Is Smart Money Smart? The Costs of Hedge Funds Trading Market Anomalies

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Abstract

Do hedge funds earn statistically significant premia on common factor trading strategies after trading costs are accounted for? Furthermore, what is the gap between what a hedge fund would earn and the paper portfolios that they hold? I answer this question by using the latest cutting-edge methodology to estimate trading costs for major financial market anomalies. This methodology uses the familiar asset-pricing Fama-MacBeth procedure to compare the on-paper compensation to factor exposures with those earned by hedge funds. I find that the typical hedge fund does not earn profits to value or momentum, and and low returns to size.

JEL classification: G12; G14; G23;

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I. Introduction

Hedge funds make up $3.2 trillion dollars of assets under management (AUM)[1] and yet very little is publicly known about their trading strategies and the costs associated with them. In fact, traditional empirical asset-pricing focuses little on net of transaction cost returns in general. Much work has instead been focused on expected gross returns and potential strong predictors of those returns (Frazzini, Israel & Moskowitz, 2015). These predictors, or factors, of cross-sectional returns, challenge traditional market efficiency models. If we assume market efficiency, then all information should be baked into prices and there should be no ex-post predictors that significantly explain future returns. However, if these predictors are unable to "survive" due to substantial implementation costs, then the "limits to arbitrage" on these predictors is crucial to the efficient market debate. Hedge funds are critical to this discussion because they are regarded as some of the most sophisticated investment vehicles in the world, leading them to have the lowest limits to arbitrage on these predicting factors. Therefore, hedge funds are a fascinating laboratory to test these predictor's real-world efficacy. If these factors are able to survive the lowest practical implementation costs in the industry, then these predictors may offer incredibly lucrative arbitrage opportunities, or represent significant risk factors that most investors are exposed to in the markets.

Furthermore, due to their size and influence on the market, hedge funds' net of transaction cost returns are interesting to study in their own right. To outsiders, many hedge funds simply have a "black box" that generates outlandish returns. During the peak of the Great Recession in 2008, hedge fund managers Jim Simons, John Paulson, and George Soros all earned payouts of

[1] Source: Estimates conducted by Hedge Fund Research (HFR) for year-end 2017, available at https://www.hedgefundresearch.com

$2.5 billion, $2.0 billion and $1.1 billion respectively.[2] These payouts came despite a wide market downturn that saw the S&P 500 lose 38.5% of its value.[3] [4]

Are these hedge funds then, able to really achieve such robust profitability, even in the wake of the sometimes-substantial trading costs they incur? Although there is a plethora of research on trading costs, never before has a researcher analyzed the trading costs faced by the hedge fund industry specifically. How much performance attrition is caused by the trading costs these firms face? Is $3.2 trillion an efficient allocation of scarce capital to these funds?

This paper attempts to answer these questions by applying a new cutting-edge methodology for measuring real-world implementation costs for factor trading strategies introduced in Andrew Patton's and Brian Weller's working paper, *What You See is Not What You Get: The Cost of Trading Market Anomalies* (2017). The novelty of this approach is that unlike previous estimates of trading costs, the technique does not require trade-level data and imposed parametric models to generate trading cost estimates. Furthermore, it does not require proprietary trading data in the hopes of generalizing those estimated costs as representative of the typical firm. Finally, the approach most importantly does not require the researcher to take a stand on the type of factor trading strategy employed. This is a necessary feature given that hedge funds likely implement academic factor-based investing strategies with lower cost industry variants that see a much lesser degree of performance attrition.

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[2] Source: Payouts reported by CNN, available at https://money.cnn.com/2009/03/25/markets/hedge_alpha/

[3] Source: Returns reported by Reutuers, available at https://www.reuters.com/article/us-usa-stocks-sp-timeline-idUSBRE9450WL20130506

[4] Further adding to the hedge fund mystique is there availability only to "sophisticated" investors. By law, hedge fund investors must be "accredited," meaning that they possess a certain minimal income, have a net worth of over one million dollars, and possess "significant" investment knowledge. Because hedge fund investors are by law required to be knowledgeable, hedge funds are often able to escape the scrupulous reporting standards mandated under the Investment Company Act of 1940. This marks a drastic difference between hedge funds and mutual funds, and also allows hedge funds to invest in a greater investable universe of assets, employ greater leverage, and also short (bet against) certain assets.

The empirical methodology follows the widely used Fama-MacBeth procedure where first, time series regressions of asset pricing factors are run on a series of representative stock portfolios and hedge fund returns. Standard stock portfolios are used from the academic literature and act as a strong proxy for real-life quantitative investment strategies. These time series betas, β_{ik}, which encapsulate the factor risks (loadings) of the different portfolios, are then used in a second-stage regression, in which they are regressed on the cross section of returns. This second stage regression thereby gives new coefficients (λ_{kt}) which represent the incremental compensation per unit of risk exposure (factor loading). By allowing λ_{kt} to vary for my test portfolios (λ_{kt}^{S}) and my fund portfolios (λ_{kt}^{HF}), I am able to then use this difference, $\lambda_{kt}^{S} - \lambda_{kt}^{HF} = \lambda_{kt}^{\Delta}$, effectively as the estimate between gross of transaction cost factor returns and net of transaction cost factor returns in order to determine the magnitude of the implementation costs faced by hedge funds. Therefore, the difference between the on-paper returns of my stock portfolios, λ_{kt}^{S}, and the real life returns of my hedge fund portfolios, λ_{kt}^{HF}, make up real-world trading costs faced by these funds.

My analysis will focus on the four predominant factor trading strategies found in the literature (Fama & French, 1992; Carhart, 1997).[5] These standard asset pricing factors include the market, size, value, and momentum factors that serve as the basis for hundreds of billions of dollars in managed money. The market factor (MKT) typically represents the excess returns on a market index such as the S&P 500. The size, or SMB factor, represents the excess returns on a basket of portfolios that is long small-cap stocks and correspondingly short large-cap stocks. Similarly, the value factor (HML) is constructed from a basket of excess returns on portfolios that are long securities that have high book equity to market capitalization (BE/ME) ratios and

[5] These risk-proxying factors can be download on Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

short corresponding portfolios that have low BE/ME ratios. Finally, the momentum factor (UMD) is long past “winners” (stocks that have done well recently) and is short past “losers.”

Under traditional asset-pricing models, these factors have been shown to credibly predict future returns (Fama & French, 1992; Carhart, 1997). These asset-pricing anomalies are often given risked based explanations. For example, the market factor represents the systematic market risk inherent in every equity investment. If a security has a $\beta_{MKT} = 2$, for example, then it is exposed quite significantly to this market risk and therefore, will need to be compensated by twice the typical market return in order to justify the increased risk. These financial time-series betas therefore represent exposure to typical risks, and therefore the magnitude of the coefficients will also determine the amount of compensation necessary for such a risk. Therefore, it is common to say that if a security has a $\beta_{MKT} = 2$, then the security has a particularly substantial “loading” (exposure) on the market risk factor. These time-series betas can also be estimated on the returns of portfolios and different types of funds (Sharpe, 1993) with the same intuition applying as above and which will be utilized extensively in this paper.

This paper proceeds as follows. Section II is a comprehensive overview of the current literature on the topic. Section III lays out the theoretical framework that my empirical analysis builds upon. Section IV describes my data. Section V lays out my empirical methodology. Section VI then discusses my results, various robustness checks, and a comparison of my findings with the current literature. Section VII lists the limitations of the methodology. Section VIII concludes.

II. Related Literature

In order to determine the real-world efficacy of certain cross-sectional predictors, much research has been conducted on the trading costs to factor-based strategies. Additionally, because of the large sums of money that hedge funds trade, much research has been done analyzing their effects on financial markets and the risks that they are exposed to. However, due the lack financial regulations subjecting hedge funds to mandatory reporting, funds typically report returns voluntarily to different database vendors. Therefore, there is a large literature detailing the potential biases these hedge fund databases incur and potential ways to minimize them. Potentially because of these database biases, never before has a researcher analyzed the trading costs faced by typical hedge funds.

A. Related Literature on Trading Costs

The literature on trading costs has focused primarily on the real-world efficacy of certain cross-sectional predictors (namely the four predominant asset pricing factors mention in Section I). The literature on trading costs has typically employed two different methodologies. The first approach derives transaction costs using price and transaction records (usually from the TAQ database) to infer parametric price impact models in order to measure the implementation costs to different factor-based strategies. Earlier studies typically paint rather pessimistic results for the real-world efficacy of these cross-sectional anomalies. For example, Lesmond, Schill, and Zhou (2004) show that majority of the returns from the momentum factor come from securities that also have the largest trading costs. Therefore, they show that momentum profits are largely illusory when implemented in the real world. Furthermore, Chen, Stanzl, and Watanabe (2002) calculate trading costs faced by factor-based strategies (specifically size, value, and momentum) by estimating price impact functions for just under 5,000 stocks in their sample. They find that these factors are largely unimplementable after trading costs are accounted for. Korajczyk and Sadka (2004) and Novy-Marx and Velikov (2016) present more favorable results for factor trading strategies. Both find break-even carrying capacities (amount of money that can be traded in a certain strategy before price impact erodes all potential excess returns) for the momentum anomaly around $5 billion and Novy-Marx and Velikov (2016) further find strong real-world efficacy for both the size and value factor. Both of these works take into account trading cost mitigation techniques likely employed by real-world investment managers when implementing these factor strategies.

The second approach uses specialized, firm specific proprietary trading data under the guise that these firms are representative of the asset management universe. These papers typically make use of Perold (1988)'s implementation shortfall measure which captures the difference between real-world profits and on-paper profits. This method is readily applied by both Keim and Madhavan (1997) and Frazzini, Israel, and Moskowitz (2015). Frazzini, Israel, and Moskowitz (2015) find that size, value, and momentum all carry break-even carrying capacities an order of magnitude larger than that what is found in the literature. They estimate that these strategies are implementable in the range of tens to hundreds of billions of dollars before significant attenuation.

Patton and Weller (2017)'s approached combines the best features of both existing approaches by effectively estimating the total costs of implementing factor strategies similar to the papers that utilize proprietary trading data, while also capturing representative asset managers of factor investing. Furthermore, Patton and Weller (2017)'s methodology does not require me to take a specific stance on the type of factor investing strategies these firms employ. This is critical for hedge funds because many funds will implement these strategies quite differently from each other while pursuing more liquid versions of these strategies in order to combat high trading costs. By combining Patton and Weller (2017)'s approach to measure real-world implementation costs with Agarwal, Daniel, and Naik (2009)'s approach to covert hedge fund net of fee returns to gross of fee returns, my approach will be novel in that it will be the first paper specifically analyzing trading costs faced by the hedge fund industry.

B. Related Literature on Hedge Fund Database Biases

There has been a variety of research documenting the flaws in hedge fund databases (Aiken, Clifford & Ellis, 2012; Fung & Hsieh, 2000; Fung & Hsieh, 2009; Liang, 2000). Because hedge funds are often exempted from the Investment Company Act of 1940, disclosures regarding holdings, fees, and returns often don't exist. The only significant regulatory disclosure that hedge funds are mandated to provide is under SEC regulation 13-f. This regulation forces hedge funds greater than $100 million in AUM to report their quarterly holdings. Even these relatively light regulations have been fought extensively by hedge funds. Funds have high incentives to keep their holdings absolutely secret (Huddart, Hughes, & Levine, 2001) or run the risk of other funds front running their trades and eroding their potential profits (Christoffersen, Danesh, & Musto, 2016).

Furthermore, hedge funds are able to delay reporting their quarterly holdings by filing a petition with the SEC that allows the regulating body to delay exposure that is "necessary or appropriate in the public interest or for the protection of investors." Until the SEC rejects or approves the petition, funds are not forced to disclose their holdings (Agarwal et al., 2013).

Due to the relative lack of mandatory reporting regulations required for hedge funds, majority of the databases that researchers have available come from hedge fund managers voluntarily reporting returns and fund characteristics. For example, under 3(c)1 and 3(c)7 exemptions to the Investment Company Act, disclosing past performance and fund size to publicly available databases is one of the few ways that hedge funds are able to market themselves to new investors (Jorion & Schwartz, 2010). This voluntary reporting causes a variety of biases in the presented data. Through constructing their own proprietary database of hedge funds who don't report to any publicly available database, Aiken, Clifford and Ellis (2012) find that the performance of these non-reporting funds are significantly worse than the funds that do report. Additionally, due to the relatively quick turnover in the hedge fund industry, it likely experiences strong survivorship bias where surviving firms report materially higher and more consistent returns and fund characteristics. This type of bias is well documented in mutual funds as well (Brown, Goetzmann, Ibbotson, and Ross (1992)). Additionally, Fung and Hsieh (2004) report that many of these publicly available databases are filled with instant history bias. This occurs when a fund enters a database and its past performance history is then appended to the database. These past returns are often selectively higher than the actual fund performance due to an "incubation" period in which fund managers allocate small amounts of money to many different "insider" funds. The funds that then perform the best are marketed and opened to outside capital. Due to statistical chance, if enough funds are incubated, managers are able to report funds with seemingly outsized returns and therefore attract capital.

