	0.042	0.044	0.051	0.203	0.319	2.926	37.196
min	0.048	0.049	0.029	-0.874	-0.993	-6.572	-198.074
25%	0.084	0.087	0.076	-0.158	-0.244	-0.868	-18.008
50%	0.102	0.106	0.096	-0.031	-0.100	0.517	2.950
75%	0.123	0.128	0.120	0.091	0.058	2.635	25.461
max	0.440	0.445	0.698	0.740	4.720	12.780	166.729

Table III

Correlations of Returns.

This table reports the correlation matrix for the time-series of risk factors and the HMI factor returns. The time period is 1999 to 2011 The frequency is monthly.

	carrytrade	hlall	hlunderall	Mkt-RF	SMB	HML	RF	UMD	strev	VIX	VIXdiff	ted	teddiff	equity	commodity	stdebt	ltdebt	stirs	rec
carrytrade	1.000	0.091	-0.133	0.046	-0.056	0.044	0.064	-0.044	-0.018	-0.158	-0.204	-0.254	-0.089	0.051	0.057	-0.118	-0.120	-0.033	-0
hlall	0.091	1.000	0.195	0.012	0.071	-0.227	-0.023	0.079	-0.002	0.091	-0.226	-0.194	-0.338	0.058	-0.030	0.031	0.076	0.188	-0
hlunderall	-0.133	0.195	1.000	0.136	0.056	-0.119	-0.078	-0.053	-0.105	0.198	-0.185	0.035	-0.047	0.121	-0.016	-0.033	0.034	-0.051	0
Mkt-RF	0.046	0.012	0.136	1.000	0.233	-0.281	0.001	-0.337	0.210	-0.418	-0.742	-0.215	-0.134	0.937	0.147	-0.312	-0.164	-0.292	-0
SMB	-0.056	0.071	0.056	0.233	1.000	-0.339	-0.139	0.067	-0.005	-0.131	-0.267	-0.115	-0.081	0.272	0.071	-0.161	-0.151	-0.052	0
HML	0.044	-0.227	-0.119	-0.281	-0.339	1.000	0.029	-0.076	-0.154	-0.305	-0.085	-0.120	0.130	-0.290	0.039	0.109	0.089	-0.027	-0
RF	0.064	-0.023	-0.078	0.001	-0.139	0.029	1.000	0.126	0.047	-0.548	0.089	0.190	0.103	-0.005	-0.018	-0.112	-0.038	-0.069	-0
UMD	-0.044	0.079	-0.053	-0.337	0.067	-0.076	0.126	1.000	-0.260	-0.145	0.258	0.049	-0.033	-0.340	-0.018	0.091	0.095	0.030	-0
strev	-0.018	-0.002	-0.105	0.210	-0.005	-0.154	0.047	-0.260	1.000	0.150	-0.208	0.053	-0.106	0.167	-0.040	0.072	0.095	0.169	0
VIX	-0.158	0.091	0.198	-0.418	-0.131	-0.305	-0.548	-0.145	0.150	1.000	0.234	0.609	-0.085	-0.411	-0.185	0.453	0.244	0.582	0
VIXdiff	-0.204	-0.226	-0.185	-0.742	-0.267	-0.085	0.089	0.258	-0.208	0.234	1.000	0.341	0.366	-0.726	-0.216	0.203	-0.053	0.204	0
ted	-0.254	-0.194	0.035	-0.215	-0.115	-0.120	0.190	0.049	0.053	0.609	0.341	1.000	0.302	-0.201	-0.263	0.130	0.087	0.190	0
teddiff	-0.089	-0.338	-0.047	-0.134	-0.081	0.130	0.103	-0.033	-0.106	-0.085	0.366	0.302	1.000	-0.145	-0.093	0.005	0.000	-0.170	-0
equity	0.051	0.058	0.121	0.937	0.272	-0.290	-0.005	-0.340	0.167	-0.411	-0.726	-0.201	-0.145	1.000	0.142	-0.409	-0.247	-0.341	-0
commodity	0.057	-0.030	-0.016	0.147	0.071	0.039	-0.018	-0.018	-0.040	-0.185	-0.216	-0.263	-0.093	0.142	1.000	-0.015	0.021	-0.096	-0
stdebt	-0.118	0.031	-0.033	-0.312	-0.161	0.109	-0.112	0.091	0.072	0.453	0.203	0.130	0.005	-0.409	-0.015	1.000	0.829	0.717	0
ltdebt	-0.120	0.076	0.034	-0.164	-0.151	0.089	-0.038	0.095	0.095	0.244	-0.053	0.087	0.000	-0.247	0.021	0.829	1.000	0.523	0
stirs	-0.033	0.188	-0.051	-0.292	-0.052	-0.027	-0.069	0.030	0.169	0.582	0.204	0.190	-0.170	-0.341	-0.096	0.717	0.523	1.000	0
recession	-0.065	-0.053	0.035	-0.146	0.053	-0.056	-0.293	-0.121	0.086	0.678	0.014	0.375	-0.081	-0.158	-0.102	0.109	0.022	0.227	1

