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Hedge Fund Performance and Derivative Hedging

Yongjia Li
University of Arkansas, Fayetteville

Hedge Fund Performance and Derivative Hedging

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by

Yongjia Li
Donghua University
Bachelor of Arts in Electronic Commerce, 2007
University of Arkansas
Master of Business Administration, 2011

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University of Arkansas

This dissertation is approved for recommendation to the Graduate Council.

Dr. Alexey Malakhov
Dissertation Director

Dr. Wayne Y. Lee
Committee Member

Dr. Timothy J. Yeager
Committee Member

Dr. Kangzhen Xie
Committee Member

Abstract

This dissertation is comprised of three essays which focus on hedge fund performance and derivative hedging. The first essay uses ETF returns as proxies for tradable risk factors in hedge fund performance evaluation and identifies contemporaneously relevant risk factors from the entire universe of ETFs. The model provides more informative estimates of alpha and beta coefficients for predicting hedge fund out-of-sample performance compared with other widely used hedge fund factor models. Portfolios of top alpha hedge funds selected by the model generate statistically significant out-of-sample performance that is substantially higher compared with portfolios selected by other models. In addition, the beta-weighted clone portfolios exhibit substantially higher out-of-sample correlations with underlying hedge funds than clone portfolios formed using alternative models.

The second essay shows that only hedge funds whose returns are driven by beta management of exposures to latent risk factors could be successfully replicated. I develop a methodology for creating a portfolio of ETFs that replicates risk factor exposures taken by successful beta active cloneable hedge funds. The methodology allows any investor to access active factor strategies employed by hedge funds. It could be interpreted as cloning beta exposures of the best beta active hedge funds, delivering outstanding long-term risk-adjusted performance. The active factor ETF portfolio only requires annual rebalancing, and is constructed with a transparent algorithmic approach, which conforms to a definition of a smart beta strategy.

The third essay investigates the use of derivatives among firms. A careful study of hedging motives and hedging effectiveness is critical to understanding the financial impact of derivative use by firms. I examine the use of commodity derivatives by oil and gas producers and

show that, on average, these firms report gains from their derivative positions. The profits from derivatives, particularly non-hedge profits, are positively associated with the extent of hedging that is classified as market timing activities.

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I. Introduction

My dissertation focuses primarily on hedge funds and corporate risk management. My hedge fund essays mitigate opaqueness in hedge fund industry, identify skilled managers who deliver alpha, and allow for successful replication of hedge fund returns originated from risk factor exposures. The essays provide value to regulators and investors including college endowments. My essay in corporate risk management examines corporate motives for hedging and the use of derivatives among oil and gas producers. The essay provides practical insights into how hedging motives and effectiveness impact shareholder value.

In the first essay, I propose a new approach to hedge fund performance evaluation by using ETFs as proxies for tradable risk factors in the return attribution factor model framework. The model comprehensively spans the space of potential risk factors, dynamically identifying specific risk factor exposures out of the entire universe of available ETFs. This results in more informative estimates of both alpha and beta coefficients for out-of-sample performance compared to other widely used hedge fund return attribution models. The essay finds that the portfolio of top alpha hedge funds selected by the model exhibits statistically significant out-of-sample performance that is substantially better compared to portfolios selected by other models. The essay also shows that the hedge fund mimicking portfolios constructed as beta-weighted factor portfolios according to the model display substantially higher out-of-sample correlations with underlying hedge funds compared to portfolios constructed from other models.

In the second essay, I propose cloning the best "beta active" hedge funds with ETF portfolios. On one hand, I utilize the "beta active" measure to identify the top beta management hedge funds that produce the outstanding long-term risk-adjusted performance. On the other hand, the cloning procedure allows identifying a homogeneous group of hedge funds suitable for replication, i.e. the ones whose returns are driven by risk factor exposures. By combing the two methodologies, I am able to replicate the top beta active cloneable hedge funds who successfully capture risk factor exposures that would deliver superior payoff in the future. The resulting "smart beta" ETF clone portfolios either match or exceed the risk-adjusted performance of their corresponding portfolios of hedge funds. Moreover, the clone portfolios only rely on annual rebalancing, and are constructed with a liquid and transparent approach. The methodology allows any investor to access active factor strategies employed by hedge funds.

In the third essay, I examine the use of commodity derivatives by oil and gas producers and show that, on average, these firms report gains from their derivative positions. By using a hand-collected data, I provide direct evidence that contradicts the risk management theory which states that firms use derivatives purely for hedging purposes. The essay shows that the profits from derivatives, particularly non-hedge profits, are positively associated with the extent a firm hedges and with the extent of hedging that is classified as market timing activities. Finally, the essay finds that among firms with losses from derivatives in a prior year, firms with greater losses increase hedging by a greater extent. This behavior can be views as a non-linear market feedback effect.

II. Essay 1: Bringing Order to Chaos: Capturing Relevant Information with Hedge Fund Factor Models [1]

Yongjia Li and Alexey Malakhov

A. Abstract

We propose using ETF returns as proxies for tradable risk factors in hedge fund performance evaluation, identifying contemporaneously relevant risk factors from the entire universe of ETFs. Our model provides more informative estimates of alpha and beta coefficients for predicting hedge fund out-of-sample performance compared with other widely used hedge fund factor models. Portfolios of top alpha hedge funds selected by our model generate statistically significant out-of-sample performance that is substantially higher compared with portfolios selected by other models. In addition, our beta-weighted clone portfolios exhibit substantially higher out-of-sample correlations with underlying hedge funds than clone portfolios formed using alternative models.

JEL Classification: G11, G23

Keywords: hedge funds, ETFs, risk factor exposures, factor selection, return attribution, alpha, beta, active investment, performance prediction

B. Introduction

With total assets under management approaching an estimated \$3 trillion,[2] hedge funds are important players in the global financial markets. Absent any restrictions on trading

[1] We would like to thank Vikas Agarwal, Wayne Lee, Gulten Mero, Tatiana Salikhova, Anna Slavutskaya, Tim Riley, Tim Yeager; participants at the 9th Annual Hedge Fund and Private Equity Research Conference; and seminar participants at Boise State University, Fairfield University, Miami University, Sam Houston State University, and the University of Arkansas for their helpful comments and suggestions. We are especially grateful to Vikas Agarwal for generously providing the factor data.

[2] According to Hedge Fund Research, Inc., the global hedge fund capital is \$2.898 trillion (July 20, 2016 press release).

strategies, hedge funds epitomize the best in active investment. They are well known for their flexibility in implementing a wide variety of strategies, and they portray themselves as alpha generators that deliver superior absolute performance to investors.

Despite numerous models proposed in the literature over the years, there is no universally accepted model for hedge fund performance evaluation. We propose a new approach to hedge fund performance evaluation by using ETF returns as proxies for tradable risk factors in the return attribution factor model framework. The model dynamically identifies specific risk factor exposures out of the entire universe of available ETFs, comprehensively spanning the space of potential risk factors. This approach results in more informative estimates of alpha and beta coefficients for out-of-sample performance prediction compared with other widely used hedge fund factor models.

In the absence of an equilibrium model for hedge fund returns, the proposed hedge fund performance evaluation factor models rely on the framework of return attribution[3] in introducing factors that capture risk exposures imbedded in a diverse set of alternative investments and option-like investment strategies.[4] Such an approach puts an emphasis on the choice of relevant risk factors that drive hedge fund returns, but there is little agreement in the literature on the appropriate set of factors. Arguably, it is impossible to even know all the possible risk factors that drive hedge fund returns, given the opacity of hedge fund investment strategies and the fact

[3] Introduced in Brinson and Fachler (1985), and applied in Sharpe (1992) in the context of mutual funds.

[4] See, for example, Fung and Hsieh (1997, 2001, 2004), Agarwal and Naik (2000, 2004), Hasanhodzic and Lo (2007), Kosowski, Naik, and Teo (2007), Bollen and Whaley (2009), Patton (2009), Jagannathan, Malakhov, and Novikov (2010), Sadka (2010), Titman and Tiu (2011), Avramov, Kosowski, Naik, and Teo (2011), Sun, Wang, and Zheng (2012), Bali, Brown, and Caglayan (2011, 2012, 2014), Avramov, Barras, and Kosowski (2013), Bollen (2013), Bollen and Fisher (2013), Jurek and Stafford (2013), Patton and Ramadorai (2013), and Agarwal, Green, and Ren (2016).

that the rapid evolution of financial markets continuously expands the space of potential investment opportunities. The complexity of hedge fund strategies and the dynamic nature of hedge fund performance challenge the reliability and sustainability of return attribution models that utilize a fixed number of factors and ignore temporal changes in opportunity sets experienced by fund managers; such models run the risk of omitting factors and picking irrelevant factors across time. Furthermore, it can be argued that actively managed portfolios of hedge fund managers reflect the dynamic information set of contemporaneous state variables in the intertemporal framework of Merton (1973). Properly identifying and dynamically adjusting the set of risk factors to reflect the relevant information set that influences hedge fund investment strategies is therefore paramount for successful return attribution. Successful return attribution yields the improved knowledge of the contemporaneous opportunity set, the ability to evaluate the skill of hedge fund managers through alpha, and the ability to replicate factor-driven hedge fund return performance through beta-weighted clone portfolios.

In this paper, we employ ETF returns as tradable proxies for potential risk factors. In our view, any automatically executed series of returns represents a proxy for a risk factor; hence, ETFs represent proxies for the quantifiable risk factors that the market finds contemporaneously attractive.[5] In other words, the set of available ETFs reflects the dynamic nature of potential risk factors that investors care about in their risk-and-return tradeoffs.[6] As low cost, liquid and transparent investment vehicles, ETFs provide access to a great variety of traditional and exotic strategies previously available only to hedge funds or institutional investors.[7] Meanwhile, the

[5] Evidenced by the capital invested in trading strategies represented by ETFs.
[6] Alternatively, ETFs could be viewed as proxies for unobserved contemporaneous values of state variables that are correlated with returns on active investment strategies employed by hedge funds.
[7] As an example of available ETF strategies, consider ALPS U.S. Equity High Volatility Put Write Index Fund (ticker HVPW) that tracks NYSE Arca U.S. Equity High Volatility Put Write

large number of available ETFs allows for complete dynamic spanning of the space of risk factors and thus delivers accurate decomposition of alpha and beta. The efficacy of our approach, compared to other widely used hedge fund factor models, is demonstrated by the successful prediction of the out-of-sample performance of portfolios formed on the basis of the model alpha and beta coefficient estimates.

We utilize the Duanmu, Li, and Malakhov (2016) (DLM thereafter) factor selection methodology by selecting appropriate ETF risk factors with cluster analysis and the LAR LASSO regression technique,[8] while simultaneously estimating the free coefficient, alpha (DLM alpha hereafter).[9] We estimate historical DLM alpha for individual hedge funds on a rolling 24-month basis, and conduct out-of-sample portfolio tests based on the ranking of each fund's historical DLM alpha. We consider annual rebalancing, thus incorporating active factor choices by hedge fund managers, and hence capturing the dynamic nature of factors that could be driving hedge fund performance. We focus on the out-of-sample testing of performance persistence, demonstrating the efficacy of the DLM model in delivering tangible benefits to investors.

First, we find strong evidence that the DLM model alpha is effective in predicting the out-of-sample performance of hedge funds. The portfolio of top DLM alpha hedge funds delivers significantly positive mean excess returns along with risk-adjusted performance including Sharpe ratios, alphas, and information ratios out-of-sample. The top decile portfolio generates an out-of-

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Index with an annual expense ratio of 0.95 percent. The ETF benchmark tracks the performance of options sold on a basket of 20 stocks chosen from the largest-capitalized equities that have the highest volatility, as determined by NYSE Arca Inc.