In addition to these biases, hedge fund databases also seem to exhibit return smoothing. For example, Asness, Kraill, and Liew (2001) note the existence of serial correlation leads reported returns to appear less risky than they actually are. Furthermore, Getmansky, Lo, and Makarov (2004) show that the only explanations that adequately address such strong autocorrelation in hedge fund returns are either non-synchronous trading or purposeful performance smoothing.

Additionally, Bollen and Pool (2012) find sets of performance flags that help predict fraudulent hedge fund activities while Bollen and Pool (2009) find that there are substantially fewer reported monthly returns that are small and negative than those that are positive. However, when aggregated to bimonthly returns, no such problem arises which suggests that funds temporarily overstate their returns. In fact, the idea that voluntary disclosures allow funds to misreport is further documented by Patton, Ramadorai, and Streatfield (2015), who find that hedge funds frequently revise returns and that 49% of the hedge funds in their sample of 12,128 have revised their previous returns by a minimum of .01% at least once and over 20% revised a previous monthly return by at least 1.0%. They also find that these "revisers" are not random, but consistently post worse returns than their non-revising peers. Researchers have even found that hedge funds' mandatory reports are subject to substantial error, such as Cici, Kempf, and Puetz (2011) who find that in 13-f filings, the value of the securities is often quite different from the prevailing closing prices reported by CRSP for the same time periods.

C. Related Literature on Hedge Funds

Despite the challenges presented by these databases, hedge funds make up ~15% of all actively managed money in the United States and therefore their study is of immense importance. In addition, to the sheer volume of active funds, hedge funds have also been shown to account for a significant fraction of aggregate trading in certain asset classes. Due to their immense impact on asset markets, one camp of academics has focused on hedge funds and their role in the stability of financial markets. For example, Kruttli, Patton, and Ramadorai (2015) show that hedge fund illiquidity has robust in and out of sample forecasting power for 72 portfolios of international equities, U.S. corporate bonds, and currencies. They show this by constructing a simple measure of hedge funds' aggregate ability to provide liquidity to asset markets.

Another camp of academics has focused their efforts on hedge funds and efficient markets. For example, Ramadorai (2012) finds that the closed end fund premium for hedge funds, which is highly correlated with that of mutual funds, is well explained by variables in rational theories and that more behavioral explanations do not find support in the data. In addition to efficient markets, other academics have attempted to discover systematic risk factors in the returns of hedge funds. Fung and Hsieh (2004) show that a seven-factor model is able to explain up to 56% of the variation in time series returns. Additionally, Fung, Hsieh, Naik, and Ramadorai (2008) find that a subset of fund-of-funds are able to consistently deliver alpha and that these funds received far greater and steadier capital inflows. They also show that in turn, these capital inflows attenuate fund performance, which is consistent with the literature regarding size and fund performance. The last major camp of academics focuses on the managerial skill, fee structures and incentives of different hedge funds. For example, Agarwal, Daniel, and Naik (2009) show that hedge funds with greater managerial incentives, higher levels of managerial ownership, and the inclusion of high-water mark provisions are associated with superior returns. Additionally, Brown, Goetzmann, and Park (2001) find that in spite of fee structures that incentivize additional volatility, especially for funds that have underperformed, reputational concerns mitigate this excess risk taking. Instead of looking at fees and incentives for mutual fund which make up half of the real-world investor return shortfall, I will be looking at trading costs, which like fees, represent the difference between how assets perform on paper, and the returns that investors actually see on their account balances.

III. Theoretical Framework

The tests run in this paper follow the procedures of Fama and MacBeth (1973). This procedure was originally devised as a way to test the efficacy of the Capital Asset Pricing Model (CAPM). Therefore, an understanding of the CAPM and the portfolio theory underlying it, are crucial to the understanding of the Fama-MacBeth procedure itself. The traditional portfolio theory of Markowitz (1959) relies on the assumption that one-period percentage returns are multivariate normally distributed and therefore can be simplified into a normal two-parameter model where investors only look at assets in terms of their expected returns, $E(\tilde{R}_i)$, and their contribution to the risk (or dispersion) of total portfolio returns, $\sigma(\tilde{R}_p)$. In the standard portfolio model, idiosyncratic risk is diversified away and therefore the predominant measure of risk is the covariance of assets with each other. If x_{ip} is the proportion of portfolio funds invested in asset *i*, $\sigma_{ij} = cov(\tilde{R}_i, \tilde{R}_j)$ is the covariance between two different assets, and N is the number of assets then

$$\sigma(\tilde{R}_p) = \sum_{i=1}^{N} x_{ip} \left| \frac{\sum_{j=1}^{N} x_{ip}\sigma_{ij}}{\sigma(\tilde{R}_p)} \right| = \sum_{i=1}^{N} x_{ip} \frac{cov(\tilde{R}_i, \tilde{R}_j)}{\sigma(\tilde{R}_p)}$$

Therefore, the risk of asset *i* in portfolio *p* is proportional to:

$$\sum_{j=1}^{N} \frac{x_{jp}\sigma_{ij}}{\sigma(\tilde{R}_p)} = \sum_{i=1}^{N} \frac{cov(\tilde{R}_i, \tilde{R}_j)}{\sigma(\tilde{R}_p)}.$$

Traditional risk averse investors want to maximize expected portfolio returns

$$E(\tilde{R}_m) = \sum_{i=1}^{N} x_{im}\, E(\tilde{R}_i),$$

subject to the constraints

$$\sigma(\tilde{R}_p) = \sigma(\tilde{R}_m) \quad \text{and} \quad \sum_{i=1}^{N} x_{im} = 1.$$

Lagrangian methods can then be shown that for any asset *i* in *m*, there must be weights, x_{im}, chosen in a way that

$$E(\tilde{R}_i) - E(\tilde{R}_m) = \lambda_m \left[\frac{\sum_{j=1}^{N} x_{jm}\sigma_{ij}}{\sigma(\tilde{R}_m)} - \sigma(\tilde{R}_m)\right] \tag{1}$$

where λ_m is the rate of change (shadow price) of $E(\tilde{R}_p)$ with respect to $\sigma(\tilde{R}_p)$ at the point of the efficient set corresponding to portfolio *m*. Even though condition (1) is only subject to the weights of each asset in a portfolio corresponding to an efficient portfolio, the equation can still be viewed in light of the relationship between risk and return of asset *i* in portfolio *m*. For example, the equation shows that the expected return of asset *i* and asset *m* is proportional to the difference in risk between asset *i* and portfolio *m* with the proportionality constant, λ_m, being the slope of the efficient set at the tangency point for a particular portfolio *m*.

Having established the efficiency condition in equation (1), a derivation of the Capital Asset Pricing Model (CAPM) is easily accessible. If we rewrite (1), we get:

$$E(\tilde{R}_i) = [E(\tilde{R}_m) - \lambda_m\sigma(\tilde{R}_m)] + \lambda_m\sigma(\tilde{R}_m)\beta_{i,} \tag{2}$$

where

$$\beta_i \equiv \frac{cov(\tilde{R}_i, \tilde{R}_m)}{\sigma^2(\tilde{R}_m)} = \frac{\sum_{j=1}^{N} x_{jm}\sigma_{ij}}{\sigma^2(\tilde{R}_m)} = \frac{cov(\tilde{R}_i, \tilde{R}_j)/\sigma(\tilde{R}_m)}{\sigma(\tilde{R}_m)} \tag{3}$$

β_i here can be defined as the risk of security *i* in regards to the total risk of the portfolio, $\sigma(\tilde{R}_m)$. Furthermore, the intercept in (2) can be rewritten to:

(4)

$$E(\tilde{R}_0) = E(\tilde{R}_m) - \lambda_m \sigma(\tilde{R}_m).$$

The intercept is equal to the zero-beta security, more commonly known as the risk-free rate. The zero-beta security is the part of the return that is uncorrelated with the portfolio and therefore is a riskless asset in terms of the portfolio *m*. From (4) it then clearly follows that

$$\lambda_m = \frac{E(\tilde{R}_m) - E(\tilde{R}_0)}{\sigma(\tilde{R}_m)}, \tag{5}$$

So that (2) can be rewritten

$$E(\tilde{R}_i) = E(\tilde{R}_0) + [E(\tilde{R}_m) - E(\tilde{R}_0)]\beta_{i,} \tag{6}$$

This risk-return relationship, frequently referred to as the CAPM, shows that security i's expected return is comprised of a riskless component, $E(\tilde{R}_0)$, plus a risk premium that is β_i times the difference between the expected portfolio return and the riskfree rate (this is also known as the market factor or MKT). This relationship has endured extensive empirical testing and is the building block for multi-factor models used extensively in the literature. For example, the Carhart (1997) four-factor model, still lauded as one of the most successful empirical asset-pricing models to date (and used extensively in this paper), can be described as

$$r_{it} - r_{ft} = \beta_1 \underbrace{(R_m - R_f)}_{MKT} + \beta_2 SMB + \beta_3 HML + \beta_4 UMD \tag{7}$$

IV. Data

My data primarily comes from MorningStar's CISDM database (formerly the Mar database)[6] which is the oldest hedge fund database available in the market. The database contains both monthly return and monthly AUM data for 4,634 active funds and 16,211 dead funds from the

[6] Data can be found via a Wharton Research Data Services (WRDS) subscription.

time period between January 1994 and December 2017. These funds are comprised of hedge funds, fund of funds, and commodity trading advisors. In addition to performance data, the database also contains fund characteristics such as domicile, base currency, management fees, performance fees, hurdle rates, high watermarks, and fund styles (general investment strategies). All performance and characteristic data are mapped to corresponding SEC identifiers. Because of the well documented issues with hedge fund databases (e.g. Aiken, Clifford and Ellis (2013) & Fung and Hsieh (2004)), I apply a detailed filtering methodology designed to limit certain database biases. A detailed look at this methodology can be seen in Appendix A.

However, a couple of steps bear mention. First, because my methodology involves using test portfolios drawing from securities located on U.S. exchanges, I attempt to filter my hedge fund sample in a way that captures only those funds that primarily invest in securities located on those exchanges. I therefore filter my funds on base currency, eliminating all funds that don't have United States dollars as their base currency. Furthermore, in an effort to limit incubation bias, I follow the advice of Berk and van Bisbergen (2015) and eliminate funds that don't have $10 million in AUM. The last step that bears mention is subjecting my funds to a 24-month continuous non-missing return restriction. Because I use a two-staged regression approach, any

Figure I: Count of Active Domestic Hedge Funds by Month

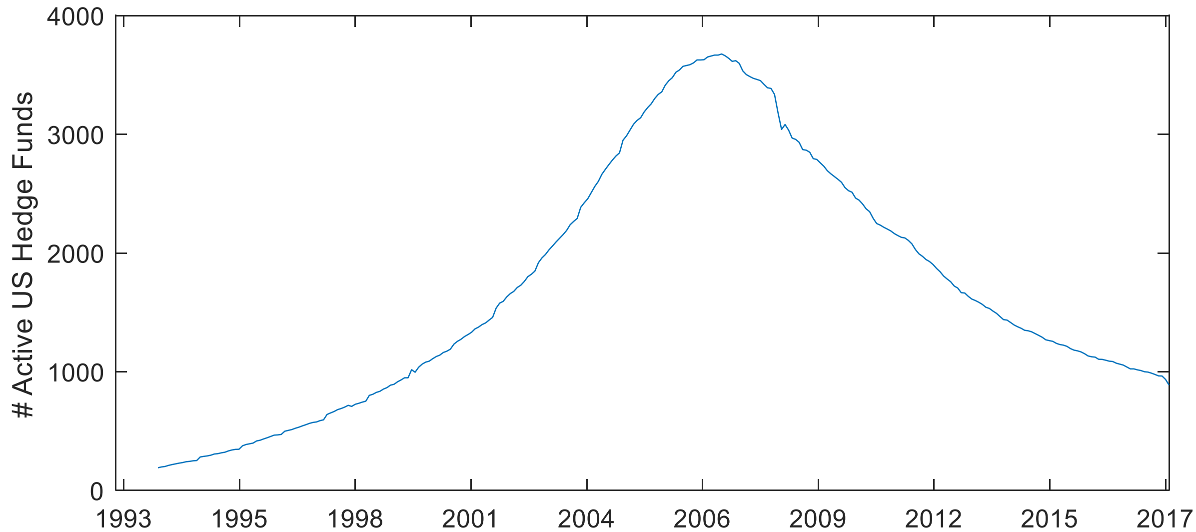

Figure shows total count of hedge funds active and reporting in my sample during my sample period (1994-2017) on a month by month basis.

funds that report less than 24 continuous returns are subject to imprecise estimates of β_{ik} which become problematic when these β_{ik} estimates are used the cross-sectional regressions. This concern over the "variable in errors" problem is further addressed in Section V.

Furthermore, because the CISDM reports all hedge fund returns net of fees, I follow the suggestions of Agarwal, Daniel, and Naik (2009) in converting my net of fee data to gross of fee data. A detailed look at this conversion can be found in Appendix B. This conversion is critical. Without it, I would be unable to differentiate between the reduction to these factor-based strategies' profitability due to trading costs, or due to a more complex combination of trading costs and fees.