Table IV
Portfolio Characteristics.

eyranks370	count	mean	std	min	25%	50%	75%	max	Sharpe	Skew	Kurtosis
0	139.00	-0.13	0.30	-0.64	-0.27	-0.17	-0.05	2.38	-1.55	4.53	35.27
1	139.00	-0.06	0.21	-0.46	-0.18	-0.10	0.01	1.38	-0.94	2.80	15.31
2	139.00	-0.04	0.20	-0.36	-0.17	-0.06	0.03	1.12	-0.63	2.35	9.80
h-l	139.00	0.10	0.19	-1.26	0.01	0.10	0.20	0.66	1.77	-2.32	17.46

Table V

Correlations of Volatility and Volatility Innovations.

The table shows pairwise Pearson Correlations for monthly innovations in model free implied volatility for all currencies included in the sample from 1999 to 2010. Panel A shows correlations for payoffs to Volatility Swaps $RV - IV$. Panel b shows correlations for the volatility swap rate, which is equivalent to the model free implied volatility.

	AUD	CAD	CHF	EUR	GBP	JPY	MXN	NOK	NZD
AUD	1.00	0.00	-0.10	0.13	-0.06	-0.26	0.02	-0.05	0.77
CAD	0.00	1.00	-0.40	-0.31	0.00	-0.55	0.12	-0.04	-0.31
CHF	-0.10	-0.40	1.00	0.88	0.19	-0.05	-0.57	0.70	-0.22
EUR	0.13	-0.31	0.88	1.00	0.28	-0.29	-0.34	0.77	-0.01
GBP	-0.06	0.00	0.19	0.28	1.00	-0.48	0.06	0.17	-0.27
JPY	-0.26	-0.55	-0.05	-0.29	-0.48	1.00	-0.18	-0.22	0.05
MXN	0.02	0.12	-0.57	-0.34	0.06	-0.18	1.00	-0.19	-0.04
NOK	-0.05	-0.04	0.70	0.77	0.17	-0.22	-0.19	1.00	-0.24
NZD	0.77	-0.31	-0.22	-0.01	-0.27	0.05	-0.04	-0.24	1.00

	AUD	CAD	CHF	EUR	GBP	JPY	MXN	NOK	NZD
AUD	1.00	0.83	0.81	0.91	0.92	0.81	0.81	0.93	0.96
CAD	0.83	1.00	0.64	0.74	0.88	0.69	0.82	0.86	0.80
CHF	0.81	0.64	1.00	0.95	0.83	0.75	0.75	0.89	0.75
EUR	0.91	0.74	0.95	1.00	0.92	0.83	0.82	0.94	0.86
GBP	0.92	0.88	0.83	0.92	1.00	0.78	0.88	0.97	0.89
JPY	0.81	0.69	0.75	0.83	0.78	1.00	0.79	0.79	0.76
MXN	0.81	0.82	0.75	0.82	0.88	0.79	1.00	0.87	0.77
NOK	0.93	0.86	0.89	0.94	0.97	0.79	0.87	1.00	0.90
NZD	0.96	0.80	0.75	0.86	0.89	0.76	0.77	0.90	1.00

Table VI

Sharpe ratios

This Table Shows Summary Statistics and Sharpe ratios for the various strategies with different look-back parameter L over which historical volatility is computed.