[8] See Tibshirani (1996) and Efron, Hastie, Johnstone, and Tibshirani (2004) for descriptions of LASSO and LAR methodologies.

[9] While the original Duanmu, Li, and Malakhov (2014) methodology does not include alpha, our alpha calculation in this paper is derived from the DLM methodology with the additional consideration of a free coefficient. Hence we refer to it as "DLM alpha".

sample average monthly alpha of 0.53% across benchmark models[10] and is significant at the 1% level. The significance of alpha is also robust if we expand the number of funds in the portfolio to the top quintile. This finding suggests that the top hedge fund managers selected by the DLM model possess active management skills valuable to investors.

Second, we find that the DLM model delivers substantially higher predictive power in out-of-sample performance persistence relative to alternative models. We conduct a horse race to compare the DLM model against prevailing factor-based models, including the basic CAPM model; the Fama and French (1993) 3-factor model; the Carhart (1997) 4-factor model; the Agarwal and Naik (2004) option-based model; the Fung and Hsieh (2004) trend-following model; the Agarwal, Green, and Ren (2016) 12-factor model; and the Agarwal, Green, and Ren (2016) 15-factor max R^2 model.[11] The portfolio of top DLM alpha hedge funds dominates the top portfolios selected by the other models in returns, Sharpe ratios, out-of-sample alphas, and information ratios. The results imply that the DLM model provides a more precise hedge fund return attribution and identifies the active funds that deliver persistent out-of-sample performance. Unlike the other hedge fund factor models, the DLM model identifies contemporaneous risk factor exposures in a parsimonious manner while successfully capturing the active component of hedge fund returns represented by alpha.

We further show that the DLM model captures relevant information unrecovered by other models, while simultaneously capturing most of the other models' informative content. We do so by considering "mutually exclusive" portfolios that isolate the top alpha funds unique to each model. Excluding the funds from the top DLM alpha portfolio that are also present in alternative

[10] We calculate the out-of-sample portfolio alphas using multiple factor models to illustrate that the success of the DLM model is not an artifact of a particular model.
[11] We are grateful to Vikas Agarwal for generously providing the factor data. We also thank Kenneth French and David Hsieh for making their data available online.

model portfolios, we find that the remaining top DLM alpha funds deliver superior and significant out-of-sample performance. In contrast, the out-of-sample performance of alternative model portfolios is weaker and loses significance after excluding the funds from those portfolios that are also present in the top DLM alpha portfolio. The results suggest that the DLM model incorporates most of the informative content of the other models and also captures relevant information unrecovered by other models.

Finally, we demonstrate the ability of the DLM model to accurately attribute hedge fund returns to underlying factor exposures relative to alternative models. We form beta-weighted factor clone portfolios, attempting to replicate the factor-driven component of hedge fund returns. We expect to see successful return attribution through high out-of-sample correlations of hedge fund returns with their beta-weighted factor clones. Consistent with our hypothesis, we find that the DLM beta-weighted factor clone portfolios display substantially higher out-of-sample correlations with underlying hedge funds compared with portfolios constructed from other models.

C. Related Literature

There have been numerous attempts in the literature at hedge fund performance evaluation, but no universally accepted model or approach has emerged. Virtually all proposed approaches, either explicitly or implicitly, rely on the framework of return attribution, as there is no equilibrium model for hedge fund returns. Introduced in Brinson and Fachler (1985), and applied for mutual funds return attribution in Sharpe (1992), return attribution relies on introducing benchmark factors that share risk-and-return profiles with portfolios to be evaluated. Given the complexity of hedge fund investment strategies, identifying the appropriate set of benchmark risk factors is not an easy task. Over the years, a number of factors models and specific factors that reflect risk-and-return profiles of hedge fund investment strategies have been introduced.[12] The number of factors that could be relevant to attributing at least some aspect of potential hedge fund risk-and-return profiles is so large that it is impossible to include all of them in a single model without overspecification, and many approaches rely on statistical selection techniques for successful return attribution.[13] However, most of the mentioned models are either static or only consider a fixed number of potential risk factors.

The dynamic nature of factor exposures in managed portfolios was first explored in Ferson and Schadt (1996) in the context of mutual funds. Ferson and Schadt (1996) capture time variation in mutual fund factor exposures by conditioning on public information variables, following the conceptual framework of Merton (1973).[14] Building on Ferson and Schadt (1996), Patton and Ramadorai (2013) investigate high-frequency dynamic factor exposures in hedge funds and condition on monthly and daily public information variables. Patton and Ramadorai (2013) find substantial variation in hedge fund risk exposures across time. Bollen and Whaley (2009) and Cai and Liang (2012b) do not directly condition on public variables, capturing the dynamic nature of hedge fund factor exposures with the optimal changepoint regression

[12] For example, Fung and Hsieh (2001, 2004), Agarwal and Naik (2004), and Jurek and Stafford (2013) introduce trend following and option based factors, Sadka (2010) introduces the liquidity factor, Bollen and Fisher (2013) rely on futures based factors, Bali, Brown, and Caglayan (2014) introduce the macroeconomic uncertainty risk factor, and Agarwal, Arisoy, and Naik (2016) introduce the volatility of aggregate volatility factor.

[13] For example, Agarwal and Naik (2004), Ammann, Huber, and Schmid (2011), and Titman and Tiu (2011) use stepwise regression, S.D.Vrontos, I.D.Vrontos, and Giamouridis (2008) use a Bayesian model averaging approach, Bollen and Whaley (2009), Jagannathan, Malakhov, and Novikov (2010), and Patton and Ramadorai (2013) use Bayesian Information Criterion and Schwarz Bayesian Criterion to select risk factors, Giamouridis and Paterlini (2010) and Weber and Peres (2013) employ RIDGE, LASSO and LAR LASSO regressions, Agarwal, Green, and Ren (2016) use max R^2 for factor selection, O’Doherty, Savin, and Tiwari (2016) apply the pooled benchmark approach.

[14] Relevant public information variables are interpreted as proxies for the contemporaneous information set that active fund managers face.

technique. Meligkotsidou and Vrontos (2008, 2014) develop a Bayesian approach to identify structural breaks in hedge fund risk exposures. Billio, Getmansky, and Pelizzon (2012) propose a Markov regime switching model, and Cai and Liang (2012a) utilize dynamic regression with Kalman filtering for measuring dynamic risk exposures of hedge funds. There are also a few studies specifically examining the market timing aspect of the hedge fund dynamic.[15]

Our methodology[16] is distinct from the previous literature in two aspects. First, we go beyond a fixed set of risk factors and comprehensively span the universe of investment opportunities with all contemporaneously available ETFs. As the space of hedge fund investment opportunities expands due to the evolution of financial markets, it is unlikely that any fixed set of public variables would be able to comprehensively capture contemporaneous information sets that hedge fund managers face. Utilizing the entire (and continuously expanding) set of available ETFs, we comprehensively capture the risk factors that the market finds contemporaneously attractive.

Second, we dynamically use cluster analysis and LAR LASSO regression to parsimoniously select the specific factors relevant for each individual hedge fund at any given time. While our approach lacks the high-frequency dynamics of correlations with predetermined public information variables, it has the advantage of flexibility in selecting factors from the expanding and most contemporaneously relevant set of ETFs. In other words, our approach involves conditioning on information through the dynamic selection of contemporaneously relevant risk factors. The out-of-sample tests confirm the efficacy of this approach in return attribution, and assure that the results are not driven by data mining.

[15] See, for example, Aragon (2002), Fung, Xu, and Yau (2002), Chen (2007), Chen and Liang (2007), Cao, Chen, Liang, and Lo (2013), and Duanmu, Malakhov, and McCumber (2016).
[16] Denoted as DLM throughout the paper.

Comparison with the widely used factor models,[17] shows that the DLM model provides superior in-sample matching quality over 24-month rolling windows. The adjusted R-square of the DLM model is higher than the adjusted R-square of all other models but one. Meanwhile, the mean monthly in-sample alpha of the DLM model is consistently lower than the in-sample alphas of other models. The results suggest that the alpha estimated by alternative models could be partially attributed to risk factor exposures revealed by the DLM model. The more precisely estimated alpha by the DLM model results in substantially better out-of-sample performance of the top DLM alpha portfolio relative to portfolios selected by other models. The more precisely estimated factor risk exposures by the DLM model result in substantially higher out-of-sample correlations between the beta-weighted mimicking factor portfolios and underlying hedge funds relative to hedge fund clone portfolios formed using alternative models.

D. Data

We obtain hedge fund data from Bloomberg[18] for the period from 2003 to 2012 on 10,506 unique hedge funds,[19] of which 2,404 are active and 8,102 are inactive. The compiled data includes comprehensive fund information on monthly returns net of management and performance fees, assets under management, management styles, and other fund characteristics. In order to minimize the survivorship bias, we include live as well as defunct hedge funds that

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[17] We test our approach against CAPM, Fama and French (1993), Carhart (1997), Agarwal and Naik (2004), Fung and Hsieh (2004), and Agarwal, Green, and Ren (2016) models.

[18] Bloomberg is the most common platform used by both hedge funds, who utilize news, analysis, research, and trading tools, and accredited investors, who use Bloomberg data to research hedge funds, private equity firms, and other alternative investment vehicles. Bloomberg aggregates data on live and dead funds inclusive of fund and parent company descriptions, manager and contact information, total assets under management, fees, past performance, and management style.

[19] We do not include funds of hedge funds in our sample.

were acquired, liquidated, or simply ceased to report during our sample period. We mitigate the backfill bias by eliminating the first 24 months of reported returns for each individual fund.[20]

Table 1 provides summary statistics of all hedge funds in our sample. Panel A reports that the typical hedge fund has a median management fee of 1.5%, a 20% incentive fee, a $250,000 minimum initial investment, and a 30 day redemption period. Live funds exhibit higher median monthly excess returns, larger assets under management, and greater longevity compared with defunct funds. Panel B shows that 79% of funds have a high water mark provision, 4% of funds impose hurdle rates, and 40% of funds are non-U.S. domiciled. Panel C shows that the most common declared style is long-short equity, which accounts for 26% of all funds.

We utilize the ETF data from Morningstar over the period 2003-2012 on all U.S. listed ETFs. Although ETF data are available before 2003, we focus on out-of-sample analysis from 2005-2012, when more than 100 ETFs per year are available, thus providing a broad coverage of potential risk factors. We manually check the description of each ETF and exclude ETFs that are not passively managed index tracking funds,[21] as well as ETFs that track hedge fund indexes, leaving us with 1,313 unique ETFs available over the sample period. Following Duanmu, Li and Malakhov (2014), we require at least two years of monthly ETF returns for our analysis, reducing the number of ETFs to 786 that are used in our LAR LASSO matching regressions. As shown in Figure 1, the number of ETFs has grown considerably over the sample period, which expands the space of investment opportunity set, provides broad coverage of risk factors available to hedge fund managers, and entails precise performance evaluation of hedge fund

[20] The 24-month backfill correction is in line with results in Jagannathan, Malakhov, and Novikov (2010) and Titman and Tiu (2011) suggesting dropping the first 25 and 27 months of returns. See Ackerman, McEnally, and Ravenscraft. (1999) and Fung and Hsieh (2000) for the backfill bias description.
[21] Benchmark indexes that retained ETFs track may not be publicly available. Some funds track in-house indexes.

returns.

E. Methodology

1. The DLM Estimation of Alpha

We conduct performance attribution by augmenting the methodology developed in Duanmu, Li, and Malakhov (2014). The methodology employs ETFs as tradable proxies for risk factors.