Figure I denotes a significant increase in the number of active hedge funds from the database's creation up until 2008. However, after the 2008 financial crisis, there has been a steady decrease in the number of active funds reporting to the database during the last 10 years. However, this result is in contrast to the growth of total assets held by hedge funds over the same

Table 1: United States Hedge Fund Sample Summary Statistics

Table reports summary statistics for my domestic hedge fund sample (1994-2017). The top sub-table provides summaries of the average count of active hedge funds reporting in my sample periods. The next two columns show average AUM across all funds starting at the beginning of the sample period (1994) and ending at the end of the sample period (2017). The next two columns then show related summaries of hedge fund fees that are necessary in the conversion of net-of-fee data to gross-of-fee data. The second sub-table shows average performance data of my hedge fund sample and their correlations. The first two panels show monthly statistics for average returns and volatility and the third column shows annualized Sharpe Ratio (risk-adjusted returns) coefficients. Finally, the last two columns show average pairwise correlations between the hedge funds themselves and the market factor which serves as a proxy for general market conditions.

Unit	Funds #	AUM 1994 Million USD	AUM 2017 Million USD	Incentive Fee	Hurdle Rate
Mean	1,719	59.8	178.1	16.2%	0.4%
Std. Dev.	1,038	120.4	555.9	7.3%	2.5%
25%	947	5.4	15.6	10.0%	0.0%
50%	1,464	17.1	45.0	20.0%	0.0%
75%	2,546	53.3	138.2	20.0%	0.0%

Unit	Mean Return % / Month	Return Volatility % / Month	Sharpe Ratio Annualized	$\bar{\rho}_{HF}$ %	$\bar{\rho}_{Mkt}$ %
Mean	0.93	3.87	0.69	24.39	0.34
Std. Dev.	1.42	3.57	1.21	32.09	0.31
25%	0.42	1.88	0.24	2.80	0.12
50%	0.76	2.89	0.59	24.51	0.39
75%	1.22	4.78	0.96	47.80	0.58

10-year period. This seems to suggest that investors' preferences are changing from smaller hedge funds, to larger, more sophisticated funds (with likely lower trading costs). Table I additionally seems to support this conclusion. The mean AUM for funds in 2017 as reported in column 3, is greater than the 75th percentile of fund's AUM. This suggests a fat right tail in the distribution of assets with large funds continuing to find success in increasing their deployable capital.

Table I further details both performance metrics and average fund characteristics. Interesting to note is column 5 in the bottom table which details that the average pairwise correlation between the market and my hedge fund sample is only ~34%. This drastically differs from the average pairwise correlation found in Patton and Weller (2009) for mutual funds (86.6%) and seems to suggest that hedge funds do give investors low market exposure. However, Patton (2009) documents that many of these seemingly "market-neutral" hedge funds are in reality, significantly non-neutral in their exposure to the market.

Because my analysis involves comparing hedge funds with similar stock portfolios based on certain risk exposures, I augment my hedge fund data with common academic test portfolios. Following the suggestions of Patton and Weller (2017), I include the Fama-French 25 size-value sorted portfolios, 25 size-prior return sorted portfolios, and 25 size-beta sorted portfolios to ensure adequate variation in factor exposures to identify risk premia in the cross section. I then supplement these test assets following the recommendation of Lewellen, Nagel, and Shanken (2010) who find that high R^2 values for tests of these factors on the portfolios mentioned above isn't a particularly high hurdle. I therefore augment my test portfolios with 49 industry portfolios, 25 size-operating profitability portfolios, 25 size-investment portfolios, 10 market capitalization-sorted portfolios, 10 beta-sorted portfolios, 10 book equity to market equity ratio (BE/ME) sorted portfolios, 10 prior-return sorted portfolios, 10 operating profitability-sorted portfolios and 10 investment-sorted portfolios for a total of 234 portfolios. All of these portfolios are readily available through Ken French's website.[7] These 234 portfolios comprise a large set of the investable universe of equities.

I also include in my analysis additional non-equity portfolios and factors knowing that hedge funds have a much greater universe of securities available to them then just equities that trade on U.S. exchanges. Following the recommendations of Fung and Hsieh (2004) I include five additional non-equity risk factors. Three of the risk factors are lookback straddles on currencies,

[7] All equity portfolio data is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

commodities, and bonds (in order to capture risk from trend-following strategies). The last two factors are the change in yield on U.S. 10-year Treasury bond (constant maturity), and the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond (in order to capture risk exposure to changing interest rates).The three lookback straddle factors are available on David Hsieh's website and the two bond factors are accessible from FRED.[8]

I also include test portfolios from other asset classes following the suggestions of He, Kelly, and Manela (2016) that are much more representative of the entire universe of investments available to domestic hedge funds. For U.S. treasury bonds, I use 10 maturity-sorted government bond portfolios provided by Fama and French. For corporate bonds, I use 10 yield spread-sorted portfolios from Nozawa (2014). For other sovereign bonds, I use 6 portfolios from Borri and Verdelhan (2012). For options, I use 18 portfolios of S&P 500 index options sorted on moneyness and maturity from Constantinides, Jackwerth, and Savor (2013). For foreign exchange, I use the 6 interest rate spread-sorted currency portfolios from Lettau, Maggiori, and Weber (2014), and another set of 6 momentum-sorted currency portfolios from Menkhoff, Sarno, Schmeling, and Schrimpf (2012). For commodities, I use the 23 equal-weighted commodity portfolios from He, Kelly, and Manela (2016). Finally, for credit default spreads (CDS), I also use the 20 spread-sorted portfolios from He, Kelly and Manela (2016). This gives me a total of 99 test portfolios for non-equity asset classes (all aggregated and available on Asaf Manela's website)[9] and a total of 333 potential test portfolios that range across all asset classes.

V. Empirical Methodology

[8] Three trend-following factors available at https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm
[9] These additional portfolios are available at http://apps.olin.wustl.edu/faculty/manela/data.html

Under the general multi-factor framework of equation (7), we can use the Fama-MacBeth two-staged regression approach to measure the returns to these factors. I consider, with cross sectional regressions, how the compensation per factor differ between representative factor stock portfolios on-paper and the returns hedge funds realize in practice. In my estimates, I assume that hedge funds have constant per-unit cost in their implementation of factor investing. Investing in a market index ($\beta_{Mkt} = 1$ by default) for example, results in a performance gap relative to the on-paper performance of the market index. Therefore, the investor would earn some fraction $\varphi\beta_{Mkt}$ where $\varphi < 1$ with implementation cost = $(1 - \varphi)\beta_{Mkt}$.

The familiar asset-pricing Fama-MacBeth procedure can be divided into two parts. First, time-series regressions are run in order to find stock and fund exposure to different risk factors (as denoted by my factors f_{kt}). These risk-measuring coefficients, β_{ik} (factor loadings), are then regressed on the cross-section of common stock portfolios and hedge fund returns in order to find the incremental compensation per unit of factor (risk) exposure. The difference between the incremental compensation per risk exposure on the stock portfolios (on-paper compensation) and the hedge fund returns (realized compensation) therefore give estimates of the trading costs associated with trading these risk factors (factor investing).

More concretely, the first-stage Fama-MacBeth regression is a standard time series regression of excess returns on the series of factors described in Section I. For those excess returns, I have $N_s = 75$ and $N_s = 234$ stock portfolios (depending on the regression specification) that proxy for the investable universe of equity securities. I then augment these test portfolios with $N_{HF} = 4{,}996$ hedge fund return series for a total return matrix of $N_{total} = 5{,}071$ or $N_{total} = 5{,}230$ depending on the specifications. Regressions of my asset-pricing factors on these N_{total} excess returns therefore yields my factor loadings, β_{ik}, that will be used in my second-stage regression. Due to the well diversified portfolios that hedge funds hold, fund betas give much more precise estimates than betas of individual stocks (because most idiosyncratic risk has been diversified away in a well-balanced portfolio) and therefore I do not need to apply any kind of characteristic sorting portfolio procedure that is common when using this methodology for individual stocks. Formally, the $N_s + N_{HF}$ time series regressions are

$$r_{it} = \alpha_i + \sum_k f_{kt}\beta_{ik} + \varepsilon_{it}, \quad \forall i, \ldots, N_s + N_{HF} \tag{8}$$

where r_{it} is the month t gross return on either a stock portfolio or hedge fund i, net of the contemporaneous risk-free rate and where $f_{kt}\ \forall\ k = 1, \ldots, K$. Equation (8) is identical to equation (7) except that it is expressed in a generalizable notation. β_{ik} contains the same economic meaning as expressed in Sharpe (1992). It is simply the risk exposure (or loading) that a certain fund has to one of the risk factors.

The second stage regressions are cross sectional in scope and attempt to measure the incremental compensation required for a unit increase in risk exposure. It can be formalized as

$$r_{it} = \sum_k \lambda_{kt}^{S}\beta_{ik}1_{i\in S} + \sum_k \lambda_{kt}^{HF}\beta_{ik}1_{i\in HF} + \varepsilon_{it}, \quad t = 1, \ldots, T. \tag{9}$$

λ_{kt}^{S} is the realized price of risk factor k at time t based on test portfolio returns, while λ_{kt}^{HF} is the same estimate except for hedge fund returns. The difference, $\lambda_{kt}^{\Delta} \equiv \lambda_{kt}^{S} - \lambda_{kt}^{HF}$, is therefore my estimate of implementation costs of a certain factor strategy. This difference should theoretically capture very real trading costs such as bid-ask spreads, commissions, slippage, and market impact. However, it should also capture less tangible measures such as investing in more liquid measures of each factor in order to ensure against redemptions and “rushes” on capital. My estimates for average trading costs faced by hedge funds are then just the averages of the monthly differences in factor compensation $\overline{\lambda_k^{\Delta}}$.

One important feature of my second stage regression is the suppression of the constant. I follow the suggestions of both Lettau, Maggiori, and Weber (2014) and Patton and Weller (2017) to follow this step because the constant and the market risk factor are otherwise indistinguishable. Similarly to Patton and Weller (2017), I find for my time period sample that the cross-sectional compensation for the market, λ_{Mkt}^{S}, and my constant terms cross-sectional compensation, λ_{α}^{S}, are of similar magnitude and strongly negatively correlated[10] which supports this conclusion. Other factors are not meaningfully affected by the inclusion of a constant. Economically, this suppression forces the zero-beta (risk-free) security or hedge fund with the risk factors used to have no excess return.

The methodology used has one major assumption that needs to be addressed. By assuming that risk exposures are constant through my 24-year window, I impose stationarity on my betas. The primary motivation for this is in order to minimize the errors in variable problem that is common in two-staged regressions. This issue arises when betas in the first stage regressions are measured imprecisely, giving forth to noisy betas that are then used in the second-stage regression. This leads to wildly inaccurate λ_{kt} estimates. Therefore, to dampen this effect, I maximize the potential time period used in my regression (a maximum of 288 monthly returns and a minimum of 24 monthly returns) in order to measure betas as precisely as possible. However, the major limitation of this is that my regression now takes on measurement error arising from time-variation in risk exposures.

[10] I find that correlations between the cross-sectional slopes of the constant and market are as high as .7 in my analyses.

VI. Fama-MacBeth Estimates of Trading Costs

The empirical results detailed below apply the Fama-MacBeth procedure (Equations (8) and (9)) to my hedge fund sample and various test portfolios. Part A details the implementation gap between my test portfolios and my unadjusted hedge fund returns. Next, following suggestions from the literature revolving around the smoothing of hedge fund returns (Asness, Krail & Liew, 2001; Getmansky, Lo, & Makarov, 2003; etc.), Part B then applies Equations (8) and (9) my various test portfolios and ARMA(1,1) adjusted and unsmoothed hedge fund returns. In order to avoid "p-hacking" and model over-fit, I include in Part C two-staged regressions for my test portfolios and ARMA(3,3) adjusted hedge fund returns. As a robustness check, Part D details the Fama-MacBeth methodology applied to ARMA(1,1) adjusted stock portfolio returns and hedge fund returns. Section E checks for omitted factor trading strategies augmented by a plethora of multi-asset class data to tease out non-equity biases. Section F than draws a comparison between my findings and those currently found in the literature.

A. Baseline Estimates

Table II presents results from Equation (9) for my unadjusted hedge fund returns and various test portfolios on a value-weighted and equal-weighted basis. λ^{Δ} in panel (3) of my tables shows that hedge funds seemingly don't incur trading costs on many of these academic anomalies. Intuitively, λ^{HF}, or the compensation that hedge funds earn per factor exposure, is greater than that earned on the stock portfolios λ^{S} for all factors besides the value factor. For the value factor, average implementation gap ranges between 2.71% and 3.83% and are largely significant. These results are robust regardless of which weighting strategy is used for the test portfolios.