L	count	mean	std	min	25%	50%	75%	max	Sharpe
30	139	0.10	0.18	-0.30	0.00	0.07	0.19	0.76	1.87
40	139	0.09	0.16	-0.23	0.00	0.08	0.19	0.68	1.95
50	139	0.11	0.17	-0.32	0.00	0.10	0.21	0.68	2.26
60	139	0.11	0.16	-0.26	0.01	0.11	0.20	0.69	2.35
70	139	0.10	0.16	-0.25	0.00	0.08	0.21	0.69	2.16
80	139	0.09	0.17	-0.64	-0.01	0.08	0.21	0.69	1.88
90	139	0.10	0.20	-1.12	-0.00	0.12	0.21	0.69	1.85
100	139	0.11	0.21	-1.12	0.01	0.12	0.22	0.69	1.80
110	139	0.10	0.21	-1.12	0.00	0.11	0.23	0.67	1.74
120	139	0.09	0.28	-2.34	-0.01	0.11	0.21	0.70	1.10
130	139	0.10	0.28	-2.34	-0.00	0.12	0.23	0.70	1.25
140	139	0.10	0.28	-2.34	-0.00	0.12	0.24	0.70	1.29
150	139	0.10	0.28	-2.34	0.01	0.12	0.23	0.70	1.24
160	139	0.10	0.27	-2.34	0.01	0.12	0.24	0.70	1.30
170	139	0.10	0.27	-2.34	0.02	0.12	0.22	0.70	1.32
180	139	0.10	0.28	-2.34	0.01	0.11	0.22	0.70	1.23
190	139	0.10	0.27	-2.34	0.01	0.11	0.22	0.70	1.23
200	139	0.09	0.27	-2.34	0.00	0.11	0.22	0.70	1.16
210	139	0.10	0.28	-2.34	-0.01	0.11	0.22	1.01	1.24
220	139	0.10	0.28	-2.34	-0.01	0.11	0.22	1.01	1.20
230	139	0.09	0.27	-2.34	-0.01	0.11	0.22	0.70	1.19
240	139	0.09	0.27	-2.34	0.00	0.10	0.22	0.70	1.16
250	139	0.10	0.24	-1.86	0.00	0.10	0.21	0.70	1.36
260	139	0.09	0.24	-1.86	0.00	0.10	0.22	0.70	1.33
270	139	0.10	0.25	-1.86	0.00	0.11	0.22	0.72	1.43
280	139	0.10	0.25	-1.86	0.01	0.10	0.22	0.72	1.43
290	139	0.10	0.20	-0.63	0.00	0.10	0.22	0.72	1.79
300	139	0.10	0.20	-0.63	0.00	0.10	0.22	0.72	1.77
310	139	0.10	0.20	-0.63	0.00	0.09	0.22	0.70	1.75
320	139	0.10	0.20	-0.63	0.00	0.09	0.22	0.72	1.74
330	139	0.10	0.20	-0.63	0.00	0.09	0.22	0.71	1.72
340	139	0.10	0.20	-0.63	0.00	0.09	0.22	0.70	1.66
350	139	0.09	0.20	-0.63	0.00	0.09	0.22	0.70	1.59
360	139	0.09	0.20	-0.63	-0.00	0.08	0.22	0.70	1.60
370	139	0.09	0.20	-0.63	-0.01	0.09	0.22	0.70	1.55
380	139	0.09	0.20	-0.63	-0.01	0.09	0.21	0.70	1.54
390	139	0.09	0.21	-0.63	-0.02	0.08	0.22	0.89	1.45
400	139	0.09	0.22	-0.63	-0.02	0.08	0.21	0.89	1.40

Panel B: Aggregate Strategy

index	count	mean	std	min	25%	50%	75%	max	Sharpe
hlall	139	0.1	0.19	-1.26	0.01	0.1	0.2	0.66	1.77

Table VII

Cross-Sectional Regressions

The table shows parameter estimates and t-statistics for Fama Macbeth regressions on volatility returns. The dependent variables are ey260 which is the HMI metric estimated with lookback parameter $L = 260$, carry is the interest rate differential versus the US Dollar, mom150 is the past 150 day return and mfree is the model-free implied volatility. T-Statistics are reported below parameter estimates in brackets.