First, we perform cluster analysis to reduce the potential multicollinearity among the comprehensive set of ETFs. We calculate each ETFs distance from the center of its cluster using the Strategy Distinctiveness Index (*SDI*) measure from Sun, Wang, and Zheng (2012). This distance measure for ETF *i* is calculated as one minus the correlation of the ETF's return with the mean return of all ETFs from the same cluster *I*, i.e.

$$SDI_i = 1 - corr(r_i, \mu_I), \\ \text{where } \mu_I = \frac{\sum_{i \in I} r_i}{count(i \in I)}. \qquad (1)$$

The lower the *SDI*, the closer the ETF is to the center of its cluster. We select the ETF with the lowest *SDI* as a proxy for all the ETFs in that cluster, and we include this ETF as a potential risk factor in the regression analysis. This approach mitigates multicollinearity while allowing for efficient spanning of the space of potential risk factors.

Second, we use LASSO (least absolute shrinkage and selection operator) regression with LAR (least angle regression) modification[22] to identify the risk factors that drive individual hedge fund performance. Introduced by Tibshirani (1996), LASSO is a regression technique that performs both regularization and variable selection to improve the prediction accuracy. For a

[22] See Hoerl and Kennard (1970), Tibshirani (1996), and Efron, Hastie, Johnstone, and Tibshirani (2004) for descriptions of RIDGE, LASSO, and LAR methodologies.

given parameter *t*, LASSO regression identifies an optimal set of factors with non-zero coefficients such that

$$\hat{\beta}_{Lasso} = \arg\min_{\beta} \| \mathbf{r} - \mathbf{X}\beta \|^2, \quad \text{such that } \sum_{j=1}^{m} |\beta_j| \leq t, \tag{2}$$

where **r** is the vector of hedge fund monthly returns in our research and **X** is the vector of ETF monthly returns.

Given the set of factors, LASSO regression determines the appropriate factors to be selected through an optimization approach. In this constrained form of ordinary least squares regression, the sum of absolute values of the beta coefficients is estimated and constrained to be smaller than a specific fixed value, *t*. For a given value of *t*, some of the beta coefficients would be set to zero if the corresponding factors reveal little or no information about the dependent variable. This approach "shrinks" the set of regression factors until the beta coefficients are the solution of the optimization problem, resulting in efficient and parsimonious factor selection. The parameter *t* controls the amount of "shrinkage", with lower values of *t* resulting in fewer factors being selected for the model. We calculate LASSO regression solutions across a range of *t* values by employing a computationally efficient least angle regression (LAR) modification of the LASSO procedure introduced in Efron, Hastie, Johnstone, and Tibshirani (2004). The optimal factor model is then selected with the lowest value of the Bayesian Information Criterion (BIC). As the last step, we estimate factor loadings, β, via the ordinary least squares (OLS) regression with the factors selected by the LAR LASSO procedure. In other words, while we rely on LAR LASSO for factor selection, we use OLS estimates of the model coefficients. This approach allows for the orthogonal decomposition of factor exposures with the error term, which is important from the return attribution perspective.

Finally, while clustering does mitigate multicollinearity among ETFs in principle, we do not know the theoretically optimal number of clusters for each fund.[23] We determine the optimal number of clusters for each fund empirically by iteratively running cluster analysis and LAR LASSO regression for each fund one hundred times, assuming that the ETFs available could be sorted into 1 to 100 clusters. We set the maximum number to 100 because we believe it is an efficient and sufficiently large set of investment opportunities. Consequently, each individual hedge fund has one hundred corresponding models with unique selection parameters. We choose the model with the highest adjusted R-square as the final factor model.

To capture the dynamic nature of hedge funds' investment activities, we run the LAR LASSO regression with OLS-estimated coefficients for each individual fund over 24-month windows, rolling annually over the sample period.[24] We use the factor model as a dynamic benchmark to obtain estimates of alpha. The basic regression model is as follows:

$$r_{i,net} - r_f = \alpha_i + \beta_{i1}(ETF_1 - r_f) + \beta_{i2}(ETF_2 - r_f) + ... + \beta_{i100}(ETF_{100} - r_f) + \varepsilon_i, \quad (3)$$

where $r_{i,net}$ is the net monthly return of fund i, and r_f is the risk-free rate proxied by the monthly return of the 30-day U.S. Treasury bill. We do not restrict beta coefficients to be positive nor add up to one, because hedge funds are flexible in their investment options to take leverage and short positions.[25] It is worth mentioning that the regression model is different from that in Duanmu, Li,

[23] On the one hand, selecting too few clusters works well for resolving multicollinearity, but results in the loss of potentially informative factors. On the other hand, selecting too many clusters provides wider coverage of the factor space, while hindering the effectiveness of the LAR LASSO procedure by relatively high levels of multicollinearity.
[24] We focus on annual rolling estimates because of high illiquidity of hedge fund investments from an investor perspective. Given typical lockup and redemption notice restrictions in the hedge fund industry, it is not reasonable to assume that investors would be able to rebalance their hedge fund portfolios with higher frequencies.
[25] For example, ter Horst, Nijman, and de Roon (2004) demonstrate that imposing unwarranted style based constraints can lead to biased risk exposure estimates.

and Malakhov (2014) in three respects. First, Duanmu, Li, and Malakhov (2014) use gross hedge fund returns on the left-hand side with the intention of fully replicating hedge fund returns before fees. We use net hedge fund returns here, because we seek to evaluate returns from the perspective of performance attribution, and we are interested in evaluating hedge fund performance after fees.[26] Second, Duanmu, Li, and Malakhov (2014) suppress the intercept, focusing on cloning of total hedge fund returns. However, we are particularly interested in the intercept, α_i, which is the DLM alpha estimate for fund *i* over the regression time window. Third, we estimate factor loadings, β_{ij}, via the ordinary least squares regression with the factors selected by the LAR LASSO procedure. This method allows for the orthogonal decomposition of factor exposures with the error term.

2. Comparison of Performance Evaluation Models

In order to investigate whether the DLM methodology quantifies the relevant risk factor exposures and produce informative alpha and beta estimates, we compare our model against prevailing factor models proposed by extent research. The models and corresponding factors include:

CAPM model: the basic single market factor (*MKTRF*) model.

Fama and French (1993) 3-factor model (denoted FF3): factors include market factor (*MKTRF*), size factor (*SMB*) and value factor (*HML*).

Carhart (1997) 4-factor model (denoted Carhart4): Fama and French 3-factors and momentum factor (*UMD*)

[26] Considering the net-of-fees hedge fund returns also enables direct comparisons of our model with the alternative hedge fund factor models that rely on the net-of-fees approach.

Agarwal and Naik (2004) 6-factor[27] model (denoted AN6): Carhart 4-factors, an out-of-the-money call option factor (*OTM_CALL*), and an out-of-the-money put option factor (*OTM_PUT*).

Fung and Hsieh (2004) 8-factor[28] model (denoted FH8): A market risk premium proxied by the S&P 500 index excess return (*SP500*), an equity size premium proxied by Russell 2000 Index return minus the S&P 500 Index return (*SizeSpread*), the MSCI Emerging Market index excess return (*EM*), the monthly excess return of a 10-year U.S. treasury bond proxied by the 10-year U.S. Treasury bond portfolio excess return from the Center for Research in Security Prices (*10Year*), a fixed income-based risk factor calculated as the total return on the Citi BBB corporate bond index minus the total return on the Fama U.S. Treasury bond portfolio as per CRSP (*CreditSpread*), and excess returns on trend-following factors constructed of lookback straddles on futures contracts of bonds (*BondTrend*), commodities (*ComTrend*), and currencies (*FxTrend*), respectively.

Agarwal, Green, and Ren (2016) 12-factor model (denoted 12-factor): Fung and Hsieh (2004) 8-factors, size factor (*SMB*), value factor (*HML*), out-of-the-money call option factor (*OTM_CALL*), and out-of-the-money put option factor (*OTM_PUT*).

Agarwal, Green, and Ren (2016) 15-factor max R^2 model (denoted Max R^2): Agarwal, Green, and Ren 12-factor plus the return on VIX (*RETVIX*), a liquidity risk factor (*LIQ*),[29] and a

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[27] This is a modified version of Agarwal and Naik (2004) model proposed in Agarwal, Green, and Ren (2016).

[28] While Fung and Hsieh (2004) specify the seven factor model, the updated specification on David Hsieh's web site at http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm includes eight factors.

[29] See Sadka (2010).

macroeconomic uncertainty risk factor (*UNCTIDX*).[30] The optimal factors are selected based on the criterion of maximum adjusted R-square.

Consistent with the previously described methodology, we use 24-month window regressions to estimate alphas for these models, rolling annually. For example, equation (4) illustrates the Fung and Hsieh (2004) eight factors model regression:

$$\begin{aligned} r_i - r_f &= \alpha_i + \beta_{i1} SP500 + \beta_{i2} EM + \beta_{i3} 10Year + \beta_{i4} SizeSpread + \\ &\quad \beta_{i5} CreditSpread + \beta_{i6} BondTrend + \beta_{i7} ComTrend + \beta_{i8} FxTrend + \varepsilon_i. \end{aligned} \tag{4}$$

The regression intercept α_i represents the FH8 alpha of fund *i*. $\beta_1, \beta_2, \ldots, \beta_8$ are the FH8 beta coefficients of fund *i*.

3. Out-of-Sample Testing of Performance Persistence

To highlight the effectiveness of the DLM model in providing informative estimates and offering tangible benefits to investors, we conduct our analysis of the efficacy of alpha and beta coefficients in the framework of out-of-sample performance persistence.

We demonstrate the efficacy of DLM alpha estimates by considering the out-of-sample performance of portfolios based on the rank of in-sample alphas. The portfolio approach also minimizes the out-of-sample survivorship bias because all hedge funds are considered until they disappear from the database. By sorting hedge funds on historical alpha, we form DLM alpha portfolios on January 1st, 2005. We invest the same dollar amount into each hedge fund within a portfolio in the beginning, and track its net-of-fees performance until December 31, 2012, rebalancing it once a year based on updated in-sample regression alphas. When a hedge fund disappears from the database, we redistribute the remaining capital in the fund equally amongst

[30] See Bali, Brown, and Caglayan (2014).

surviving funds in the portfolio.[31] This procedure produces a time series of 96 monthly returns for hedge fund portfolios, which is then used to evaluate long-term portfolio performance across diverse economic conditions. We calculate end-of-sample dollar values based upon a $1 initial investment, mean excess monthly returns, Sharpe ratios, and attrition rates for each time series of monthly portfolio returns from January 2005 until December 2012. Importantly, since the out-of-sample alpha is sensitive to the benchmark model used, we calculate multiple out-of-sample portfolio alphas and information ratios by regressing the time series of portfolio returns on every model.[32] We apply the same procedure to form CAPM, FF3, Carhart4, AN6, FH8, 12-Factor, and Max R^2 portfolios and examine their out-of-sample performance respectively. This approach provides an impartial comparison of the tangible out-of-sample benefit provided by each model alpha estimates.

We demonstrate the efficacy of the DLM beta estimates relative to other models by considering the out-of-sample performance of beta-weighted hedge fund clones compared to the underlying hedge funds. For every hedge fund we construct beta–weighted clone portfolios based on factors and corresponding beta estimates from each model. The more effective selection of relevant factors along with more informative estimates of beta coefficients results in higher out-of-sample matching quality for individual funds proxied by out-of-sample correlations between the beta-weighted clones and the underlying hedge funds, and the adjusted R-squares from regressions of the beta-weighted clones on the underlying hedge funds.

[31] This is somewhat conservative as it is possible that a fund simply chooses to stop reporting to the database, which is likely for well performing funds that are no longer accepting new investor flows. However, without returns data we obviously cannot keep the fund in the portfolio.
[32] For Agarwal, Green, and Ren (2016) 15-factor Max R^2 model, we calculate the out-of-sample alpha based on Max R^2 approach which maximizes the explanatory power of risk factors. See Agarwal, Green, and Ren (2016).