Table II: Fama-MacBeth Estimates of Implementation Costs – Baseline Specifications

Table reports implementation costs for Fama-MacBeth estimates as the difference of average cross-sectional compensation per factor exposure for value-weighted and equal-weighted stock portfolios, λ^S (top panel), and US based hedge funds, λ^{HF}(second panel). This difference $\lambda^S - \lambda^{HF} = \lambda^\Delta$ is represented in the third (bottom) panel. This cross-sectional compensation is averaged across all funds, $\bar{\lambda}_k$, and is found by monthly regressions of excess returns r_{it} on fund by fund time series betas $\hat{\beta}_{ik}$,

$$r_{it} = \sum_k \lambda_{kt}^S \hat{\beta}_{ik} 1_{i \in S} + \sum_k \lambda_{kt}^{HF} \hat{\beta}_{ik} 1_{i \in HF} + \varepsilon_{it}, \quad t = 1, \ldots, T.$$

where k indexes to one of the four factors used extensively in the literature (e.g. Fama French (1992) & Carhart (1997)). Again, λ^Δ represents the trading costs faced by the typical hedge fund during implementation of a factor strategy. All coefficients are reported in percent and annualized. T represents the number of monthly time periods in the sample and $\bar{N}_{HF}$ represents the average number of hedge funds active and reporting during the sample. All t-statistics are in parentheses.

(a) Value-Weighted Stock Portfolios

			1994 - 2017		
	N_S	*MKT*	*SMB*	*HML*	*UMD*
λ^S	75	8.18***	1.42	4.98**	5.93*
t-stat		(2.66)	(0.59)	(2.07)	(1.65)
λ^S	234	8.56***	0.68	3.87	6.67*
t-stat		(2.81)	(0.28)	(1.55)	(1.85)
λ^{HF}	75	11.80***	7.73***	1.14	9.08*
t-stat		(3.60)	(2.78)	(0.42)	(1.84)
λ^{HF}	234	11.82***	7.62***	1.17	8.97*
t-stat		(3.60)	(2.73)	(0.43)	(1.82)
λ^Δ	75	-3.62***	-6.31***	3.83**	-3.15
t-stat		-(2.92)	-(4.55)	(2.49)	-(0.88)
λ^Δ	234	-3.26***	-6.94***	2.71*	-2.30
t-stat		-(2.63)	-(5.14)	(1.65)	-(0.65)
T	288	288	288	288	288
$\bar{N}_{HF}$	1715	1715	1715	1715	1715

**p < .10, ** p < .05, ***p < .01*

(b) Equal-Weighted Stock Portfolios

			1994 - 2017		
	N_S	*MKT*	*SMB*	*HML*	*UMD*
λ^S	75	8.20***	3.61	5.27**	5.44
t-stat		(2.61)	(1.37)	(2.16)	(1.50)
λ^S	234	9.30***	3.43	3.83	7.60**
t-stat		(2.96)	(1.26)	(1.51)	(2.05)
λ^{HF}	75	11.91***	7.54***	1.12	9.30*
t-stat		(3.63)	(2.70)	(0.41)	(1.88)
λ^{HF}	234	11.91***	7.57***	1.13	9.31*
t-stat		(3.63)	(2.72)	(0.42)	(1.87)
λ^Δ	75	-3.71***	-3.93**	4.15***	-3.86
t-stat		-(2.67)	-(2.32)	(2.65)	-(1.06)
λ^Δ	234	-2.61*	-4.14**	2.70	-1.70
t-stat		-(1.79)	-(2.43)	(1.61)	-(0.46)
T	288	288	288	288	288
$\bar{N}_{HF}$	1715	1715	1715	1715	1715

**p < .10, ** p < .05, ***p < .01*

However, what are the other three factor's compensation telling us? How are hedge funds generating more compensation per risk factor than the gross of transaction cost stock portfolios? There are largely two plausible explanations for this phenomenon.

First, based off the current literature, hedge funds smooth returns, therefore downwardly revising their risk exposures which in turn artificially raises their compensation on these risk factors. This phenomenon is further explored in great depth in Parts B-E of my results.

The second plausible explanation is that the sample of test portfolios isn't truly representative of the assets hedge funds invest in, and therefore all of risk factors, that hedge funds are exposed to. This result seems entirely feasible. Hedge funds clearly invest in a greater investable universe than just domestic equities. Therefore, many risk exposures inherent in other asset classes are therefore being captured in my λ^{HF} estimates, further biasing upwards my results. These concerns are addressed in Part E. Most likely, a combination of both of these phenomena are significantly affecting my baseline results here.

B. ARMA(1,1) Adjusted Hedge Fund Return Estimates

Hedge funds smoothing their reported returns is not novel. Asness, Krail, and Liew (2001) were the first to empirically show that at first glance, traditional factor models (specifically regressions of hedge fund returns against a market proxy such as the S&P 500) did a poor job at explaining the returns posted by hedge funds and therefore showed little correlation between the market and hedge fund returns (strong market neutrality). However, they then show that these results are largely misleading. If they also included lagged market factors in their model, then hedge fund returns showed serious correlations with the market. These results were largely confirmed by Patton (2009) who shows that market-neutral hedge funds often understate there true market neutrality. Asness, Krail, and Liew (2001) hypothesized that non-synchronous trading was a plausible explanation for why hedge fund returns were so positively correlated with the market after lagged terms were included. Non-synchronous trading is simply the concept that certain securities are not marked-to-market daily, and therefore hedge fund managers are able to either extrapolate prices for these illiquid securities or use the last available price which could significantly differ from the true value of the asset.

These results were formalized in Getmansky, Lo, and Markarov (2004) (referred to as GLM from now on). GLM wrestle with the question of serial correlation in hedge fund returns. Often labeled the best and the brightest in the industry, hedge fund managers, as predicated by market efficiency, shouldn't allow serial correlations to exist amongst there returns. If hedge fund managers knew of serial correlation in their returns, then they would alter their behavior because any other behavior would mean leaving potential profit on the table. For intuition purposes, if a hedge fund manager knew a priori, that good returns today would mean good returns tomorrow, then in good months, managers would load more heavily on risk exposures so that they could experience positive returns in the next period as well. Serial autocorrelation in returns therefore violates market efficiency. GLM discuss many potential explanations for this autocorrelation but find that the point estimates generated from many of these explanations are either not strong enough to explain the trend seen in the data or are of the wrong sign.

The two explanations shown by GLM to adequately explain performance smoothing are non-synchronous trading and intentional performance smoothing. The first, non-synchronous trading, forces managers to take their best guesses as to what the value is of their illiquid assets that have stale prices. The second explanation posited, though ineloquent, is that managers purposely "massage" the returns of their assets in order to present their funds in a more favorable light.

This “performance smoothing” is rather distasteful, but Chandar and Brickar (2002) find that certain closed-end mutual funds use some accounting leniencies to smooth returns around different benchmarks. Therefore, given the relatively unregulated environment that hedge funds operate in, this explanation must be considered.

While remaining agnostic to reasons behind return smoothing, GLM formalize this idea as presented below in Equation (10)

$$r_t^{obs} = \theta_0 r_t^{true} + \theta_1 r_{t-1}^{true} + \theta_2 r_{t-2}^{true} + \cdots + \theta_p r_{t-p}^{true} \quad where \sum_0^p \theta_p = 1 \tag{10}$$

where r_t^{obs} is the observed return one would see in the database while r_t^{true} is the true return biased by some smoothing coefficient θ_0. Because hedge funds aren’t able to generate returns out of thin air, $\sum_0^p \theta_p$ must equal 1. A simple two period model then could be represented as

$$r_t^{obs} = \theta r_t^{true} + (1-\theta) r_{t-1}^{true}$$

Therefore, when these returns are used in the first stage of the Fama-MacBeth procedure,

$$cov\left(r_t^{obs}, f_{kt}\right) \neq cov(r_t^{true}, f_{kt})$$

In fact, assuming that $cov(f_t, f_{t-1}) = 0$,[11] my time series B_{ik} are biased downwards by a factor of θ where $\theta < 1$. Therefore, in reality, instead of using β_{ik}^{true} I am instead using $\theta_i \beta_{ik}$ in my estimates of equation (9) found in Table II which leads to inflated estimates of λ^{HF}.[12]

[11] This turns out to not be a bad assumption. Durand, Lim, and Zumwalt (2011), using the Ljung-Box Q statistic to test for autocorrelation, fail to reject the null that there is no autocorrelation for the market factor. While they do reject the null for the other three Carhart (1997) factors, the point estimates are sufficiently small as to not significantly change the form of the equations above. I confirm these results by plotting ACFs for my factors and find small point estimates for the average autocorrelations.

[12] The math can be further explored in either Getmansky, Lo, Markarov (2004) or Huang, Liechty, Rossi (2018).

The simplest way to unsmooth these hedge fund returns is to invert an auto-regressive moving average model (ARMA). This method is used in the literature to recover r^{true} (Li, Xu, & Zhang, 2016). The basic intuition of the ARMA model in this context is that the autoregressive component helps pick up the effects of nonsynchronous trading while the moving average component helps pick up the effects of other performance smoothing behaviors. A general representation of an ARMA(p,q) model is presented below

$$r_t = \emptyset r_{t-1} + \emptyset r_{t-2} + \cdots + \emptyset x_{r-p} + \varepsilon_t + \theta\varepsilon_{t-1} + \theta\varepsilon_{t-2} + \cdots + \theta\varepsilon_{t-q} \quad (11)$$

By inverting this model (solving for ε_t), I am able to recover the fundamental innovations, or shocks, to hedge fund returns and therefore generate a much better estimate of r^{true}.

Before jumping in to my ARMA adjusted results,[13] I need to address two first-order concerns when working with ARMA models: stationarity and varying time-series variances. I assume stationarity in my hedge fund returns. This is generally a safe assumption when working with return data because returns by definition are calculated as $\frac{r_t}{r_{t-1}} - 1$ and this division by a lagged return factor effectively keep returns safely bounded. Further, when estimating an ARMA model for fund i, I assume constant variance. A more robust approach to this would be to generate a maximum likelihood estimator using my entire hedge fund sample set to infer time varying variances. However, this is outside the scope of this paper and will be left to future research.

Table III therefore reports my results from equation (9) with my various stock portfolios and my ARMA(1,1) adjusted hedge fund returns. The recovered innovations and corresponding λ^{HF}'s of my hedge fund return sample now looks significantly more plausible. Hedge funds on average face trading costs between 1.0% and 1.5% depending on the test portfolios selected for

[13] By ARMA adjusted results, I am referring to the process in equation (11) where I invert an ARMA process in order to recover the fundament shocks to my hedge fund return series.

Table III: Fama-MacBeth Estimates of Implementation Costs – ARMA(1,1) Specification

Table reports implementation costs for Fama-MacBeth estimates as the difference of average cross-sectional compensation per factor exposure for stock portfolios, λ^S (top panel), and ARMA(1,1) adjusted domestic hedge funds, λ^{HF}(second panel). This difference, $\lambda^S - \lambda^{HF} = \lambda^{\Delta}$, is represented in the third (bottom) panel. This cross-sectional compensation is averaged across all funds, $\bar{\lambda}_k$, and is found by monthly regressions of excess returns r_{it} on fund by fund time series betas $\hat{\beta}_{ik}$,

$$r_{it} = \sum_k \lambda_{kt}^S \hat{\beta}_{ik} 1_{i \in S} + \sum_k \lambda_{kt}^{HF} \hat{\beta}_{ik} 1_{i \in HF} + \varepsilon_{it}, \quad t = 1, \dots, T.$$

where k indexes to one of the four factors used extensively in the literature (e.g. Fama French (1992) & Carhart (1997)). Again, λ^{Δ} represents the trading costs faced by the typical hedge fund during implementation of a factor strategy. All coefficients are reported in percent and annualized. T represents the number of monthly time periods in the sample and $\bar{N}_{HF}$ represents the average number of hedge funds active and reporting during the sample. All t-statistics are in parentheses.

(a) Value-Weighted Stock Portfolios

			1994 - 2017		
	N_S	*MKT*	*SMB*	*HML*	*UMD*
λ^S	75	8.18***	1.42	4.98**	5.93*
t-stat		(2.66)	(0.59)	(2.07)	(1.65)
λ^S	234	8.56***	0.68	3.87	6.67*
t-stat		(2.81)	(0.28)	(1.55)	(1.85)
λ^{HF}	75	7.12**	2.86	1.32	5.10
t-stat		(2.16)	(1.03)	(0.51)	(1.04)
λ^{HF}	234	7.12**	2.85	1.32	5.10
t-stat		(2.16)	(1.02)	(0.51)	(1.05)
λ^{Δ}	75	1.06	-1.44	3.66***	0.83
t-stat		(0.85)	-(0.95)	(2.58)	(0.23)
λ^{Δ}	234	1.44	-2.17	2.56*	1.57
t-stat		(1.15)	-(1.48)	(1.66)	(0.44)
T	288	288	288	288	288
$\bar{N}_{HF}$	1715	1715	1715	1715	1715

$*p < .10$, $** p < .05$, $***p < .01$

(b) Equal-Weighted Stock Portfolios

			1994 - 2017		
	N_S	*MKT*	*SMB*	*HML*	*UMD*
λ^S	75	8.20***	3.61	5.27**	5.44
t-stat		(2.61)	(1.37)	(2.16)	(1.50)
λ^S	234	9.30***	3.43	3.83	7.60**
t-stat		(2.96)	(1.26)	(1.51)	(2.05)
λ^{HF}	75	7.19**	2.78	1.29	4.97*
t-stat		(2.18)	(1.00)	(0.50)	(1.01)
λ^{HF}	234	7.17**	2.76	1.31	5.09*
t-stat		(2.17)	(1.00)	(0.51)	(1.03)
λ^{Δ}	75	1.01	0.83	3.98***	0.46
t-stat		(0.74)	(0.44)	(2.75)	(0.13)
λ^{Δ}	234	2.12	0.67	2.51	2.52
t-stat		(1.49)	(0.35)	(1.56)	(0.68)
T	288	288	288	288	288
$\bar{N}_{HF}$	1715	1715	1715	1715	1715

$*p < .10$, $** p < .05$, $***p < .01$

the market factor. These point estimates are not statistically significant nor economically significant. It is unsurprising that hedge funds are relatively good at implementing the widely used market factor.