		I	II	III	IV
HMI220	slopes	0.42	0.49	0.42	0.64
	tstats	(5.19)	(5.91)	(4.92)	(5.60)
carry	slopes		-3.44		5.32
	tstats		(-0.83)		(0.70)
mom150	slopes				-0.23
	tstats				(-0.88)
mfree	slopes			0.60	1.21
	tstats			(1.45)	(2.10)
intercept	slopes	-0.07	-0.06	-0.11	-0.17
	tstats	(-3.71)	(-3.35)	(-2.88)	(-3.49)

Table VIII

HMI Factor Risk

This table shows premia for FX portfolios formed on HMI betas

level_0	level_1	
rollingbetaHMI	slopes	-0.000
rollingbetaHMI	t-stats	-1.254
intercept	slopes	0.000
intercept	t-stats	0.785

Table IX

Risk-Adjusted Returns

The table reports the results of OLS estimation of four different factor models for HMI FX volatility returns. The dependent variable are excess returns to a zero-cost strategy that is long FX volatility swaps of one month maturity ranked by HMI and short the bottom third. Explanatory factors include the Fama and French (1992) factors, the Carhart (1997) momentum factor, and a short-term mean-reversion factor available on Ken French's website. Also included is a carry factor based on a zero-cost strategy applied to the sample currencies. Equity is an international equity factor constructed from the most liquid equity index futures, commodity is a factor constructed from the most liquid commodity futures, stdebt is constructed from the most liquid short-term government bond futures, lt. debt is constructed from the most liquid long term government bond futures and stirs is constructed form the most liquid short- term interest futures. The sample period is from 1999 to 2011. Resulting alphas and betas are computed using equation (6) in the text. T-Statistics are reported below parameter estimates in brackets.

	I	II	III	IV	V
Mkt-RF		-0.00	-0.00	-0.02	
		(-0.72)	(-0.43)	(-1.59)	
SMB		0.00	-0.00	-0.00	
		(0.02)	(-0.05)	(-0.30)	
HML		-0.02	-0.01	-0.01	
		(-2.99)	(-2.86)	(-2.44)	
UMD			0.00	0.00	
			(0.60)	(0.84)	
strev				-0.00	
				(-0.82)	
carrytrade	0.73			0.79	
	(1.21)			(1.34)	
equity				1.25	0.26
				(1.77)	(1.01)
commodity				-0.02	-0.02
				(-0.15)	(-0.21)
stdebt				-8.57	-10.56
				(-1.89)	(-2.32)
ltdebt				2.67	2.58
				(1.76)	(1.68)
stirs				35.73	40.53
				(3.03)	(3.53)
intercept	0.09	0.10	0.10	0.09	0.09
	(5.61)	(6.19)	(6.03)	(4.89)	(4.99)

Table X

Long Volatility Benchmark

The table reports summary statistics for equal-weighted FX volatility returns. The benchmark is constructed by taking the equal-weighted cross-sectional average of volatility long positions for each of the sample currencies. The time period is from 1999 to 2011.

count	mean	std	min	25%	50%	75%	max	skew	kurt	Sharpe
139	-0.08	0.22	-0.47	-0.20	-0.11	0.00	1.63	3.72	24.28	-1.17

Table XI

Long Volatility Benchmark Adjusted Returns

The table reports summary statistics for equal-weighted FX volatility returns. The benchmark is constructed by taking the equal-weighted cross-sectional average of volatility long positions for each of the sample currencies. The time period is from 1999 to 2011.

L	FXvolatility	intercept	t-FXvolatility	t-intercept
30	0.15	0.11	2.31	6.87
40	-0.03	0.09	-0.55	6.10
50	-0.02	0.11	-0.32	7.15
60	0.02	0.11	0.28	7.63
70	-0.06	0.10	-0.92	6.67
80	-0.30	0.07	-4.89	4.98
90	-0.43	0.07	-6.72	4.69
100	-0.46	0.07	-6.77	4.52
110	-0.45	0.07	-6.57	4.29
120	-0.78	0.03	-9.54	1.50
130	-0.77	0.04	-9.41	2.12
140	-0.77	0.04	-9.45	2.29
150	-0.83	0.04	-10.53	1.95
160	-0.77	0.04	-9.46	2.34
170	-0.76	0.05	-9.33	2.41
180	-0.78	0.04	-9.60	2.02
190	-0.76	0.04	-9.39	2.03
200	-0.77	0.03	-9.70	1.73
210	-0.72	0.04	-8.37	2.20
220	-0.73	0.04	-8.43	2.03
230	-0.74	0.04	-9.17	1.89
240	-0.76	0.03	-9.65	1.72
250	-0.64	0.05	-8.71	2.65
260	-0.63	0.05	-8.27	2.56
270	-0.61	0.06	-7.61	3.04
280	-0.60	0.06	-7.58	3.05
290	-0.37	0.08	-5.29	4.62
300	-0.34	0.08	-4.66	4.63
310	-0.33	0.08	-4.66	4.54
320	-0.32	0.08	-4.46	4.54
330	-0.34	0.08	-4.63	4.47
340	-0.36	0.07	-5.12	4.17
350	-0.35	0.07	-5.02	3.95
360	-0.34	0.07	-4.71	4.01
370	-0.34	0.07	-4.69	3.85
380	-0.33	0.07	-4.57	3.85
390	-0.34	0.06	-4.42	3.57
400	-0.32	0.06	-4.11	3.43