F. Empirical Results

1. In-Sample Matching and Out-of-Sample Portfolio - DLM Model

As described in the previous section, our in-sample matching procedure is based on LAR LASSO regression with OLS estimates of coefficients. Table 2 reports the results for annual rolling two-year matching regressions from 2005 to 2012. The results suggest that on average hedge funds do not produce high alphas in the sample period. The average in-sample monthly DLM alpha between 2005 and 2012 is 0.04%, and most alphas are negative in the first half of the sample period. The average matching adjusted R-square is 0.60, and it rises over time indicating an improved matching quality. The average number of factors selected by LAR LASSO is 2.51 for the whole sample period, which suggests that our model results in a parsimonious factor selection.

We apply the portfolio approach to analyzing the out-of-sample performance of hedge funds. To highlight the predictive power of DLM alpha on performance persistence, we first sort hedge funds into deciles on the basis of in-sample DLM alpha. The out-of-sample performance of hedge funds in top and bottom DLM alpha deciles is presented in Table 3 Panel A. The top hedge fund portfolio delivers a portfolio end value of $2.21, a significant mean monthly return of 0.72%, and a significant Sharpe ratio of 0.29. In addition, the portfolio exhibits a low attrition rate of 7.62% relative to the attrition rate of 12.96% across all hedge funds in our sample. On the other hand, the portfolio of hedge funds in the bottom DLM alpha decile fails to provide significant risk-adjusted performance and has a much higher attrition rate of 20.70%. Although we are not able to take short positions on the hedge fund with bottom DLM alpha, the result still provides valuable information on screening unskilled hedge funds. Furthermore, we increase the number of funds in the out-of-sample portfolios by considering hedge funds in the top and bottom quintile of DLM alpha. The results in Panel B show that robust risk-adjusted performance still holds when more hedge funds are included in the portfolio.

2. In-Sample Matching and Out-of-Sample Portfolio - All Models

We then investigate the in-sample matching statistics of all models during the whole sample period. Table 4 shows that the average in-sample DLM alpha is significantly lower than alphas estimated by other models. On the other hand, the DLM model yields better in-sample matching as measured by higher adjusted R-square. The average in-sample DLM adjusted R-square is much higher than all other models except the Max R^2 model. The difference may suggest that a proportion of hedge fund returns, which other models consider not attributable, could be attributed to risk factors identified by the DLM model. Moreover, although DLM model explores a comprehensive set of potential risk factors, it only selects an average of 2.51 factors, which is parsimonious compared to other multifactor models. The dynamic Max R^2 model provides the highest in-sample adjusted R-square; however, its average number of factors selected and standard deviation of the number of factors are both higher than that of the DLM model.

In an out-of-sample portfolio horse race, we validate whether the DLM model delivers superior risk-adjusted performance by comparing it with the other models. As described previously, for each model we form an out-of-sample portfolio sorted on in-sample alpha, and we compare the risk-adjusted performance among different models. Tables 5 and 6 report the comparison results.

As shown in Panel A of Table 5, the portfolio formed on the top decile of DLM alpha dominates the performance of other model portfolios in mean monthly excess return, portfolio end value, and Sharpe ratio. We consider quintile portfolios in Panel B and find consistent results.

Table 6 examines the out-of-sample alpha and information ratio of each portfolio. Because out-of-sample alpha is sensitive to the benchmark model used, we calculate multiple out-of-sample portfolio alphas by regressing the time series of portfolio returns on every model. This approach allows for an impartial comparison of the tangible out-of-sample benefit provided by each model. It is worth noting that it is impossible to use the DLM model as a benchmark for evaluating alpha with a consistent set of factors for the entire time period because the universe of ETF factors changes across time. Therefore, we calculate out-of-sample portfolio alphas by using all other models except the DLM model. In Panel A, for example, the DLM column represents the out-of-sample portfolio formed on the top decile of in-sample DLM alpha. This portfolio delivers a monthly CAPM alpha of 0.58%, a monthly FH8 alpha of 0.49%, and a monthly Max R^2 alpha of 0.51%. The DLM model dominates other models on all risk-adjusted alpha measures including CAPM alpha, FF3 alpha, Carhart4 alpha, AN6 alpha, FH8 alpha, 12-Factor alpha and Max R^2 alpha. Remarkably, all of the out-of-sample alphas provided by the DLM model are statistically significant at 1% level. The superior performance holds consistently in Panel B where we form portfolios using quintile specification. The CAPM, FH8, 12-Factor and Max R^2 models show some predictive power of future performance but the predictive power is much weaker than that of the DLM model. Furthermore, we find that the top portfolios sorted on AN6 option-based model fail to predict out-of-sample risk-adjusted performance, while the bottom portfolios sorted on the AN6 model deliver somewhat significant mean returns, Sharpe ratios, and out-of-sample alphas. Panels C and D report out-of-sample information ratios. Not surprisingly, the DLM model still outperforms other models.

3. Relationship with the Other Models

In this section, we show that the DLM model captures relevant information unrecovered by other models, while capturing most of the other models' informative content. Table 7 presents performance metrics from "mutually exclusive" portfolios that isolate the top alpha funds unique to each model. For example, the column "DLM Ex CAPM" in Panel A includes hedge funds present in the top decile of the DLM alpha portfolio, but not present in top decile of the CAPM alpha portfolio, and the column "CAPM Ex DLM" includes hedge funds present in the top decile of the CAPM alpha portfolio but not present in top decile of the DLM alpha portfolio. Interestingly, when we exclude funds from the DLM portfolio that also present in alternative factor model portfolios, we find that the remaining DLM funds deliver statistically significant out-of-sample performance including end value, mean excess returns, Sharpe ratios, out-of-sample alphas, and information ratios. The opposite, however, is not true. When we exclude funds from the alternative factor model portfolios that also present in the DLM portfolio, the predictive power remains insignificant or becomes weaker. The quintile specification in Panel B provides similar evidence. The results suggest that the DLM model exhibits superior predictive power by incorporating most of the informative content of the other models and capturing relevant information unrecovered by other models.

We further investigate the relationship among the models by summarizing correlations between the in-sample alphas of different models in Panel A of Table 8, and correlations between the in-sample adjusted R-squares in Panel B. We find that the DLM in-sample alpha has relatively high positive correlations with CAPM, FF3, Carhart4 AN6 and FH8 alphas, and relatively low positive correlations with 12-Factor and Max R^2 alphas, which utilize more risk factors. On the other hand, the DLM in-sample R-square has a relatively high positive correlation with the FH8 R-square and a moderately positive correlation with other R-squares.

4. Longer-Term Persistence of Performance

We argue that the truly skillful managers should be able to deliver persistent outperformance through time. Therefore, instead of rebalancing the portfolio annually, we conduct portfolio rebalancing over two-year intervals. For example, in the scenario of two-year rebalancing for DLM model, we form DLM portfolios on January 1st, 2005, rebalancing it once every two years based on updated in-sample DLM alphas. We are particularly interested in whether the superior performance in skilled managers[33] is able to persist with respect to longer rebalancing intervals.

Table 9 Panel A presents the out-of-sample performance of top decile portfolios. We show that the portfolio in the top decile of DLM alpha is able to deliver dominant risk-adjusted performance, with higher end value, Sharpe ratio, information ratio, mean monthly return and out-of-sample alpha compared with other models. The approach is applied to the top quintile alpha portfolios in Panel B, and the results largely remain. The finding provides evidence of persistence in the performance of funds selected on DLM alpha - either a hedge fund manager has the skill or does not. The DLM model alpha identifies the talented hedge funds that possess active investment skill and are able to provide the long-term absolute performance to investors.

5. Quality of Out-of-Sample Individual Beta-Weighted Matches

Finally, to directly validate the efficacy of the DLM model in selecting relevant risk factors and producing informative estimates of beta coefficients, we compare the out-of-sample performance of beta-weighted hedge fund clones with the performance of the underlying hedge funds. We construct hedge fund clones for each hedge fund as a beta-loaded portfolio of risk

[33] We argue that the alpha from a return attribution model that successfully captures risk factor exposures could be interpreted as a proxy for managerial skill.

factors, with the beta weights and the factors determined from in-sample regressions. The out-of-sample hedge fund clone performance after the in-sample matching period is given by

$$\textit{Clone Return}_{i,t} = r_{f,t} + \sum_{j=1}^{n} \beta_{j,t-1}(\textit{Factor Return}_{j,t} - r_{f,t}), \qquad (5)$$

where $\beta_{j,t-1}$ is the factor coefficient from the previous two-year in-sample regression.

Table 10 presents the out-of-sample correlations between the beta-weighted clones and the underlying hedge funds for each model in Panel A, and the out-of-sample adjusted R-squares from regressions of the beta-weighted clones on the underlying hedge funds in Panel B. We find that the average out-of-sample correlation of the DLM model is the highest among all models in the sample period from 2005 to 2012. The DLM adjusted R-square is also consistently higher than that of other models across the sample period. The results indicate that the hedge fund mimicking portfolios constructed as beta-weighted factor portfolios according to our model display considerably better out-of-sample matches with underlying hedge funds compared to portfolios constructed from other models. This result is consistent with the interpretation of the higher efficacy in hedge fund return attribution of the DLM model by selecting more contemporaneously relevant risk factors and producing more informative estimates of beta coefficients relative to alternative models.

G. Conclusion

Properly identifying the risk factors underlying hedge fund investment strategies and dynamically adjusting the set of factors to reflect the current information set is paramount for successful return attribution in active investments vehicles. There has been a growing interest among researchers and practitioners to decompose hedge fund returns to a replicable beta component and an active alpha component.

This research redefines performance evaluation by employing ETFs as tradable proxies to capture the intertemporal aspect of the information set. We select ETF risk factors with cluster analysis and LAR LASSO regression procedure, while simultaneously estimating the free coefficient, alpha. The methodology demonstrates substantial improvement in hedge fund performance attribution compared to the commonly used factor models. The benefits of successful return attribution include the improved knowledge of the contemporaneous information set, the ability to evaluate the skill of hedge fund managers through alpha, and the ability to make beta-driven investments without investing in hedge funds by forming beta-weighted clone portfolios.

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Figure 1: Number of ETFs, 1999-2012

Number of ETFs available, and number of ETFs used in LASSO regressions are reported. ETF data is collected from Morningstar.