Interestingly, hedge funds still earn some premia above and beyond the value-weighted portfolios, and close to that of the equal-weighted portfolios for the size (SMB) factor. The equal-weighted stock portfolios earn more compensation per size factor than do the value-weighted portfolios because of the increased significance put on smaller companies during the equal-weighted portfolios construction. The fact that hedge funds earn compensation similar to that of the equal-weighted portfolios shows that they are increasingly adept at managing liquidity risks (the SMB factor is often thought about as a type of liquidity risk). This conclusion is supported in the hedge fund literature with Sadka (2010) finding that funds that load on liquidity risk earn about 6.0% more than funds with low loadings on this risk factor. This work confirms Sadka (2010)'s conclusion that hedge funds implement liquidity risk well. Hedge funds only show implementation costs between 0.7% and 0.8% for the size factor for the equal-weighted test portfolios.

Column 3 of my table shows that hedge funds, similar to the baseline specification, earn very low compensation on the value factor. Trading costs erode between 2.6% and 3.7% of its returns depending on the test portfolios selected. This results in hedge fund's compensation for value to have low point estimates that are statistically insignificant from zero. This result is particularly surprising given the large amount of funds that have a value bent. These point estimates are about 1.0% lower than what Patton and Weller (2017) find in their results for mutual funds. One potential explanation for these low point estimates could be due the over-abundance of value funds chasing the same few trades, and therefore seeing significant realized performance attrition due to adverse price impacts. However, while plausible, this explanation is outside the scope of the results I present. Another explanation given by Frazzini, Israel, and Moskowitz (2015) is that much of the value premia lies in microcap companies that hedge funds aren't able to adequately invest in. Regardless of the explanation, I find that the typical hedge fund does not earn significant premia on the value factor when facing real-world trading costs.

The final column of Table III shows the compensation earned on the momentum factor. Similar to the size factor, hedge funds appear to be good at implementing momentum. Because momentum has particularly high turnover, this strategy tends to incur higher trading costs than the other factors. Lesmond, Schill, and Zhou (2004), for example, find that momentum strategies have difficulty achieving robust profitably in the wake of the trading costs they incur. The results in Table III however, suggest that hedge funds actually are quite proficient at implementing the momentum factor and earn compensation of ~5.0%.[14] Additionally, the trading costs faced by hedge funds implementing this strategy appear to be low (0.8% and 1.6% depending on the set of value-weighted portfolios used).[15]

C. ARMA(3,3) Adjusted Hedge Fund Return Estimates

Table IV reports the results from equation (9) with ARMA(3,3) adjusted hedge fund returns. This model serves as a further robustness check of my results presented in Part B above. I use three-month lags for both my autoregressive component and my moving average component in order to fully capture the potential performance smoothing biases that occur in my sample. Intuitively, it does not make sense to use a model that moves beyond three-month lags because hedge funds are (1) forced to reveal their quarterly holdings via SEC regulation 13-f, and (2)

[14] The fact that momentum's compensation is a relatively large point estimate and yet not statistically different from zero (small t-statistic) is explained by the relatively low dispersion of momentum betas in the time series first-stage regression step.
[15] All results are robust to the choice of outlier threshold factor (3,5,10) used in my analysis.

Table IV: Fama-MacBeth Estimates of Implementation Costs – ARMA(3,3) Specifications

Table reports implementation costs for Fama-MacBeth estimates as the difference of average cross-sectional compensation per factor exposure for stock portfolios, λ^S (top panel), and ARMA(3,3) adjusted domestic hedge funds, λ^{HF}(second panel). This difference, $\lambda^S - \lambda^{HF} = \lambda^\Delta$, is represented in the third (bottom) panel. This cross-sectional compensation is averaged across all funds, $\bar{\lambda}_k$, and is found by monthly regressions of excess returns r_{it} on fund by fund time series betas $\hat{\beta}_{ik}$,

$$r_{it} = \sum_k \lambda_{kt}^S \hat{\beta}_{ik} 1_{i\in S} + \sum_k \lambda_{kt}^{HF} \hat{\beta}_{ik} 1_{i\in HF} + \varepsilon_{it}, \quad t = 1, \dots, T.$$

where k indexes to one of the four factors used extensively in the literature (e.g. Fama French (1992) & Carhart (1997)). Again, λ^Δ represents the trading costs faced by the typical hedge fund during implementation of a factor strategy. All coefficients are reported in percent and annualized. T represents the number of monthly time periods in the sample and $\bar{N}_{HF}$ represents the average number of hedge funds active and reporting during the sample. All t-statistics are in parentheses.

(a) Value-Weighted Stock Portfolios

			1994 - 2017		
	N_S	*MKT*	*SMB*	*HML*	*UMD*
λ^S	75	8.18***	1.42	4.98**	5.93*
t-stat		(2.66)	(0.59)	(2.07)	(1.65)
λ^S	234	8.56***	0.68	3.87	6.67*
t-stat		(2.81)	(0.28)	(1.55)	(1.85)
λ^{HF}	75	6.39*	0.98	-1.38	4.27
t-stat		(1.95)	(0.35)	-(0.53)	(0.88)
λ^{HF}	234	6.41*	0.94	-1.39	4.33
t-stat		(1.95)	(0.34)	-(0.53)	(0.90)
λ^Δ	75	1.79	0.44	6.36***	1.66
t-stat		(1.43)	(0.30)	(4.47)	(0.47)
λ^Δ	234	2.15*	-0.26	5.26***	2.34
t-stat		(1.71)	-(0.18)	(3.43)	(0.68)
T	288	288	288	288	288
$\bar{N}_{HF}$	1702	1702	1702	1702	1702

**p < .10, ** p < .05, ***p < .01*

(b) Equal-Weighted Stock Portfolios

			1994 - 2017		
	N_S	*MKT*	*SMB*	*HML*	*UMD*
λ^S	75	8.20***	3.61	5.27**	5.44
t-stat		(2.61)	(1.37)	(2.16)	(1.50)
λ^S	234	9.30***	3.43	3.83	7.60**
t-stat		(2.96)	(1.26)	(1.51)	(2.05)
λ^{HF}	75	6.48**	0.86	-1.43	4.16
t-stat		(1.97)	(0.31)	-(0.55)	(0.85)
λ^{HF}	234	6.45**	0.87	-1.39	4.29
t-stat		(1.96)	(0.31)	-(0.54)	(0.87)
λ^Δ	75	1.72	2.75	6.70***	1.28
t-stat		(1.25)	(1.48)	(4.63)	(0.36)
λ^Δ	234	2.85**	2.56	5.22***	3.31
t-stat		(1.99)	(1.36)	(3.26)	(0.91)
T	288	288	288	288	288
$\bar{N}_{HF}$	1702	1702	1702	1702	1702

**p < .10, ** p < .05, ***p < .01*

because most hedge funds issue quarterly reports to their investors and therefore publicly reveal there performance. These strong incentives (and accountability) to report returns in a consistent manner therefore strongly dampen the effect of potential performance smoothing beyond this quarterly window.[16]

The results reported in Table IV confirm much of what was reported in Table III. Across all factors, λ^{HF} is further attenuated. This can perhaps be attributed to a slight over-fitting of the model. The value factor again sees the worse attrition with its cross-sectional compensation for my hedge fund sample showing a negative point estimate and massive trading costs (5.3%-6.4% depending on the value-weighted stock portfolios chosen). Hedge funds see slight attrition of their momentum strategies, but the implementation costs of momentum are still lower (between 1.7%-2.3%) than that which is typically found in the literature. Finally, the cross-sectional compensation for the size factor is also attenuated by about 2% for my hedge funds. The economic significance of this attenuation is that the size factor likely loads on the most illiquid holdings of these hedge funds' portfolios and therefore the most likely to face non-synchronous trading effects that are captured by the additional lags.

D. ARMA(1,1) Adjusted Stock and Hedge Fund Return Estimates

Table V shows my estimates from equation (9) for which I apply my ARMA inversion step to my stock portfolios as well as well as to my hedge fund returns. While lacking economic intuition, by recovering the fundamental innovations on my stock portfolios, I have the added benefit of being able to compare like-to-like as a further robustness check to my model. Table V shows attenuation in the compensation earned by my stock portfolios across all factors.

[16] Furthermore, it is increasingly difficult to estimate a model precisely with more than six parameters for the limited time series monthly observations ($T = 288$) that I have available to me.

Table V: Fama-MacBeth Estimates of Implementation Costs – Total ARMA(1,1) Specifications

Table reports implementation costs for Fama-MacBeth estimates as the difference of average cross-sectional compensation per factor exposure for ARMA(1,1) adjusted stock portfolios, λ^S (top panel), and ARMA(1,1) adjusted domestic hedge funds, λ^{HF}(second panel). This difference, $\lambda^S - \lambda^{HF} = \lambda^\Delta$, is represented in the third (bottom) panel. This cross-sectional compensation is averaged across all funds, $\bar{\lambda}_k$, and is found by monthly regressions of excess returns r_{it} on fund by fund time series betas $\hat{\beta}_{ik}$,

$$r_{it} = \sum_k \lambda_{kt}^S \hat{\beta}_{ik} 1_{i \in S} + \sum_k \lambda_{kt}^{HF} \hat{\beta}_{ik} 1_{i \in HF} + \varepsilon_{it}, \quad t = 1, \dots, T.$$

where k indexes to one of the four factors used extensively in the literature (e.g. Fama French (1992) & Carhart (1997)). Again, λ^Δ represents the trading costs faced by the typical hedge fund during implementation of a factor strategy. All coefficients are reported in percent and annualized. T represents the number of monthly time periods in the sample and $\bar{N}_{HF}$ represents the average number of hedge funds active and reporting during the sample. All t-statistics are in parentheses.

(a) Value-Weighted Stock Portfolios

			1994 - 2017		
	N_S	*MKT*	*SMB*	*HML*	*UMD*
λ^S	75	5.29*	3.21	3.92	2.59
t-stat		(1.71)	(1.33)	(1.60)	(0.71)
λ^S	234	5.54*	2.40	4.86*	3.63
t-stat		(1.81)	(1.00)	(1.92)	(0.98)
λ^{HF}	75	7.04**	2.98	1.33	4.90
t-stat		(2.13)	(1.08)	(0.51)	(1.00)
λ^{HF}	234	7.08**	2.87	1.34	4.94
t-stat		(2.14)	(1.03)	(0.51)	(1.01)
λ^Δ	75	-1.74	0.23	2.59*	-2.30
t-stat		-(1.40)	(0.15)	(1.79)	-(0.63)
λ^Δ	234	-1.54	-0.47	3.52**	-1.31
t-stat		-(1.24)	-(0.33)	(2.32)	-(0.36)
T	288	288	288	288	288
$\bar{N}_{HF}$	1715	1715	1715	1715	1715

**p* < .10, ** *p* < .05, ****p* < .01

(b) Equal-Weighted Stock Portfolios

			1994 - 2017		
	N_S	*MKT*	*SMB*	*HML*	*UMD*
λ^S	75	6.69**	2.97	3.89	3.13
t-stat		(2.12)	(1.14)	(1.54)	(0.84)
λ^S	234	7.42**	2.68	2.61	4.65
t-stat		(2.35)	(1.01)	(1.02)	(1.22)
λ^{HF}	75	7.17**	2.79	1.29	5.02
t-stat		(2.17)	(1.00)	(0.50)	(1.02)
λ^{HF}	234	7.16**	2.78	1.31	5.10
t-stat		(2.17)	(1.00)	(0.51)	(1.03)
λ^Δ	75	-0.48	0.18	2.60*	-1.89
t-stat		-(0.36)	(0.10)	(1.69)	-(0.51)
λ^Δ	234	0.26	-0.10	1.30	-0.45
t-stat		(0.18)	-(0.06)	(0.80)	-(0.12)
T	288	288	288	288	288
$\bar{N}_{HF}$	1715	1715	1715	1715	1715

**p* < .10, ** *p* < .05, ****p* < .01

However, the one factor that isn't able to clear this lowered hurdle is again the value factor. Even with the compensation earned by HML lower on three of the four sample stock portfolios, λ_{HML}^{HF} still faces implementation costs between 2.6% and 3.5% that significantly affect its efficacy as a profitable trading strategy.

The cross-sectional compensations for my stock portfolios that see the largest attenuation include the market and momentum factors. Because momentum is constructed based on returns of past winners, it is unsurprising that it sees attrition after an autoregressive component is included in the model. With these lowered hurdles for the compensation earned by hedge funds, all λ^{HF}'s besides λ_{HML}^{HF} survive trading costs and show positive signs of real-world efficacy.