Panel B: Aggregate Strategy

	FXvolatility	intercept	t-FXvolatility	t-intercept
0	-0.48	0.06	-7.84	4.32

Table XII

HMI during Different Sub-Samples

The table reports Sharpe ratios for the HMI volatility portfolios during different sub-samples. The sub-samples are NBER recessions and expansions. Calm and volatile periods are defined as the top and bottom half of the FXVIX index during the sample period. HighTED and LowTED divides the sample by the value of the TED spread.

Regime	0.0	1.0	2.0	HMI
Calm	-1.54	-0.94	-0.76	1.24
Volatile	-1.55	-1.15	-0.50	1.76
NBER Expansion	-2.18	-1.44	-0.79	1.75
NBER Recession	-0.40	-0.03	0.03	0.74
LowTED	-3.12	-1.72	-1.11	2.55
HighTED	-0.80	-0.56	-0.19	0.96

Table XIII

Impact of Transaction Costs

The Table reports the impact of transaction costs on means, standard deviations and Sharpe ratios of the strategy. The scenarios are to trade at 100% of the quoted spread, 75% of the quoted spread, and 50% of the quoted spread. For comparison also the case with no transaction costs is included.

%spread	mean	std	Sharpe
0.00	0.10	0.22	1.77
0.50	0.07	0.22	1.38
0.75	0.06	0.22	1.19
1.00	0.05	0.22	0.99

Table XIV

Sharpe ratios for Underlying Currency Portfolios

This Table Shows Summary Statistics and Sharpe ratios for long-short portfolios of the underlying Currencies formed on HMI with different look-back parameter L over which historical volatility is computed.

L	count	mean	std	min	25%	50%	75%	max	Sharpe
30	139	0.00	0.02	-0.09	-0.01	0	0.01	0.07	0.28
40	139	0.00	0.02	-0.06	-0.01	0	0.01	0.06	0.19
50	139	0.00	0.02	-0.06	-0.01	0	0.02	0.07	0.33
60	139	-0.00	0.02	-0.06	-0.01	-0	0.01	0.07	-0.06
70	139	0.00	0.02	-0.06	-0.01	-0	0.02	0.07	0.01
80	139	0.00	0.02	-0.05	-0.01	-0	0.01	0.07	0.03
90	139	0.00	0.02	-0.05	-0.01	-0	0.02	0.08	0.30
100	139	0.00	0.02	-0.05	-0.01	-0	0.02	0.08	0.30
110	139	0.00	0.02	-0.06	-0.01	0	0.01	0.08	0.20
120	139	0.00	0.02	-0.06	-0.01	0	0.02	0.08	0.32
130	139	0.00	0.02	-0.08	-0.01	0	0.02	0.08	0.44
140	139	0.00	0.02	-0.08	-0.01	0	0.02	0.08	0.32
150	139	0.00	0.02	-0.07	-0.01	0	0.02	0.08	0.52
160	139	0.00	0.02	-0.07	-0.01	0	0.02	0.08	0.47
170	139	0.00	0.02	-0.08	-0.01	0	0.02	0.08	0.49
180	139	0.00	0.02	-0.07	-0.01	0	0.02	0.07	0.51
190	139	0.00	0.02	-0.08	-0.01	0	0.02	0.07	0.45
200	139	0.00	0.02	-0.07	-0.01	0	0.02	0.07	0.50
210	139	0.00	0.02	-0.07	-0.01	0	0.02	0.07	0.65
220	139	0.00	0.02	-0.05	-0.01	0	0.02	0.07	0.70
230	139	0.00	0.02	-0.05	-0.01	0	0.02	0.07	0.75
240	139	0.01	0.02	-0.05	-0.01	0	0.02	0.07	0.83
250	139	0.01	0.02	-0.05	-0.01	0	0.02	0.07	0.79
260	139	0.00	0.02	-0.05	-0.01	0	0.02	0.07	0.62
270	139	0.00	0.02	-0.05	-0.01	0	0.02	0.08	0.72
280	139	0.00	0.02	-0.05	-0.01	0	0.02	0.08	0.71
290	139	0.00	0.02	-0.07	-0.01	0	0.02	0.08	0.57
300	139	0.00	0.02	-0.07	-0.01	0	0.02	0.08	0.58
310	139	0.00	0.02	-0.07	-0.01	0	0.02	0.08	0.60
320	139	0.00	0.02	-0.07	-0.01	0	0.02	0.08	0.56
330	139	0.00	0.02	-0.09	-0.01	0	0.02	0.08	0.58
340	139	0.00	0.02	-0.09	-0.01	0	0.02	0.08	0.55
350	139	0.00	0.02	-0.05	-0.01	0	0.02	0.08	0.73
360	139	0.00	0.02	-0.09	-0.01	0	0.02	0.08	0.56
370	139	0.00	0.02	-0.09	-0.01	0	0.02	0.08	0.55
380	139	0.00	0.02	-0.09	-0.01	0	0.02	0.08	0.55
390	139	0.00	0.02	-0.09	-0.01	0	0.02	0.08	0.46
400	139	0.00	0.02	-0.09	-0.01	0	0.02	0.08	0.54