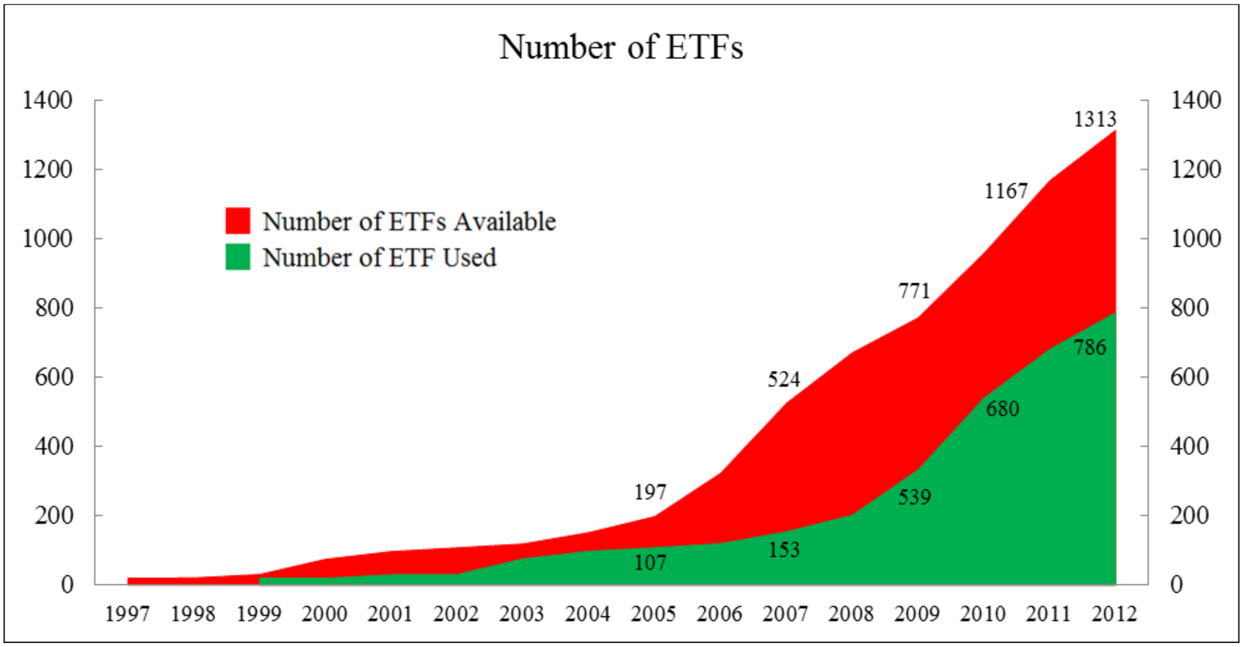

Table 1: Summary Statistics

Summary statistics of all hedge funds from 2003-2012. Panel A reports returns, fees, and investor liquidity measures. Panel B reports means of indicator variables of fund characteristics, and Panel C reports self-declared fund styles.

Panel A	Full Sample (10,506 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly excess return	0.15	0.27	-1.25	1.37	4.57
Assets ($M)	208.33	44.55	3.68	368.47	1462.98
Min Invest ($M)	1.36	0.25	0.03	1	12.84
Mgmt Fee (%)	1.50	1.50	0.75	2	0.65
Perf Fee (%)	17.21	20	0	20	7.09
Hurdle Rate (%)	0.31	0	0	0	1.60
Lockup Period (days)	76.11	0	0	360	251.67
Redemption Notice (days)	12.29	0	0	45	26.65
Redemption Period (days)	51.52	30	30	90	52.00
Total Redemption (days)	64.77	35	30	120	62.16
Longevity (months)	41.74	33	6	96	33.59
	Active Funds (2,404 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly excess return	0.73	0.57	-0.22	1.51	6.23
Assets ($M)	258.62	85.35	9.86	653.28	582.74
Min Invest ($M)	1.47	0.25	0.03	1	12.35
Mgmt Fee (%)	1.51	1.50	0.85	2	0.62
Perf Fee (%)	17.20	20	0	20	6.93
Hurdle Rate (%)	0.36	0	0	0	1.68
Lockup Period (days)	86.38	0	0	360	370.65
Redemption Notice (days)	21.60	2	0	65	32.39
Redemption Period (days)	49.65	30	7	90	52.22
Total Redemption (days)	71.76	55	21	150	67.44
Longevity (months)	56.52	48	11	120	38.37
	Inactive Funds (8,102 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly excess return	-0.02	0.16	-1.54	1.29	3.92
Assets ($M)	193.61	35.99	2.94	292.82	1,632.95
Min Invest ($M)	1.33	0.25	0.03	1	12.99
Mgmt Fee (%)	1.50	1.50	0.75	2	0.66
Perf Fee (%)	17.21	20	0	20	7.14
Hurdle Rate (%)	0.29	0	0	0	1.57
Lockup Period (days)	72.67	0	0	360	196.22
Redemption Notice (days)	9.41	0	0	30	23.88
Redemption Period (days)	52.14	30	30	90	51.91
Total Redemption (days)	62.44	30	30	120	60.13
Longevity (months)	37.36	29	5	83	30.69

Table 1: Summary Statistics (Cont.)

Panel B - Indicator	% of Funds		
	Full Sample	Active Funds	Inactive Funds
High Water Mark	0.79	0.87	0.77
Hurdle Rate	0.04	0.06	0.04
Offshore (non-US)	0.40	0.38	0.41
Closed to New Inv	0.05	0.05	0.04
Liquidated	0.37	0.00	0.48
Acquired	0.03	0.00	0.03

Panel C - Fund Styles	% of Funds		
	Full Sample	Active Funds	Inactive Funds
Long-Short	0.26	0.26	0.26
Multi Strategy	0.12	0.12	0.12
Undisclosed	0.08	0.00	0.11
Market Neutral	0.06	0.05	0.06
Long Biased	0.05	0.07	0.04
Discretionary	0.05	0.04	0.05
Fixed Income Diversified	0.05	0.06	0.04
Systematic	0.05	0.08	0.03
Discretionary Thematic	0.04	0.05	0.04
Emerging Market	0.03	0.04	0.03
Macro Diversified	0.03	0.03	0.03
Distressed Securities	0.02	0.01	0.02
Fixed Income Arbitrage	0.02	0.02	0.02
Statistical Arbitrage	0.02	0.01	0.02
Systematic Diversified	0.02	0.03	0.01
Merger Arbitrage	0.01	0.01	0.02
Convertible Arbitrage	0.01	0.01	0.02
Event Driven Diversified	0.01	0.02	0.01
Cap Structure/Credit Arbitrage	0.01	0.01	0.01
Emerging Market Debt	0.01	0.01	0.01
Asset-Backed Securities	0.01	0.02	0.01
Currency	0.01	0.01	0.01
Equity Hedge Diversified	0.01	0.01	0.01
Mortgage-Backed	0.01	0.01	0.01
Special Situation	0.01	0.01	0.00
Short Biased	0.00	0.00	0.00
Activist	0.00	0.00	0.00

Table 2: In-Sample Statistics, DLM Model

In-sample LASSO matching regression results for the sample period 2005-2012 are reported. Regressions are run over 24-month window, rolling annually. *ETFs Used* represent all ETFs available for LASSO regressions, while *ETFs Selected* represent ETFs that were selected by LASSO as regressors for individual hedge funds. Mean excess returns, DLM alphas, LASSO adjusted R-squares, BIC values, and numbers of matched LASSO regressors are reported for each matching window. Standard deviations are reported in parentheses.

Year	Number of Hedge Funds	Number of ETFs Used	Number of ETFs Selected	Mean Excess Return	DLM Alpha	Adj. R^2	BIC	Number of Regressors
2003-2004	1331	107	103	0.36 (1.41)	0.08 (1.04)	0.51 (0.23)	25.13 (38.54)	2.49 (1.41)
2004-2005	1629	119	108	0.71 (1.33)	-0.13 (0.92)	0.55 (0.23)	17.73 (36.58)	2.31 (1.32)
2005-2006	1993	153	111	0.58 (1.27)	-0.08 (0.81)	0.56 (0.22)	17.61 (34.41)	2.43 (1.36)
2006-2007	2310	201	127	-1.75 (3.15)	-0.04 (0.91)	0.60 (0.22)	18.12 (34.37)	2.65 (1.51)
2007-2008	2381	332	123	1.42 (2.87)	-0.08 (1.19)	0.65 (0.26)	34.78 (32.6)	2.68 (1.62)
2008-2009	2598	539	133	0.71 (1.63)	0.11 (1.4)	0.65 (0.23)	43.84 (30.76)	2.54 (1.38)
2009-2010	2913	680	138	-0.47 (1.48)	0.37 (1.51)	0.63 (0.24)	31.69 (33.85)	2.54 (1.42)
2010-2011	3116	786	134	0.38 (2.19)	0.06 (1.06)	0.67 (0.24)	26.18 (32.69)	2.47 (1.29)
Average				**0.24**	**0.04**	**0.60**	**26.89**	**2.51**

Table 3: Out-of-Sample Portfolios, DLM Model

Annual returns and cumulative risk-adjusted performances of portfolios formed on the basis of in-sample matching regression DLM alphas. Portfolios of hedge funds are formed on January 1, 2005, and rebalanced annually on updated DLM alphas. End values are as of December 31, 2012. Attrition rates are calculated as averages across annual rates at which hedge funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio hedge funds. Panel A reports results for top (bottom) decile portfolios formed on the basis of in-sample DLM alphas. Panel B reports results for top (bottom) quintile portfolios formed on the basis of in-sample DLM alphas. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Panel A - DLM Alpha, Decile

	DLM Alpha Top Decile			DLM Alpha Btm Decile		
Year	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return
2005	134	130	20.26	134	120	7.12
2006	163	156	20.98	163	138	12.91
2007	200	182	15.32	200	160	13.15
2008	232	197	-11.00	232	168	-7.26
2009	239	222	19.28	239	184	52.14
2010	260	249	22.17	260	209	7.74
2011	292	265	-7.97	292	221	-13.20
2012	312	284	10.45	312	233	-5.68
End Value		2.21			1.70	
Mean Return		0.72***			0.48	
(t-stat)		(2.84)			(1.24)	
Sharpe Ratio		0.29***			0.13	
(t-stat)		(2.76)			(1.23)	
Attrition rate		7.62%			20.70%	

Table 3: Out-of-Sample Portfolios, DLM Model (Cont.)

Panel B - DLM Alpha, Quintile

	DLM Alpha Top Quintile			DLM Alpha Btm Quintile		
Year	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return
2005	267	261	14.90	267	236	5.84
2006	326	313	16.52	326	286	16.04
2007	399	365	14.54	399	337	13.50
2008	463	398	-13.66	463	333	-12.51
2009	477	444	17.41	477	369	41.73
2010	520	489	16.61	520	407	9.08
2011	583	527	-6.66	583	454	-11.45
2012	624	560	8.77	624	480	-0.83
End Value		1.84			1.66	
Mean Return		0.52**			0.43	
(t-stat)		(2.22)			(1.30)	
Sharpe Ratio		0.23**			0.13	
(t-stat)		(2.18)			(1.28)	
Attrition rate		7.69%			19.63%	

Table 4: Comparison of In-Sample Statistics

In-sample matching regression results for the sample period 2005-2012 are reported for each model. Regressions are run over 24-month window, rolling annually. Models include CAPM, FF3, Carhart4, AN6, FH8, 12-Factor, Max R^2, and DLM. Means and standard deviations of alpha estimates, adjusted R-squares, and numbers of matched regressors are reported for each model.

	Alpha		Adj. R^2		# of Regressors	
	Mean	SD	Mean	SD	Mean	SD
CAPM	0.35	1.05	0.24	0.23	1	-
FF3	0.26	1.07	0.27	0.26	3	-
Carhart4	0.21	1.06	0.29	0.26	4	-
AN6	0.19	1.39	0.30	0.27	6	-
FH8	0.22	1.14	0.38	0.23	8	-
12-Factor	0.25	1.70	0.40	0.32	12	-
Max R^2	0.64	3.12	0.66	0.19	7.75	2.22
DLM	0.04	1.10	0.60	0.23	2.51	1.41

Table 5: Out-of-Sample Performance, Portfolio Comparison

The table reports annual returns and cumulative risk-adjusted performance measures of portfolios formed on the basis of in-sample matching regression alphas for each model. Portfolios of hedge funds are formed on January 1, 2005, and rebalanced annually on updated in-sample alphas. End values are as of December 31, 2012. Attrition rates are calculated as average annual rates at which hedge funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio hedge funds. Panel A reports results for top (bottom) decile portfolios formed on the basis of in-sample alphas for each model. Panel B reports results for top (bottom) quintile portfolios formed on the basis of in-sample alphas for each model. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Panel A - Out-of-Sample Portfolio Performance, Deciles

	Top Decile							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	Max R^2	DLM
End Value	2.04	1.76	1.83	1.59	1.83	1.83	2.02	2.21
Mean Return	0.66*	0.50	0.54*	0.38	0.52*	0.53*	0.64**	0.72***
	(1.88)	(1.47)	(1.65)	(1.3)	(1.92)	(1.79)	(1.99)	(2.84)
Sharpe Ratio	0.19*	0.15	0.17	0.13	0.19*	0.18*	0.20**	0.29***
	(1.86)	(1.46)	(1.63)	(1.29)	(1.89)	(1.76)	(1.96)	(2.76)
Attrition Rate	6.68%	7.23%	7.69%	8.35%	7.69%	10.42%	10.24%	7.62%

	Btm Decile							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	Max R^2	DLM
End Value	1.37	1.64	1.79	2.11	1.49	1.81	1.62	1.70
Mean Return	0.24	0.44	0.53	0.71*	0.34	0.54	0.43	0.48
	(0.70)	(1.19)	(1.44)	(1.77)	(0.89)	(1.40)	(1.10)	(1.24)
Sharpe Ratio	0.07	0.12	0.15	0.18*	0.09	0.14	0.11	0.13
	(0.70)	(1.19)	(1.43)	(1.76)	(0.89)	(1.39)	(1.10)	(1.23)
Attrition Rate	24.40%	23.64%	22.92%	19.96%	22.05%	19.95%	16.78%	20.32%

Table 5: Out-of-Sample Performance, Portfolio Comparison (Cont.)