E. Do Omitted Factor Trading Strategies and Asset Classes Explain Low Trading Costs?

I have only considered up to this point equity-based factors for explaining the cross section of returns for hedge funds. However, hedge funds have access to many different asset classes and therefore also have exposure to many different risk factors in addition to the four factors as presented in my analysis so far. In order to account for these two issues, I augment my test portfolios with 99 additional non-equity portfolios[17] in order to adequately capture non-equity risk factor loadings. I also augment Carhart (1997)'s four factor model with an additional five non-equity factors that have been shown to explain (when also coupled with the market and size factors) up to 56% of the time series variation in hedge fund *index* returns. Although these Fung and Hsieh (2004) factors were originally constructed to explain time series variation, and not cross-sectional variation of hedge fund returns, I follow Sadka (2010) and use them as risk controls.

[17] Mentioned in detail in Section IV of this paper.

An explanation of the five additional factors are as follows. In order to capture common risk components for fixed-income funds, I use Fung and Hsieh's bond market factor (Bond_MKT) that measures the monthly change in the 10-year treasury (held with constant maturity) and the credit spread factor (Credit_Spread) which measures the changes in Moody's Baa bonds less the changes in the constant maturity 10-year treasury yield. Because the strategies hedge funds employ in the fixed income markets often revolve around these instruments' interest rates, fixed-income funds' risk exposures can be well modeled by their interest rate exposure captured by these two factors. Fung and Hsieh (2004) show these two factors explain a majority of the variation in fixed-income funds because these hedge funds typically buy bonds that have lower credit ratings (typically less liquid off-the-run treasury securities) and sell bonds (short) that have higher credit ratings (typically more liquid on-the-run treasury securities). Because these trades often revolve around profiting on tight spreads, leverage is frequently employed to amplify returns.[18] The cost of financing these trades then depends on the overall liquidity of the credit markets, and therefore is reflected by the credit spread factor (during times of illiquidity, this factor will be high as investors prioritize safe assets while during times of ample liquidity, this spread will be much lower). Therefore, both the way and nature in which these bets are placed are capture by my two factors.

The other three factors used by Fung and Hsieh (2004) attempt to explain the variation in trend-following strategies. These strategies typically revolve around identifying a trend in the price of a security and then "riding the tide" as the trend continues to play out. Interestingly, Fung and Hsieh (1997b) show that these strategies typically perform most successfully during the best and worse months for the world equity markets (typically when markets were the most

[18] See Roger Lowenstein's *When Genius Fails* for an example of this trading strategy.

volatile). They additionally show that the returns of these trend-following funds are typically nonlinear in nature. Fung and Hsieh (2001) therefore shows that the returns from these trend-following funds can be empirically modeled successfully using look-back straddles for bonds (PTFSD), foreign exchange (PTFSFX), and commodities (PTFSCOM). A straddle is a type of options strategy that buys call and put options at the same strike price, hoping to profit off of volatile moves in the underlying asset's price. The lookback feature is an exotic derivative provision that allows an option holder to "lookback" and earn compensation for the highest and lowest levels achieved by the underlying asset's price. These lookback straddle factors therefore dynamically capture the non-linear relationship between risk and return for these trend-following funds as well as these fund's reliance on market volatility to make money.

Table VI and VII show the results of equation (9) when applied to my full test portfolio set, my hedge fund returns and my augmented nine factor model. Table VI shows baseline results. Table VII shows results when I invert an ARMA(1,1) process to unsmooth my hedge fund returns.

Table VI shows significant attenuation for the momentum (UMD) factor when compared to our baseline results in Table II (by ~7.0%). The market factor and size factor are negligibly impaired (< 1.0%). The value factor takes a negative point estimate when benchmarked against those baseline results with moderate attenuation. Momentum sees the biggest attrition in my augmented model likely caused by the three trending-following controls. Momentum, in a way, is a type of trend-following strategy itself and therefore it is unsurprising that its compensation point estimate, λ_{UMD}^{HF}, is significantly attenuated as other trend-following factors are introduced as controls for other asset class strategies.

Table VI: Fama-MacBeth Estimates of Implementation Costs – Baseline Nine Factor Model Specifications

Table reports implementation costs for Fama-MacBeth estimates as the difference of average cross-sectional compensation per factor exposure for all portfolios (as specified in Section VI, Part E), λ^S (top panel), and unadjusted domestic hedge funds, λ^{HF}(second panel). This difference, $\lambda^S - \lambda^{HF} = \lambda^{\Delta}$, is represented in the third (bottom) panel. This cross-sectional compensation is averaged across all funds, $\bar{\lambda}_k$, and is found by monthly regressions of excess returns r_{it} on fund by fund time series betas $\hat{\beta}_{ik}$,

$$r_{it} = \sum_k \lambda_{kt}^S \hat{\beta}_{ik} 1_{i \in S} + \sum_k \lambda_{kt}^{HF} \hat{\beta}_{ik} 1_{i \in HF} + \varepsilon_{it}, \quad t = 1, \ldots, T.$$

where k indexes to one of the four factors used extensively in the asset-pricing literature (e.g. Fama French (1992) & Carhart (1997)) and one of the five non-equity factors used in the hedge fund literature (Fung and Hsieh 2004) and further described in Section VI, Part __. Again, λ^{Δ} represents the trading costs faced by the typical hedge fund during implementation of a factor strategy. All coefficients are reported in percent and annualized. T represents the number of monthly time periods in the sample and $\overline{N}_{HF}$ represents the average number of hedge funds active and reporting during the sample. All t-statistics are in parentheses.

(a) Value-Weighted Stock Portfolios

	1994 - 2017									
	N_S	*MKT*	*SMB*	*HML*	*UMD*	*Bond_MKT*	*Credit_Spread*	*PTFSBD*	*PTFSFX*	*PTFSCOM*
λ^S	333	8.59***	0.84	3.32	5.77	-0.60	0.37	-0.17	0.94**	-0.24
t-stat		(2.82)	(0.35)	(1.34)	(1.60)	-(1.48)	(1.19)	-(0.56)	(2.51)	-(0.85)
λ^{HF}	333	11.31***	6.89**	-0.85	2.74	0.35	-0.68***	0.25*	0.59***	0.22
t-stat		(3.52)	(2.56)	-(0.34)	(0.67)	(1.47)	-(4.14)	(1.65)	(3.34)	(1.52)
λ^{Δ}	333	-2.72***	-6.05***	4.17***	3.04	-0.95**	1.05***	-0.41	0.35	-0.46*
t-stat		-(2.68)	-(5.20)	(3.18)	(1.32)	-(2.32)	(3.93)	-(1.45)	(0.98)	-(1.76)
T	288	288	288	288	288	288	288	288	288	288
N_{HF}	1715	1715	1715	1715	1715	1715	1715	1715	1715	1715

**p < .10, ** p < .05, ***p < .01*

(b) Equal-Weighted Stock Portfolios

	1994 - 2017									
	N_S	*MKT*	*SMB*	*HML*	*UMD*	*Bond_MKT*	*Credit_Spread*	*PTFSBD*	*PTFSFX*	*PTFSCOM*
λ^S	333	9.44***	2.56	3.27	6.38*	-0.81*	0.37	-0.66**	1.36***	-0.21
t-stat		(3.02)	(0.98)	(1.23)	(1.74)	-(1.90)	(1.33)	-(2.09)	(3.41)	-(0.63)
λ^{HF}	333	11.31***	6.89**	-0.85	2.74	0.35	-0.68***	0.25*	0.59***	0.22
t-stat		(3.52)	(2.56)	-(0.34)	(0.67)	(1.47)	-(4.14)	(1.65)	(3.34)	(1.52)
λ^{Δ}	333	-1.87	-4.33***	4.12***	3.64	-1.16***	1.06***	-0.91***	0.77**	-0.43
t-stat		-(1.58)	-(2.94)	(2.60)	(1.52)	-(2.66)	(4.48)	-(2.99)	(2.01)	-(1.41)
T	288	288	288	288	288	288	288	288	288	288
N_{HF}	1715	1715	1715	1715	1715	1715	1715	1715	1715	1715

**p < .10, ** p < .05, ***p < .01*

Table VI further shows that now, even for unadjusted returns, hedge funds face serious implementation costs for these factor-based strategies for momentum and value. For the analysis when value-weighted test portfolios are used, hedge funds face trading costs of a little over 4.1% when implementing the value factor and of around 3.0% when implementing the momentum factor. This result for momentum is corroborated by Frazzini, Israel, and Moskowitz (2015) who find that their real-life arbitrageur faces implementation costs of around 3.0% for the momentum factor. Little attention is paid to the trading costs on the non-equity factors in my analysis. This is because the other five factors were not originally intended to explain the cross-section of returns for hedge funds, but rather to significantly explain the time series dispersion of hedge fund returns. As Sadka (2010) notes, they still are useful controls in cross-sectional regressions. But the fact that these factors weren't intended to be used in the cross section makes their economic interpretation difficult (this is coupled by the fact that my additional 99 portfolios by no means captures every asset class available to hedge funds which likely distorts my average compensation per factor for my stock portfolios. However, they are still useful for controlling for hedge fund non-equity exposure giving my equity factors a more robust interpretation.).

Table VII presents the same augmented model as Table VI except that it uses the inverted ARMA(1,1) unsmoothing procedure as detailed above for my hedge fund returns. We see relative attenuation for λ^{HF}'s for all factors besides value. Now, similar to the literature, momentum faces the most significant implementation costs of all of my factors. One sees that when trading costs are accounted for, they substantially erode the relatively high compensation found on paper. In fact, the momentum factor does not survive (earn positive profits) after trading costs are accounted for.

Table VII: Fama-MacBeth Estimates of Implementation Costs – ARMA(1,1) Adjusted Return & Nine Factor Model Specifications

Table reports implementation costs for Fama-MacBeth estimates as the difference of average cross-sectional compensation per factor exposure for all portfolios (as specified in Section VI, Part E), λ^S (top panel), and ARMA(1,1) adjusted domestic hedge funds, λ^{HF}(second panel). This difference, $\lambda^S - \lambda^{HF} = \lambda^{\Delta}$, is represented in the third (bottom) panel. This cross-sectional compensation is averaged across all funds, $\bar{\lambda}_k$, and is found by monthly regressions of excess returns r_{it} on fund by fund time series betas $\hat{\beta}_{ik}$,

$$r_{it} = \sum_k \lambda_{kt}^S \hat{\beta}_{ik} 1_{i \in S} + \sum_k \lambda_{kt}^{HF} \hat{\beta}_{ik} 1_{i \in HF} + \varepsilon_{it}, \quad t = 1, \ldots, T.$$

where k indexes to one of the four factors used extensively in the asset-pricing literature (e.g. Fama French (1992) & Carhart (1997)) and one of the five non-equity factors used in the hedge fund literature (Fung and Hsieh 2004) and further described in Section VI, Part __. Again, λ^{Δ} represents the trading costs faced by the typical hedge fund during implementation of a factor strategy. All coefficients are reported in percent and annualized. T represents the number of monthly time periods in the sample and $\bar{N}_{HF}$ represents the average number of hedge funds active and reporting during the sample. All t-statistics are in parentheses.

(a) Value-Weighted Stock Portfolios

					1994 - 2017					
	N_S	*MKT*	*SMB*	*HML*	*UMD*	*Bond_MKT*	*Credit_Spread*	*PTFSBD*	*PTFSFX*	*PTFSCOM*
λ^S	333	8.59***	0.84	3.32	5.77	-0.60	0.37	-0.17	0.94**	-0.24
t-stat		(2.82)	(0.35)	(1.34)	(1.60)	-(1.48)	(1.19)	-(0.56)	(2.51)	-(0.85)
λ^{HF}	333	7.08**	2.41	-0.59	-2.14	0.06	-0.27*	0.35**	0.36**	0.24*
t-stat		(2.16)	(0.89)	-(0.24)	-(0.53)	(0.26)	-(1.68)	(2.36)	(2.03)	(1.65)
λ^{Δ}	333	1.52	-1.57	3.91***	7.91***	-0.66	0.64**	-0.51*	0.58	-0.48*
t-stat		(1.34)	-(1.21)	(3.04)	(3.47)	-(1.59)	(2.35)	-(1.80)	(1.64)	-(1.83)
T	288	288	288	288	288	288	288	288	288	288
N_{HF}	1715	1715	1715	1715	1715	1715	1715	1715	1715	1715

**p < .10, ** p < .05, ***p < .01*

(b) Equal-Weighted Stock Portfolios

					1994 - 2017					
	N_S	*MKT*	*SMB*	*HML*	*UMD*	*Bond_MKT*	*Credit_Spread*	*PTFSBD*	*PTFSFX*	*PTFSCOM*
λ^S	333	9.44***	2.56	3.27	6.38*	-0.81*	0.37	-0.66**	1.36***	-0.21
t-stat		(3.02)	(0.98)	(1.23)	(1.74)	-(1.90)	(1.33)	-(2.09)	(3.41)	-(0.63)
λ^{HF}	333	7.08**	2.41	-0.59	-2.14	0.06	-0.27*	0.35**	0.36**	0.24*
t-stat		(2.16)	(0.89)	-(0.24)	-(0.53)	(0.26)	-(1.68)	(2.36)	(2.03)	(1.65)
λ^{Δ}	333	2.36*	0.15	3.87**	8.52***	-0.87*	0.65***	-1.01***	1.01***	-0.44*
t-stat		(1.90)	(0.09)	(2.49)	(3.59)	-(1.99)	(2.62)	-(3.32)	(2.61)	-(1.45)
T	288	288	288	288	288	288	288	288	288	288
N_{HF}	1715	1715	1715	1715	1715	1715	1715	1715	1715	1715

**p < .10, ** p < .05, ***p < .01*

Furthermore, when trading costs are accounted for, hedge funds don't on average earn positive returns for the value factor during my sample period. Trading costs erode about 3.9% of the premia that these hedge funds would see on paper for HML, making this factor strategy infeasible. Again, the size factor is robust to the factor model used. Again, this confirms Sadka (2010)'s conclusion that hedge funds that load on illiquidity risk outperform those that don't.