Panel B: Aggregate Strategy

index	count	mean	std	min	25%	50%	75%	max	Sharpe
hlunderall	139	0	0.02	-0.04	-0.01	0	0.02	0.06	0.59

Table XV

Cross-Sectional Regressions for Currency Returns

The table shows parameter estimates and t-statistics for Fama Macbeth regressions on underlying currency returns. The dependent variables are HMI260 which is the HMI metric estimated with look-back parameter $L = 260$, carry is the interest rate differential versus the US Dollar, mom150 is the past 150 day return, FEER is a proxy for deviations from the fundamental real exchange rate, and mfree is the model-free implied volatility. T-Statistics are reported below parameter estimates in brackets.

		I	II	III	IV	V
HMI220	slopes	0.01	0.02	0.01	0.01	0.02
	tstats	(2.05)	(1.86)	(1.11)	(0.54)	(2.13)
carry	slopes		0.64		3.00	
	tstats		(1.32)		(1.57)	
mom150	slopes				0.15	
	tstats				(0.97)	
mfree	slopes			-0.01	-0.53	
	tstats			(-0.14)	(-1.27)	
FEER	slopes				0.03	0.02
	tstats				(0.62)	(2.03)
intercept	slopes	0.00	0.00	0.00	0.04	0.00
	tstats	(0.87)	(0.23)	(0.18)	(0.99)	(1.61)

Table XVI

Risk-Adjusted Returns for Underlying Currencies

The table reports the results of OLS estimation of four different factor models for HMI FX returns. The dependent variable are excess returns to a zero-cost strategy that is long the top third of currencies ranked by HMI and short the bottom third. Explanatory factors include the Fama and French (1992) factors, the Carhart (1997) momentum factor, and a short-term mean-reversion factor available on Ken French's website. Also included is a carry factor based on a zero-cost strategy applied to the sample currencies. Equity is an international equity factor constructed from the most liquid equity index futures, commodity is a factor constructed from the most liquid commodity futures, stdebt is constructed from the most liquid short-term government bond futures, lt. debt is constructed from the most liquid long term government bond futures and stirs is constructed form the most liquid short-term interest futures. The sample period is from 1999 to 2011. Resulting alphas and betas are computed using equation (6) in the text. T-Statistics are reported below parameter estimates in brackets.

	I	II	III	IV	V
Mkt-RF		0.00	0.00	0.00	
		(1.41)	(1.17)	(1.04)	
SMB		-0.00	0.00	0.00	
		(-0.00)	(0.03)	(0.00)	
HML		-0.00	-0.00	-0.00	
		(-1.07)	(-1.10)	(-1.40)	
UMD			-0.00	-0.00	
			(-0.32)	(-1.03)	
strev				-0.00	
				(-2.25)	
carrytrade	-0.10			-0.10	
	(-1.76)			(-1.74)	
equity				-0.04	0.03
				(-0.58)	(1.36)
commodity				-0.00	-0.01
				(-0.42)	(-0.51)
stdebt				-0.39	-0.24
				(-0.91)	(-0.56)
ltdebt				0.19	0.16
				(1.34)	(1.14)
stirs				0.11	-0.26
				(0.10)	(-0.25)
intercept	0.00	0.00	0.00	0.01	0.00
	(2.34)	(2.11)	(2.13)	(2.91)	(1.90)