Panel B - Out-of-Sample Portfolio Performance, Quintiles

	Top Quintile							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	Max R^2	DLM
End Value	1.89	1.66	1.69	1.45	1.68	1.70	1.75	1.84
Mean Return	0.56*	0.43	0.44	0.28	0.43*	0.44*	0.48*	0.52**
	(1.83)	(1.44)	(1.54)	(1.00)	(1.72)	(1.72)	(1.66)	(2.22)
Sharpe Ratio	0.19*	0.15	0.16	0.10	0.17*	0.17*	0.17*	0.23**
	(1.81)	(1.43)	(1.53)	(1.00)	(1.70)	(1.70)	(1.65)	(2.18)
Attrition Rate	7.02%	7.39%	7.61%	8.78%	7.99%	9.95%	10.69%	7.69%
	Btm Quintile							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	Max R^2	DLM
End Value	1.50	1.71	1.74	1.92	1.56	1.67	1.67	1.66
Mean Return	0.32	0.46	0.48	0.59*	0.38	0.45	0.44	0.43
	(1.06)	(1.45)	(1.53)	(1.75)	(1.09)	(1.31)	(1.33)	(1.30)
Sharpe Ratio	0.11	0.15	0.16	0.18	0.11	0.13	0.14	0.13
	(1.06)	(1.44)	(1.52)	(1.73)	(1.09)	(1.31)	(1.32)	(1.28)
Attrition Rate	21.40%	20.35%	20.01%	18.22%	19.72%	17.34%	15.76%	19.44%

Table 6: Out-of-Sample Alphas and Information Ratios, Portfolio Comparison

The table reports out-of-sample portfolio alphas and information ratios of portfolios formed on the basis of in-sample matching regression alphas for each model (column). Portfolios of hedge funds are formed on January 1, 2005, and rebalanced annually on updated in-sample alphas. Panel A reports risk-adjusted alphas of top (bottom) decile portfolios formed on the basis of in-sample alphas for each model. Panel B reports risk-adjusted alphas of top (bottom) quintile portfolios formed on the basis of in-sample alphas for each model. Panels C and D report information ratios for top (bottom) deciles and quintiles portfolios respectively. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Panel A - Out-of-Sample Portfolio Alpha, Deciles

	Top Decile							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	Max R^2	DLM
CAPM Alpha	0.49*	0.33	0.37	0.23	0.39*	0.40*	0.51*	0.58***
	(1.86)	(1.31)	(1.57)	(1.09)	(1.88)	(1.66)	(1.84)	(3.3)
FF3 Alpha	0.50*	0.34	0.39*	0.24	0.40*	0.40*	0.52*	0.58***
	(1.95)	(1.42)	(1.68)	(1.16)	(1.92)	(1.69)	(1.89)	(3.33)
Carhart4 Alpha	0.48*	0.33	0.37*	0.22	0.39*	0.39*	0.51*	0.58***
	(1.95)	(1.4)	(1.66)	(1.12)	(1.89)	(1.67)	(1.87)	(3.31)
AN6 Alpha	0.44*	0.29	0.30	0.26	0.38*	0.46**	0.55*	0.51***
	(1.79)	(1.18)	(1.24)	(1.23)	(1.76)	(1.96)	(1.95)	(2.96)
FH8 Alpha	0.33*	0.22	0.29	0.13	0.39**	0.35*	0.41	0.49***
	(1.67)	(1.06)	(1.45)	(0.69)	(2.2)	(1.67)	(1.56)	(3.38)
12-Factor Alpha	0.37**	0.28	0.29	0.22	0.40**	0.42**	0.46*	0.49***
	(2.14)	(1.45)	(1.53)	(1.3)	(2.24)	(2.18)	(1.84)	(4.02)
Max R^2 Alpha	0.32*	0.20	0.25	0.18	0.38**	0.40**	0.49**	0.51***
	(1.94)	(1.18)	(1.57)	(1.15)	(2.34)	(2.18)	(2.37)	(4.23)
	Btm Decile							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	Max R^2	DLM
CAPM Alpha	0.06	0.25	0.35	0.50*	0.12	0.32	0.20	0.31
	(0.25)	(0.94)	(1.24)	(1.79)	(0.52)	(1.33)	(0.86)	(1.01)
FF3 Alpha	0.06	0.26	0.35	0.50*	0.12	0.33	0.20	0.32
	(0.26)	(0.95)	(1.25)	(1.78)	(0.53)	(1.33)	(0.86)	(1.03)
Carhart4 Alpha	0.08	0.27	0.36	0.51*	0.13	0.34	0.21	0.33
	(0.31)	(1)	(1.28)	(1.83)	(0.58)	(1.37)	(0.9)	(1.06)
AN6 Alpha	-0.05	0.14	0.27	0.39	0.00	0.13	0.08	0.26
	(-0.17)	(0.45)	(0.82)	(1.19)	(-0.01)	(0.49)	(0.32)	(0.73)
FH8 Alpha	-0.01	0.10	0.21	0.34	-0.06	0.11	0.07	0.19
	(-0.06)	(0.4)	(0.76)	(1.34)	(-0.27)	(0.55)	(0.34)	(0.67)
12-Factor Alpha	-0.10	0.02	0.14	0.25	-0.11	-0.02	-0.02	0.13
	(-0.4)	(0.06)	(0.51)	(0.92)	(-0.54)	(-0.1)	(-0.08)	(0.4)
Max R^2 Alpha	-0.32	-0.12	-0.08	0.08	-0.28	-0.09	-0.24	-0.25
	(-1.59)	(-0.56)	(-0.39)	(0.39)	(-1.62)	(-0.50)	(-1.34)	(-1.04)

Table 6: Out-of-Sample Alphas and Information Ratios, Portfolio Comparison (Cont.)

Panel B - Out-of-Sample Portfolio Alpha, Quintiles

	Top Quintile							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	Max R^2	DLM
CAPM Alpha	0.40*	0.27	0.29	0.13	0.30*	0.31	0.34	0.39***
	(1.84)	(1.32)	(1.47)	(0.67)	(1.67)	(1.64)	(1.54)	(2.6)
FF3 Alpha	0.41*	0.28	0.30	0.14	0.31*	0.32*	0.35	0.39***
	(1.92)	(1.43)	(1.58)	(0.76)	(1.74)	(1.68)	(1.62)	(2.69)
Carhart4 Alpha	0.40*	0.27	0.29	0.13	0.30*	0.31*	0.34	0.38***
	(1.9)	(1.39)	(1.55)	(0.72)	(1.71)	(1.66)	(1.6)	(2.66)
AN6 Alpha	0.34	0.20	0.21	0.08	0.25	0.33*	0.32	0.30**
	(1.62)	(0.95)	(1.01)	(0.41)	(1.37)	(1.77)	(1.44)	(2.11)
FH8 Alpha	0.27	0.17	0.20	0.02	0.26*	0.25	0.22	0.30**
	(1.61)	(0.97)	(1.21)	(0.1)	(1.72)	(1.57)	(1.14)	(2.56)
12-Factor Alpha	0.28*	0.18	0.19	0.05	0.25*	0.28*	0.24	0.29***
	(1.82)	(1.06)	(1.12)	(0.32)	(1.67)	(1.88)	(1.28)	(2.83)
Max R^2 Alpha	0.25*	0.18	0.19	0.07	0.25*	0.26*	0.30*	0.36***
	(1.82)	(1.29)	(1.40)	(0.44)	(1.86)	(1.84)	(1.76)	(3.42)

	Btm Quintile							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	Max R^2	DLM
CAPM Alpha	0.16	0.29	0.32	0.41*	0.18	0.25	0.25	0.27
	(0.78)	(1.32)	(1.39)	(1.81)	(0.85)	(1.21)	(1.28)	(1.09)
FF3 Alpha	0.16	0.29	0.32	0.41*	0.18	0.25	0.25	0.28
	(0.8)	(1.33)	(1.4)	(1.81)	(0.87)	(1.24)	(1.28)	(1.13)
Carhart4 Alpha	0.17	0.30	0.32	0.42*	0.19	0.26	0.25	0.28
	(0.85)	(1.37)	(1.42)	(1.84)	(0.91)	(1.26)	(1.31)	(1.15)
AN6 Alpha	0.03	0.18	0.23	0.29	0.07	0.10	0.13	0.20
	(0.15)	(0.72)	(0.92)	(1.15)	(0.32)	(0.45)	(0.64)	(0.75)
FH8 Alpha	0.05	0.15	0.17	0.27	0.01	0.07	0.12	0.16
	(0.26)	(0.72)	(0.78)	(1.34)	(0.05)	(0.44)	(0.74)	(0.74)
12-Factor Alpha	-0.03	0.07	0.12	0.18	-0.04	-0.01	0.05	0.11
	(-0.17)	(0.34)	(0.53)	(0.87)	(-0.2)	(-0.08)	(0.32)	(0.46)
Max R^2 Alpha	-0.17	-0.04	-0.08	0.04	-0.06	-0.11	-0.15	-0.12
	(-1.05)	(-0.25)	(-0.45)	(0.23)	(-0.41)	(-0.73)	(-1.04)	(-0.61)

Table 6: Out-of-Sample Alphas and Information Ratios, Portfolio Comparison (Cont.)