F. Comparison of Empirical Results with those Estimated in the Prior Literature

Table VIII shows a comparison of the trading costs on factor strategies that I estimate for hedge funds with the prior literature. I compare my results with those of Patton and Weller (2017) and Frazzini, Israel, and Moskowitz (2015). I choose this literature for comparison because Patton and Weller (2017) use the same Fama-MacBeth methodology as I do except applied to the domestic mutual fund domain. Therefore, holding methodology constant, one can compare the net of cost returns earned on these factor-based strategies between hedge funds and mutual funds. I additionally choose Frazzini, Israel, and Moskowitz (2015) because their live trading data that they use to estimate trading costs on factor strategies comes from a large, institutional hedge fund. Therefore, holding type of fund constant, one can directly compare the trading costs faced by hedge funds.

One caveat to this comparison is that the years used in the sample do differ. For example, 2017 was a particularly difficult year for value investors,[19] which helps explain the gap between λ_{HML}^{S} in Patton and Weller (2017)'s work and my own λ_{HML}^{S}. However, the compensation earned by investment managers tracks the compensation earned by these stock portfolios closely[20], so this concern is minimized.

[19] Further discussion on this topic can be found here https://www.ft.com/content/6563efaa-467c-11e7-8519-9f94ee97d996
[20] All correlations > .75.

Table VIII: Comparison of Findings with Current Literature on Trading Costs

Table presents a comparison between my Fama-MacBeth estimates of implementation costs from Section VI Part C and Part E with the current literature. I regress standard four-factor & nine-factor models from the literature (e.g. Fama-French (1993), Carhardt (1997) & Fung Hsieh (2004)) on common value-weighted stock portfolios detailed in Section III and ARMA(1,1) adjusted hedge fund returns to find factor risk exposures, and then use these risk coefficients (β_{ik}) in cross-sectional regressions to estimate incremental compensation per unit of risk for stocks, λ^{s}, and hedge funds, λ^{HF}, and use this difference, λ^{Δ}, as an estimate of trading costs for the typical hedge fund. Patton and Weller (2017) use the exact same methodology except applied to all domestic equity mutual funds. Our common stock portfolios are largely the same except for the sample period measured (1994-2017 vs. 1993-2016) and the data below can be found in Table II of their paper. Frazzini, Israel, and Moskowitz (2015) use live trading data from a large institutional arbitrageur and the data reported below comes from Table IV of their paper with the exception of r_{Δ} which is found through subtracting r_{net} from r_{gross}. Trading cost estimates are bolded. T-statistics are represented in parentheses.

Current Trading Cost Literature		*SMB*	*HML*	*UMD*
Cross-Sectional Compensation with ARMA(1,1) Adjusted Hedge Fund Returns (1994-2017)	λ^{S}	0.68	3.87	6.67*
	t-stat	(0.28)	(1.55)	(1.85)
	λ^{HF}	2.85	1.32	5.10
	t-stat	(1.02)	(0.51)	(1.05)
	$\boldsymbol{\lambda^{\Delta}}$	**-2.17**	**2.56***	**1.57**
	t-stat	-(1.48)	(1.66)	(0.44)
Cross-Sectional Compensation with ARMA(1,1) Adjusted Hedge Fund Returns With Augmented 9 Factor Model (1994-2017)	λ^{S}	0.84	3.32	5.77
	t-stat	(0.35)	(1.34)	(1.60)
	λ^{HF}	2.41	-0.59	-2.14
	t-stat	(0.89)	-(0.24)	-(0.53)
	$\boldsymbol{\lambda^{\Delta}}$	**-1.57**	**3.91*** **	**7.91*** **
	t-stat	-(1.21)	(3.04)	(3.47)
Patton & Weller (2017) (1993-2016)	λ^{S}	1.18	4.61	6.67*
	t-stat	(0.49)	(1.62)	(1.80)
	λ^{MF}	2.21	2.19	1.27
	t-stat	(0.92)	(0.79)	(0.34)
	$\boldsymbol{\lambda^{\Delta}}$	**-1.03**	**2.42*** **	**5.40*** **
	t-stat	-(1.32)	(3.72)	(3.37)
Frazzini, Israel, and Moskowitz (2015) (1998-2013)	r_{gross}	7.98***	4.86	2.26
	t-stat	(3.01)	(1.12)	(0.40)
	r_{net}	6.52**	3.51	-0.77
	t-stat	(2.48)	(0.80)	-(0.14)
	$\boldsymbol{r_{\Delta}}$	**1.46**	**1.35**	**3.03**

**p < .10, ** p < .05, ***p < .01*

One sees that in comparison to mutual funds, hedge funds compare unilaterally worse when implementing of the value factor. Although trading costs are comparable (although slightly worse, 2.56% vs. 2.42%) for the value factor between my Part C results and those found in Patton and Weller (2017), they perform far worse when compared to my augmented 9 factor model (3.91% vs. 2.42%).

Patton and Weller (2017) estimate around a 5.4% implementation costs for momentum. This is significantly higher than the costs that I estimate in my Part C results (I estimate implementation costs of 1.57%). However, when trend following strategies are augmented to my model, I see that implementation costs become significantly prohibitive at 7.91%. In comparison to the size factor, both Patton and Weller (2017) and I conclude that these funds tend to implement the size factor better than (or when looking at the results from Part E, as equally well as) the stock portfolios we have chosen in our sample. However, both of our point estimates are not statistically different from zero.

In comparison to the large hedge fund that Frazzini, Israel, and Moskowitz (2015) analyze, I find that factor-based trading strategies for the *typical* hedge fund suffer significantly more attrition. I find that the typical hedge fund suffers around double the trading costs for the value factor than the firm analyzed by Frazzini, Israel, and Moskowitz (2015). Furthermore, when looking at the results from my augmented factor model (Part E results), I see that the typical hedge fund suffers more than double the attrition brought on by trading costs. This seems to rebuff the argument by Frazzini, Israel, and Moskowitz that they are a marginal agent of the hedge fund industry. They are certainly not representative of the typical hedge fund in terms of AUM with their analyzed firm having several magnitudes more AUM than the typical hedge fund reported in Column 3 of Table I. The fact, therefore, that the large hedge fund analyzed by

Frazzini, Israel, and Moskowitz (2015) has significantly lower implementation costs for these factor trading strategies is unsurprising given their size, level of sophistication, and leverage over prime brokers that the typical fund does not have.

VII. Limitations – Can Hedge Funds be Saved?

First, it is important to note that my results indicate trading costs for the average hedge fund, and therefore, are not indicative of all alternative asset managers. Some hedge funds, such as the ones presented in Frazzini, Israel, and Moskowitz (2015), are able to implement these strategies exceedingly well. However, my results seem to suggest that the value and momentum market anomalies are out of reach for the typical hedge fund.

A second major limitation of my methodology is that it assumes that returns on factors (especially the equity factors) are linear. However, hedge funds often employ dynamic trading strategies that lead to time varying risk exposures and other non-linearities (Fung & Hsieh, 2001; Agarwal & Naik, 2004). However, this non-linear modeling is outside the scope of this paper and will be left to future research.

Finally, another limitation of my methodology is that I include all hedge funds regardless of trading strategy or assets held into my analysis. I try to correct for this by my augmented model presented in Section VI Part E, however, potential biases because of this inclusion are bound to exist. I include all hedge funds in my analysis simply because of the tracking error involved in actually understanding an investment manager's strategy and what they hold in their portfolio. For example, a majority of funds in my sample labeled themselves as "multi-strategy" and it is impossible to therefore know the total exposure that these types of funds have to different asset classes or the trading strategies that they employ. Furthermore, funds often experience style drift, wherein they tell databases (even sometimes investors) what type of strategy their fund employs and then (sometimes substantially) drift from this strategy.[21] However, further research should be dedicated to minimizing this tracking error and calculating implementation costs for hedge funds that employ different strategies.

VIII. Conclusion

I apply the empirical asset-pricing Fama-MacBeth procedure to hedge fund returns and a comprehensive set of test portfolios in order to measure the real-world efficacy of factor trading strategies. I corroborate what both Lesmond, Schill, and Zhou (2004) and Patton and Weller (2017) find in that the momentum factor does not survive its corresponding real-world trading costs. Furthermore, I surprisingly find that the typical hedge fund is unable to implement the value factor effectively after trading costs are accounted for. Finally, I confirm Sadka (2010)'s conclusion that hedge funds typically implement liquidity risk well, and I find that the typical hedge fund earns profits to the size factor robust to multiple specifications.

The methodology, used first in Patton and Weller (2017), is novel in that it is free of most of the assumptions that plague other measures of trading costs. Old-school approaches typically impose parametric price impact functions or use proprietary trading data in the hopes of being representative of the market as a whole. The methodology used in this paper not only capture tangible trading costs (bid-ask spreads, commissions, etc.) but also more intangible costs (opportunity costs of using more liquid versions of these factors, etc.) without making any of the assumptions of the pre-existing approaches. Because hedge funds are regarded as the most sophisticated investment managers in the world, the trading costs faced by these firms should

[21] A great example of this is the hedge fund, Amaranth, who blew up after a commodity trader, Brian Hunter, lost the fund $6 billion dollars in two weeks. Amaranth was a multi-strategy hedge fund which traditionally had little exposure to energy trading.

represent a lower bound. Therefore, hedge funds are a curious testing field of different cross-sectional predictors found in the literature. In future research, I hope to further apply this methodology considering different trading strategies employed by the funds while also augmenting my model to allow for certain non-linear pricing features.

Appendix A: Hedge Fund Filtering and Cleaning Methodology

Hedge fund data as noted throughout can be difficult to work with. First, there are no universal regulations regarding hedge fund performance reporting, and therefore, majority of the funds that report do so as a type of marketing. Therefore, all hedge fund returns and AUM data available to researchers is voluntarily reported (opening up rooms for biases). Although, current research has shown that manager's incentives to report correctly are relatively in-line with truthful reporting (Agarwal, Daniel, and Naik 2009), as Getmansky, Lo, and Markarov (2004) and Bollen and Pool (2009) show, these incentives don't always play out in reality.

Because of the concerns about different hedge fund data biases, multiple steps have been taken in this paper to address them. Below is a detailed filtering methodology I used to clean and substantiate my data.

1. I first unstack my return and AUM data using Matlab's unstack command in order to generate a [T by N] table where T represents the time series values of my returns or AUM data, and N represents my funds. I then map these funds using their unique SEC identifiers to their characteristics (such as fees, lock-ups, etc.)
2. After my data is mapped correctly, I filter my data based on funds that invest primarily in assets posted on U.S. exchanges. Generally, a clear way to find which funds are located in the U.S. and therefore likely to invest in instruments trading on U.S. exchanges is through

domicile. However, because of the different tax laws and regulations governing hedge funds, many of the funds in the sample are registered in places such as Ireland and the Cayman Islands, even though their operational headquarters are in the United States. Because of this, I instead use fund base currency as a filter for funds that invest in U.S. securities. Because investments in securities outside the United States typically involve the conversion of currency, I assume that investment managers that denominate their funds in United States dollars are most likely to invest primarily in securities located on U.S. exchanges. This filtering step reduces the amount of funds in my sample from 20,845 total funds to 13,140 total funds. If I filtered on domicile instead, I would have been left with a sample of only 5,723 funds. Therefore, in order to not eliminate valuable information, fund denominated currency is the clear choice.

3. Because hedge funds report data net of fees, I filter my data according to the availability of a fund's incentive fees. Additionally, when annual hurdle rate data is available, I use monthly Libor as the hurdle rate. The rationale for this is that investors will expect returns at least greater than the relatively risk-free monthly Libor rate, and therefore, if managers are unable to surpass this benchmark, than they are unlikely to surpass their own hurdle rate provision. Furthermore, given the relatively little significance it has on the conversion (and given the trade-off between tossing valuable fund observations), any fund that doesn't report a hurdle rate, I assume it to equal zero. This enables me to keep significantly more funds in my sample. The calculation for the conversion between net returns and gross returns is explicitly detailed in Appendix B. This filtering step reduces the funds in my sample from 13,140 total funds to 8,872 funds.