Panel C - Out-of-Sample Portfolio Information Ratio, Deciles

	Top Decile							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	Max R^2	DLM
CAPM IR	0.19	0.14	0.16	0.11	0.19	0.17	0.19	0.34
FF3 IR	0.20	0.15	0.17	0.12	0.20	0.17	0.19	0.34
Carhart4 IR	0.20	0.14	0.17	0.11	0.19	0.17	0.19	0.34
AN6 IR	0.18	0.12	0.13	0.13	0.19	0.20	0.21	0.30
FH8 IR	0.19	0.12	0.17	0.08	0.24	0.18	0.18	0.38
12-Factor IR	0.24	0.18	0.20	0.15	0.26	0.24	0.22	0.42
Max R^2 IR	0.21	0.13	0.17	0.13	0.25	0.24	0.27	0.46

	Btm Decile							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	Max R^2	DLM
CAPM IR	0.03	0.10	0.13	0.18	0.05	0.13	0.09	0.10
FF3 IR	0.03	0.10	0.13	0.18	0.05	0.13	0.09	0.10
Carhart4 IR	0.03	0.10	0.13	0.19	0.06	0.14	0.09	0.11
AN6 IR	-0.02	0.05	0.10	0.14	0.00	0.05	0.03	0.08
FH8 IR	-0.01	0.05	0.10	0.17	-0.03	0.07	0.04	0.08
12-Factor IR	-0.06	0.01	0.07	0.13	-0.07	-0.01	-0.01	0.05
Max R^2 IR	-0.18	-0.06	-0.04	0.04	-0.18	-0.06	-0.15	-0.11

Panel D - Out-of-Sample Portfolios Information Ratio, Quintiles

	Top Quintile							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	Max R^2	DLM
CAPM IR	0.19	0.14	0.15	0.07	0.17	0.17	0.16	0.27
FF3 IR	0.20	0.15	0.16	0.08	0.18	0.17	0.16	0.28
Carhart4 IR	0.19	0.14	0.16	0.07	0.17	0.17	0.16	0.27
AN6 IR	0.16	0.11	0.11	0.04	0.14	0.18	0.15	0.22
FH8 IR	0.19	0.11	0.14	0.01	0.19	0.17	0.13	0.29
12-Factor IR	0.21	0.14	0.15	0.04	0.19	0.21	0.15	0.31
Max R^2 IR	0.20	0.14	0.15	0.05	0.20	0.20	0.20	0.40

	Btm Quintile							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	Max R^2	DLM
CAPM IR	0.08	0.14	0.14	0.19	0.09	0.12	0.13	0.11
FF3 IR	0.08	0.14	0.14	0.18	0.09	0.13	0.13	0.11
Carhart4 IR	0.09	0.14	0.15	0.19	0.09	0.13	0.13	0.11
AN6 IR	0.02	0.09	0.11	0.13	0.03	0.05	0.07	0.08
FH8 IR	0.03	0.09	0.10	0.17	0.01	0.05	0.09	0.09
12-Factor IR	-0.02	0.05	0.07	0.11	-0.03	-0.01	0.04	0.06
Max R^2 IR	-0.12	-0.03	-0.05	0.03	-0.05	-0.08	-0.12	-0.07

Table 7: Out-of-Sample Mutually Exclusive Portfolios

The table reports annual returns and cumulative risk-adjusted performance measures, including alphas and information ratios, of mutually exclusive portfolios. For example, "DLM Ex CAPM" portfolio includes hedge funds in the top DLM alpha portfolio but not in the top CAPM alpha portfolio. "CAPM Ex DLM" portfolio includes hedge funds in the top CAPM alpha portfolio but not in the top DLM alpha portfolio. Portfolios of hedge funds are formed on January 1, 2005, and rebalanced annually on updated in-sample alphas. End values are as of December 31, 2012. Panel A includes top (bottom) decile mutually exclusive portfolios. Panel B includes top (bottom) quintile mutually exclusive portfolios. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Panel A - Out-of-Sample Portfolios, Top Decile

	Top Decile									
	DLM Ex CAPM	CAPM Ex DLM	DLM Ex Carhart4	Carhart4 Ex DLM	DLM Ex FH8	FH8 Ex DLM	DLM Ex 12-Factor	12-Factor Ex DLM	DLM Ex Max R^2	Max R^2 Ex DLM
End Value	1.89	1.62	2.18	1.41	2.27	1.61	2.27	1.63	2.32	2.00
Mean Return	0.54**	0.46	0.70***	0.30	0.75***	0.40	0.74***	0.41	0.76***	0.63*
	(2.39)	(1.01)	(2.87)	(0.71)	(2.72)	(1.22)	(3.16)	(1.29)	(3.22)	(1.90)
Sharpe Ratio	0.25**	0.10	0.29***	0.07	0.28***	0.12	0.32***	0.13	0.33***	0.19*
	(2.37)	(1.0)	(2.82)	(0.71)	(2.66)	(1.21)	(3.08)	(1.27)	(3.12)	(1.88)
Attrition Rate	8.10%	5.74%	7.19%	7.68%	7.81%	8.35%	7.19%	11.56%	7.73%	11.25%
CAPM Alpha	0.42***	0.24	0.57***	0.09	0.60***	0.27	0.61***	0.29	0.64***	0.51*
	(2.66)	(0.69)	(3.37)	(0.28)	(3.27)	(0.98)	(3.85)	(1.04)	(3.77)	(1.72)
Carhart4 Alpha	0.42***	0.23	0.56***	0.09	0.59***	0.27	0.61***	0.28	0.64***	0.51*
	(2.65)	(0.71)	(3.33)	(0.31)	(3.3)	(1.01)	(3.9)	(1.04)	(3.8)	(1.76)
FH8 Alpha	0.33**	-0.01	0.45***	-0.04	0.44***	0.30	0.49***	0.23	0.51***	0.36
	(2.1)	(-0.03)	(2.78)	(-0.17)	(3.14)	(1.27)	(3.73)	(0.95)	(3.51)	(1.31)
12-Factor Alpha	0.30**	0.07	0.41***	-0.02	0.41***	0.30	0.45***	0.31	0.45***	0.38
	(2.25)	(0.29)	(3.18)	(-0.08)	(3.5)	(1.1)	(4.09)	(1.29)	(3.83)	(1.34)
Max R^2 Alpha	0.47***	-0.04	0.53***	-0.07	0.48***	0.30	0.55***	0.25	0.49***	0.50**
	(3.88)	(-0.18)	(3.68)	(-0.34)	(3.88)	(1.35)	(5.11)	(1.13)	(3.7)	(2.16)
CAPM IR	0.28	0.07	0.35	0.03	0.34	0.10	0.40	0.11	0.39	0.18
Carhart4 IR	0.28	0.07	0.35	0.03	0.33	0.10	0.40	0.11	0.39	0.18
FH8 IR	0.25	0.00	0.31	-0.02	0.34	0.13	0.43	0.10	0.41	0.15
12-Factor IR	0.26	0.03	0.34	-0.01	0.34	0.14	0.43	0.15	0.40	0.17
Max R^2 IR	0.42	-0.02	0.46	-0.04	0.42	0.15	0.55	0.12	0.45	0.23

Table 7: Out-of-Sample Mutually Exclusive Portfolios (Cont.)

Panel B - Out-of-Sample Portfolios, Top Quintile

	Top Quintile									
	DLM Ex CAPM	CAPM Ex DLM	DLM Ex Carhart4	Carhart4 Ex DLM	DLM Ex FH8	FH8 Ex DLM	DLM Ex 12-Factor	12-Factor Ex DLM	DLM Ex Max R^2	Max R^2 Ex DLM
End Value	1.62	1.71	1.82	1.42	1.92	1.63	1.85	1.60	1.88	1.73
Mean Return	0.38*	0.49	0.50**	0.28	0.57**	0.41	0.52**	0.38	0.54**	0.47
	(1.85)	(1.22)	(2.24)	(0.76)	(2.24)	(1.34)	(2.22)	(1.34)	(2.42)	(1.54)
Sharpe Ratio	0.19*	0.12	0.23**	0.08	0.23***	0.14	0.23**	0.14	0.25**	0.16
	(1.83)	(1.21)	(2.20)	(0.76)	(2.20)	(1.33)	(2.19)	(1.33)	(2.37)	(1.53)
Attrition Rate	8.83%	6.84%	8.38%	8.52%	8.02%	8.81%	7.95%	11.89%	7.60%	12.61%
CAPM Alpha	0.26**	0.29	0.38***	0.09	0.42***	0.28	0.39**	0.26	0.41***	0.33
	(2.11)	(0.98)	(2.61)	(0.35)	(2.76)	(1.12)	(2.57)	(1.12)	(2.87)	(1.37)
Carhart4 Alpha	0.26**	0.29	0.38***	0.10	0.42***	0.28	0.39***	0.26	0.41***	0.34
	(2.22)	(1.01)	(2.64)	(0.39)	(2.83)	(1.16)	(2.7)	(1.13)	(2.95)	(1.42)
FH8 Alpha	0.15	0.06	0.26**	-0.04	0.26**	0.21	0.27**	0.17	0.29***	0.17
	(1.38)	(0.3)	(2.22)	(-0.19)	(2.48)	(1.02)	(2.17)	(0.87)	(2.62)	(0.81)
12-Factor Alpha	0.11	0.10	0.21*	-0.06	0.20**	0.17	0.21**	0.19	0.25***	0.16
	(1.08)	(0.47)	(1.95)	(-0.24)	(2.07)	(0.75)	(1.96)	(0.99)	(2.59)	(0.76)
Max R^2 Alpha	0.15*	0.06	0.21**	-0.08	0.25**	0.25	0.17*	0.19	0.28***	0.23
	(1.67)	(0.33)	(2.04)	(-0.43)	(2.42)	(1.31)	(1.76)	(1.07)	(2.68)	(1.29)
CAPM IR	0.22	0.10	0.27	0.04	0.29	0.11	0.27	0.12	0.30	0.14
Carhart4 IR	0.23	0.10	0.27	0.04	0.29	0.12	0.28	0.11	0.30	0.14
FH8 IR	0.17	0.03	0.25	-0.02	0.28	0.11	0.26	0.09	0.31	0.09
12-Factor IR	0.14	0.06	0.23	-0.03	0.23	0.09	0.23	0.11	0.28	0.09
Max R^2 IR	0.18	0.04	0.23	-0.05	0.29	0.14	0.19	0.11	0.33	0.14

Table 8: Correlations between the Models in Alpha and Adjusted R^2 Measures

Panel reports Pearson correlation between alphas of different models; Panel B reports Pearson correlation coefficients between adjusted R-squares of different models.

Panel A - Correlation of Alpha

	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	MaxR^2	DLM
CAPM	1							
FF3	0.94	1						
Carhart4	0.91	0.97	1					
AN6	0.71	0.76	0.77	1				
FH8	0.73	0.71	0.74	0.60	1			
12-Factor	0.54	0.53	0.53	0.74	0.69	1		
Max R^2	0.29	0.27	0.26	0.39	0.31	0.41	1	
DLM	0.78	0.77	0.77	0.60	0.67	0.47	0.17	1

Panel B - Correlation of Adj. R2

	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	MaxR^2	DLM
CAPM	1							
FF3	0.94	1						
Carhart4	0.90	0.96	1					
AN6	0.86	0.91	0.95	1				
FH8	0.77	0.77	0.76	0.74	1			
12-Factor	0.67	0.70	0.72	0.76	0.87	1		
Max R^2	0.65	0.66	0.68	0.71	0.82	0.89	1	
DLM	0.68	0.69	0.67	0.63	0.74	0.66	0.66	1

Table 9: Long-Term Out-of-Sample Performance Persistence, Portfolio Comparison

The table reports annual returns and cumulative risk-adjusted performance measures, including alphas and information ratios, of portfolios sorted on in-sample alphas for each model. Portfolios of hedge funds are formed on January 1, 2005, and rebalanced every two years on updated in-sample alphas. End values are as of December 31, 2012. Panel A reports performance measures of top (bottom) decile portfolios formed on the basis of in-sample alphas for each model. Panel B reports performance measures of top (bottom) quintile portfolios formed on the basis of in-sample alphas for each model. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Panel A - Out-of-Sample Portfolios, 2-Year Rebalancing, Top Decile