4. Before the I convert my net of fee returns to gross of fee returns, I additionally filter out missing value flags inherent in the CISDM return series database. These missing value flags are represented as the values 9999.9999 or 99.999999. I therefore convert them to Matlab's missing value identifier, NaN. I find that there were 1,246 of these missing return flags in my dataset.
5. Although my filtering process so far contains 8,872 funds left in my sample, some of these funds fail to report any returns. These funds are still included in the database, however, because they report some of their funds' characteristics. Because my empirical methodology relies on return series data, I next eliminate all funds that don't report any returns. After eliminating these non-reporting funds, I am left with a total of 7,851 funds.
6. I then follow the suggestions of Berk and van Binsbergen (2015) to filter my data further based on size of AUM. One common technique that hedge funds and mutual funds use is what is called incubating a fund. Incubation is the practice where an investment manager allocates a small portion of its total assets to a plethora of very small funds in order to see which new strategies or investment styles they should add to the overall flagship fund. However, this is commonly used as a marketing tool whereby managers attempt to build attractive track records of funds before attempting to scale them. If an investment manager allocates a relatively small amount of money to 100 funds, then it is statistically likely that 1 or 2 of them will demonstrate extremely strong returns. These couple of funds are then marketed to investors and scaled. Because of this incubation bias, Berk and van Binsbergen (2015) suggest that micro funds should be excluded from any analysis that looks at performance evaluation because these funds are not representative of a manager's skill or the wider market as a whole. I follow their filtering methodology and filter out any fund that has

AUM under 10 million dollars. Additionally, for funds that cross this boundary during the life of the fund, I filter out any returns that occur before a fund reaches the 10-million-dollar mark. This filtering technique reduces my sample further from 7,851 funds to 5,610 funds.

7. I next ensure that that my hedge fund return series sample has at least 24 non-missing cumulative returns. Because of my two-stage regression approach, it is critical to minimize the errors in variable problem of running a second regression strictly on noise. This noise will strongly bias the coefficients that are to be found in the second stage regression. I therefore ensure that a fund contains 24 consecutive returns to allow for a certain safety threshold when estimating my time series betas in the first-stage regression. This step reduces the amount of funds in my sample to 4,966 from 5,610 total funds.
8. My final data cleaning step utilizes Matlab's filloutliers command. This function takes a table of returns, and then column by column, identifies outliers by identifying elements that are a specified number of median absolute deviations away from the median. Median absolute deviation is an ideal outlier technique for financial time series data because unlike standard z-scoring techniques, the median is not biased upwards from outliers. For example, take CISDM's database as an example. Using standard z-score techniques, it would correctly identify 9999.9999 as an outlier. However, if the flag 99.99999 was also included in the funds' return series, the first outlier would bias the mean in such a way as to inflate it, potentially making the 99.9999 look like a reasonable event. The threshold factor I use in my results is 10 MADs. While this potentially seems like too high of a threshold, because hedge funds have been shown to have rather large fat tails[22], I use this cutoff to ensure I am not

[22] LTCM's risk management models for example, showed that the fund was experiencing a ten-sigma event during its collapse in the late 1990s. See Roger Lowenstein's *When Genius Failed* for more details.

throwing away valuable data. Results are further run with the threshold factor equal to 3 and 5, and my results remain largely unchanged.

Appendix B: Conversion of Net of Fee Returns into Gross of Fee Returns

In order to parse out the effect of trading costs on returns, it is crucial that the returns analyzed are gross of fee returns. However, hedge funds report returns almost exclusively net of fees to database vendors. The CISDM database is no exception and therefore one must convert this net of fee data to gross of fee data. Luckily, the CISDM database, in its fund characteristics data, provides adequate information to do this. In order to estimate gross of fee return data, I follow Agarwal, Daniel, and Naik (2009) and use their methodology with slight modification. A funds gross return can be calculated as follows:

$$gross_t = \begin{cases} \dfrac{net_t - hurdle_t * I}{1 - I}, & if\ net_t > hurdle_t \\ net_t, & otherwise \end{cases}$$

where, I = yearly incentive fees and $hurdle_t = libor_t$ if the fund has a hurdle rate, and zero if it does not. The calculation follows directly from Agarwal, Daniel, and Naik (2009). Furthermore, I assume that management fees cover all fixed costs.

Works Cited

Agarwal, V. , Daniel, N. D. and Naik, N. Y. (2009), Role of Managerial Incentives and Discretion in Hedge Fund Performance. The Journal of Finance, 64: 2221-2256.

Agarwal, V. , Jiang, W. , Tang, Y. and Yang, B. (2013), Uncovering Hedge Fund Skill from the Portfolio Holdings They Hide. The Journal of Finance, 68: 739-783.

Aiken, A., Clifford, C., & Ellis, J. (2013). Out of the Dark: Hedge Fund Reporting Biases and Commercial Databases. The Review of Financial Studies, 26(1), 208-243.

Amihud, Yakov. 2002. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." Journal of Financial Markets 5 (1):31—56.

Asness Cliff, S., Robert Krail, and John M. Liew. 2001. "Do hedge funds hedge?" Journal of Portfolio Management 28, 6–19.

Bollen, Nicolas P. B., and Veronika K. Pool, 2009. "Do hedge fund managers misreport returns? Evidence from the pooled distribution." Journal of Finance 64, 2257–2288.

Bollen, N. P., & Pool, V. K. (2012). Suspicious patterns in hedge fund returns and the risk of fraud. The Review of Financial Studies, 25(9), 2673-2702.

Borri, Nicola, and Adrien Verdelhan, 2012, Sovereign risk premia, Working paper, LUISS University.

Brown, Stephen J., William Goetzmann, Roger G. Ibbotson, and Stephen A. Ross. 1992. "Survivorship Bias in Performance Studies." Review of Financial Studies, vol. 5, no. 4 (Winter):553-580.

Brown, S. J., Goetzmann, W. N. and Park, J. (2001), Careers and Survival: Competition and Risk in the Hedge Fund and CTA Industry. The Journal of Finance, 56: 1869-1886.

Carhart, Mark M. 1997. "On Persistence in Mutual Fund Performance." The Journal of Finance 52 (1):57–82.

Christoffersen, Susan E. K., Danesh, Erfan, and Musto, David. 2017. "Why Do Institutions Delay Reporting Their Shareholdings? Evidence from Form 13F." Working paper, University of Pennsylvania.

Chen, Zhiwu, Werner Stanzl, and Masahiro Watanabe. 2002. "Price Impact Costs and the Limit of Arbitrage." Working paper, Yale School of Management.

Cici, Gjergji, Alexander Kempf, and Alexander Puetz. 2011. "The valuation of hedge funds' equity positions." Working paper, College of William and Mary.

Constantinides, George M., Jens Carsten Jackwerth, and Alexi Savov, 2013, The puzzle of index option returns, Review of Asset Pricing Studies 3, 229–257.

Corwin, Shane A. and P. Schultz. 2012. “A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices.” The Journal of Finance 67 (2):719—760.

Durand, R. B., Lim, D., & Zumwalt, J. K. (2011). Fear and the Fama-French factors. Financial Management, 40(2), 409-426.

Fama, Eugene F. and Kenneth R. French. 1992. “The Cross-Section of Expected Stock Returns.” Journal of Finance 47 (2):427–465.

Fama, Eugene F. and James D. MacBeth. 1973. “Risk, Return, and Equilibrium: Empirical Tests.” Journal of Political Economy 81 (3):607–636.

Frazzini, Andrea, Ronen Israel, and Tobias J. Moskowitz. 2015. “Trading Costs of Asset Pricing Anomalies.” Working paper, AQR Capital Management.

Frazzini, Andrea and Lasse Heje Pedersen. 2014. “Betting Against Beta.” Journal of Financial Economics 111 (1):1—25.

Agarwal, V., & Naik, N. Y. (2004). Risks and portfolio decisions involving hedge funds. The Review of Financial Studies, 17(1), 63-98.

Fung, W. , Hsieh, D. A., Naik, N. Y. and Ramadorai, T. (2008), Hedge Funds: Performance, Risk, and Capital Formation. The Journal of Finance, 63: 1777-1803.

Fung, W., & Hsieh, D. A. (1997). Empirical characteristics of dynamic trading strategies: The case of hedge funds. The review of financial studies, 10(2), 275-302.

Fung, William, and David A. Hsieh. 2000. “Performance characteristics of hedge funds and commodity funds: Natural vs. spurious biases.” Journal of Financial and Quantitative Analysis 35, 291–307.

Fung, W., & Hsieh, D. A. (2001). The risk in hedge fund strategies: Theory and evidence from trend followers. The review of financial studies, 14(2), 313-341.

Fung, William and Hsieh, A. David. 2004. "Hedge Fund Benchmarks: A Risk Based Approach." Financial Analyst Journal 60 (2004), 65-80.

Fung, William, and Hsieh, A. David. 2009. “Measurement biases in hedge fund performance data: An update.” Financial Analysts Journal 65, 36–38.

Getmansky, M., Lo, A. W., & Makarov, I. (2004). An econometric model of serial correlation and illiquidity in hedge fund returns. Journal of Financial Economics, 74(3), 529-609.

He, Zhiguo, Bryan Kelly, and Asaf Manela. 2017. “Intermediary Asset Pricing: New Evidence from Many Asset Classes.” Journal of Financial Economics.

Huang, J. Z., Liechty, J., & Rossi, M. (2009). Return smoothing and its implications for performance analysis of hedge funds. Available at SSRN 1571421.

Huddart, S. , Hughes, J. S. and Levine, C. B. (2001), Public Disclosure and Dissimulation of Insider Trades. Econometrica, 69: 665-681.

Jorion, Philippe, and Christopher Schwarz. 2010. "Strategic motives for hedge fund advertising." Working paper, University of California, Irvine.

Keim, Donald B. and Ananth Madhavan. 1997. "Transactions Costs and Investment Style: An InterExchange Analysis of Institutional Equity Trades." Journal of Financial Economics 46 (3):265– 292.

Korajczyk, Robert A. and Ronnie Sadka. 2004. "Are Momentum Profits Robust to Trading Costs?" The Journal of Finance 59 (3):1039–1082.

Kruttli, Mathias and Patton, Andrew J. and Ramadorai, Tarun. 2015. "The Impact of Hedge Funds on Asset Markets." *The Society for Financial Studies*.

Lesmond, D. A., Schill, M. J., & Zhou, C. (2004). The illusory nature of momentum profits. Journal of financial economics, 71(2), 349-380.

Lettau, Martin, Matteo Maggiori, and Michael Weber, 2014, Conditional risk premia in currency markets and other asset classes, Journal of Financial Economics 114, 197–225.

Lewellen, Jonathan, Stefan Nagel, and Jay Shanken. 2010. "A Skeptical Appraisal of Asset Pricing Tests." Journal of Financial Economics 96 (2):175—194.

Liang, Bing. 2000. "Hedge Funds: The living and the dead, Journal of Financial & Quantitative Analysis." 35, 309–326.

Li, H., Xu, Y., & Zhang, X. (2016). Hedge Fund Performance Evaluation under the Stochastic Discount Factor Framework. Journal of Financial and Quantitative Analysis, 51(1), 231-257.

Markowitz, H. Portfolio Selection: Efficient Diversification of Investments. New York: Wiley, 1959.

Menkhoff, Lukas, Lucio Sarno, Maik Schmeling, and Andreas Schrimpf, 2012, Carry trades and global foreign exchange volatility, Journal of Finance 67, 681–718.

Nagel, Stefan. 2012. "Evaporating Liquidity." Review of Financial Studies 25 (7):2005—2039.

Novy-Marx, Robert and Mihail Velikov. 2016. "A Taxonomy of Anomalies and Their Trading Costs." The Review of Financial Studies 29 (1):104–147.

Nozawa, Yoshio, 2014, What drives the cross-section of credit spreads?: A variance decomposition approach, Working paper, University of Chicago.

Pastor, Lubos and Robert F. Stambaugh. 2003. "Liquidity Risk and Expected Stock Returns." Journal of Political Economy 111 (3):642—685.

Patterson, Scott. The Quants: the Maths Geniuses Who Brought down Wall Street. Cornerstone Digital, 2012.

Patton, A. J. (2008). Are “market neutral” hedge funds really market neutral?. The Review of Financial Studies, 22(7), 2495-2530.

Patton, A. J., Ramadorai, T. and Streatfield, M. (2015), Change You Can Believe In? Hedge Fund Data Revisions. The Journal of Finance, 70: 963-999.

Patton, Andrew and Weller, Brian. 2017. “What You See is Not What You Get: The Cost of Trading Market Anomalies.” Working paper, Duke University.

Perold, Andre F. 1988. “The Implementation Shortfall: Paper Versus Reality.” The Journal of Portfolio Management 14 (3):4–9.

Ramadorai, T. (2012). The Secondary Market for Hedge Funds and the Closed Hedge Fund Premium. The Journal of Finance, 67(2), 479-512.

Sadka, R. (2010). Liquidity risk and the cross-section of hedge-fund returns. Journal of Financial Economics, 98(1), 54-71.

Sharpe, W. F. (1992). Asset allocation: Management style and performance measurement. Journal of portfolio Management, 18(2), 7-19.