	Top Decile							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	Max R^2	DLM
End Value	1.95	2.03	1.96	1.56	1.74	1.77	1.66	2.16
Mean Return	0.62	0.65**	0.61*	0.36	0.48	0.50	0.44	0.70**
	(1.62)	(1.97)	(1.88)	(1.21)	(1.59)	(1.53)	(1.26)	(2.57)
Sharpe Ratio	0.16	0.20*	0.19*	0.12	0.16	0.16	0.13	0.26**
	(1.60)	(1.94)	(1.86)	(1.21)	(1.57)	(1.52)	(1.25)	(2.52)
Attrition Rate	8.82%	9.46%	9.66%	10.37%	9.77%	11.18%	10.17%	9.61%
CAPM Alpha	0.43	0.48**	0.44*	0.20	0.33	0.34	0.27	0.56***
	(1.54)	(2.05)	(1.91)	(1.0)	(1.46)	(1.4)	(1.04)	(2.8)
FF3 Alpha	0.45*	0.49**	0.46**	0.21	0.35	0.35	0.28	0.57***
	(1.69)	(2.16)	(2.04)	(1.06)	(1.57)	(1.47)	(1.1)	(2.89)
Carhart4 Alpha	0.43*	0.48**	0.45**	0.20	0.34	0.34	0.27	0.56***
	(1.66)	(2.13)	(2.01)	(1.02)	(1.54)	(1.44)	(1.07)	(2.87)
AN6 Alpha	0.26	0.35	0.31	0.18	0.26	0.31	0.22	0.44**
	(1.0)	(1.52)	(1.36)	(0.88)	(1.17)	(1.35)	(0.9)	(2.04)
FH8 Alpha	0.19	0.30	0.27	0.10	0.27	0.28	0.12	0.42***
	(1.0)	(1.64)	(1.52)	(0.56)	(1.45)	(1.26)	(0.56)	(2.63)
12-Factor Alpha	0.15	0.25	0.21	0.12	0.23	0.26	0.13	0.38**
	(0.86)	(1.5)	(1.31)	(0.74)	(1.28)	(1.28)	(0.64)	(2.35)
Max R^2 Alpha	0.31*	0.28	0.14	0.20	0.20	0.41	0.20	0.30**
	(1.75)	(1.63)	(0.88)	(1.2)	(1.11)	(1.54)	(1.11)	(2.19)
CAPM IR	0.16	0.21	0.20	0.10	0.15	0.15	0.11	0.29
FF3 IR	0.17	0.22	0.21	0.11	0.16	0.15	0.11	0.30
Carhart4 IR	0.17	0.22	0.21	0.10	0.16	0.15	0.11	0.29
AN6 IR	0.10	0.16	0.14	0.09	0.12	0.14	0.09	0.23
FH8 IR	0.11	0.19	0.18	0.06	0.16	0.15	0.06	0.31
12-Factor IR	0.09	0.17	0.15	0.08	0.14	0.16	0.07	0.29
Max R^2 IR	0.20	0.20	0.10	0.14	0.13	0.25	0.12	0.24

Table 9: Long-Term Out-of-Sample Performance Persistence, Portfolio Comparison (Cont.)

Panel B - Out-of-Sample Portfolios, 2-Year Rebalancing, Top Quintile

	Top Quintile							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	Max R^2	DLM
End Value	1.78	1.76	1.77	1.56	1.67	1.67	1.61	1.87
Mean Return	0.51	0.49*	0.49*	0.35	0.43*	0.43	0.40	0.53**
	(1.52)	(1.7)	(1.75)	(1.36)	(1.58)	(1.52)	(1.27)	(2.23)
Sharpe Ratio	0.15	0.17*	0.18*	0.14	0.16	0.15	0.13	0.23**
	(1.50)	(1.68)	(1.73)	(1.35)	(1.57)	(1.51)	(1.26)	(2.19)
Attrition Rate	8.58%	9.52%	9.42%	10.52%	9.51%	10.77%	11.09%	9.28%
CAPM Alpha	0.33	0.33*	0.34*	0.20	0.29	0.27	0.24	0.40**
	(1.44)	(1.76)	(1.82)	(1.25)	(1.51)	(1.46)	(1.07)	(2.52)
FF3 Alpha	0.35	0.34*	0.35*	0.21	0.30	0.28	0.24	0.41***
	(1.58)	(1.87)	(1.94)	(1.32)	(1.61)	(1.53)	(1.13)	(2.63)
Carhart4 Alpha	0.34	0.33*	0.34*	0.21	0.29	0.27	0.24	0.41***
	(1.55)	(1.84)	(1.91)	(1.29)	(1.58)	(1.51)	(1.1)	(2.61)
AN6 Alpha	0.20	0.21	0.23	0.16	0.21	0.25	0.15	0.30*
	(0.93)	(1.19)	(1.27)	(1.02)	(1.14)	(1.4)	(0.7)	(1.84)
FH8 Alpha	0.14	0.20	0.20	0.14	0.22	0.23	0.08	0.29**
	(0.89)	(1.39)	(1.44)	(1)	(1.41)	(1.39)	(0.43)	(2.36)
12-Factor Alpha	0.11	0.15	0.15	0.13	0.18	0.21	0.06	0.25**
	(0.77)	(1.16)	(1.19)	(0.98)	(1.22)	(1.4)	(0.36)	(2.23)
Max R^2 Alpha	0.18	0.07	0.09	0.15	0.15	0.19	0.09	0.28**
	(1.32)	(0.59)	(0.75)	(1.2)	(0.98)	(1.29)	(0.58)	(2.42)
CAPM IR	0.15	0.18	0.19	0.13	0.15	0.15	0.11	0.26
FF3 IR	0.16	0.19	0.20	0.13	0.16	0.16	0.11	0.27
Carhart4 IR	0.16	0.19	0.19	0.13	0.16	0.15	0.11	0.27
AN6 IR	0.09	0.12	0.13	0.10	0.11	0.14	0.07	0.20
FH8 IR	0.10	0.16	0.16	0.12	0.15	0.16	0.05	0.28
12-Factor IR	0.08	0.12	0.13	0.11	0.14	0.17	0.04	0.26
Max R^2 IR	0.15	0.06	0.08	0.13	0.12	0.15	0.07	0.29

Table 10: Out-of-Sample Comparison of Individual Beta-Weighted Matches

Comparisons of out-of-sample individual matching between hedge funds and beta-weighted factor clones for each model are reported. We consider each individual hedge fund's corresponding risk factors and weights determined through the previous two-year window regression and construct out-of-sample beta-weighted clones by loading the selected risk factors with regression determined weights. Panel A reports correlations between hedge fund returns and their beta-weighted clone returns based on one year out-of-sample data. Panel B reports adjusted R-squares from regressing out-of-sample returns of beta-weighted clones on returns of underlying hedge funds based on one year out-of-sample data.

Panel A - Out-of-Sample Correlation

Year	Out-of-Sample Correlation							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	$MaxR^2$	DLM
2005	0.34	0.35	0.32	0.29	0.33	0.29	0.27	0.40
2006	0.38	0.37	0.34	0.30	0.40	0.26	0.18	0.49
2007	0.35	0.23	0.25	0.15	0.37	0.15	0.10	0.43
2008	0.35	0.31	0.33	0.32	0.38	0.36	0.34	0.45
2009	0.48	0.35	0.29	0.30	0.33	0.28	0.25	0.52
2010	0.51	0.50	0.51	0.46	0.38	0.39	0.38	0.57
2011	0.51	0.49	0.49	0.45	0.41	0.33	0.34	0.55
2012	0.49	0.43	0.46	0.45	0.47	0.46	0.39	0.50
Average	**0.43**	**0.38**	**0.37**	**0.34**	**0.38**	**0.31**	**0.28**	**0.49**

Panel B - Out-of-Sample Adj. R^2

Year	Out-of-Sample Adj. R^2							
	CAPM	FF3	Carhart4	AN6	FH8	12-Factor	$MaxR^2$	DLM
2005	0.17	0.18	0.15	0.15	0.18	0.16	0.15	0.25
2006	0.20	0.19	0.18	0.16	0.22	0.16	0.14	0.29
2007	0.15	0.12	0.13	0.10	0.15	0.09	0.09	0.24
2008	0.27	0.22	0.21	0.20	0.24	0.20	0.19	0.35
2009	0.20	0.12	0.10	0.07	0.14	0.13	0.15	0.29
2010	0.38	0.34	0.33	0.29	0.20	0.22	0.21	0.39
2011	0.34	0.30	0.29	0.27	0.26	0.25	0.25	0.39
2012	0.34	0.25	0.27	0.29	0.29	0.29	0.24	0.37
Average	**0.26**	**0.22**	**0.21**	**0.19**	**0.21**	**0.19**	**0.18**	**0.32**

III. Essay 2: Active Factor Investing: Hedge Funds vs. the Rest of Us[34]

Jun Duanmu, Yongjia Li and Alexey Malakhov

A. Abstract

We argue that only hedge funds whose returns are driven by beta management of exposures to latent risk factors could be successfully replicated. We develop a methodology for creating a portfolio of ETFs that replicates risk factor exposures taken by successful beta active cloneable hedge funds. The methodology allows any investor to access active factor strategies employed by hedge funds. It could be interpreted as cloning beta exposures of the best beta active hedge funds, delivering outstanding long-term risk-adjusted performance. The active factor ETF portfolio only requires annual rebalancing, and is constructed with a transparent algorithmic approach, which conforms to a definition of a smart beta strategy.

JEL Classification: G11, G23

Keywords: hedge funds, risk factor exposures, factor investing, return replication, performance prediction, beta active management, smart beta

B. Introduction

Hedge funds, which experienced tremendous growth in recent years with more than $2.82 trillion in global investments currently under management,[35] are widely criticized for their lack of transparency, liquidity, and hefty 2-20 fee structures. Numerous attempts at cloning hedge fund returns with liquid investment alternatives have been made in academic literature[36] and also

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[34] We would like to thank participants in the 2015 Financial Management Association Annual Meeting, and seminar participants at University of Arkansas for their helpful comments and suggestions.

[35] According to Hedge Fund Research, Inc. October 20, 2014 press release.

[36] See, for example, Kat and Palaro (2005), Jaeger and Wagner (2005), Hasanhodzic and Lo (2007), Amenc, Gehin, Martellini, and Meyfredi (2008), Amenc, Martellini, Meyfredi, and Ziemann (2010), Giamouridis and Paterlini (2010), Freed and McMillan (2011), Weber and Peres (2013), and Duanmu, Li, and Malakhov (2016).

among major asset management companies.[37] Ideally, hedge fund clones should alleviate all three major problems with hedge funds by providing transparency and liquidity at much lower costs. However, it is not clear that hedge fund returns can be replicated in the first place, as truly active proprietary fund management strategies could be beyond replication efforts.[38] For example, the S.A.C. Capital Advisors' strategy in trading Elan and Wyeth stocks based on insider tips obviously can't be replicated with any algorithmic approach.[39] But as John H. Cochrane observes, hedge fund returns may be predominantly driven by beta exposures to latent risk factors not readily discernible to average investors:

> *As I look across the hedge fund universe, 90% of what I see is not "picking assets to exploit information not reflected in prices," it is "taking exposure to factors that managers understand and can trade better than clients."*[40]

If hedge fund returns are indeed driven by alternative risk factor exposures,[41] then it is reasonable to presume that it is possible to come up with a procedure for replicating hedge fund returns at a lower cost for all investors with a portfolio of alternative risk factors. The factor approach to hedge fund cloning is being employed by Hasanhodzic and Lo (2007), Amenc, Martellini, Meyfredi, and Ziemann (2010), Giamouridis and Paterlini (2010), and Weber and Peres (2013). There are, however, two problems with prevailing methods. First, only a limited

[37] For example, Goldman Sachs, Morgan Stanley, Barclays, Credit Suisse, Societe Generale, and BNP Paribus offer hedge fund clone products.
[38] Such strategies are often referred to as "pure alpha strategies", synonymous with true managerial skill of hedge fund managers.
[39] This strategy is also illegal. See *The Empire of Edge* by P.R. Keefe in The New Yorker (October 13, 2014 issue).
[40] See John H. Cochrane's "Hedge Funds" lecture notes at http://faculty.chicagobooth.edu/john.cochrane/teaching/35150_advanced_investments/hedge_notes_and_questions.pdf
[41] An example of such a strategy could be writing out-of-the-money put options on the S&P 500 index.

number of potential risk factors[42] are considered. Second, the prevailing focus is on replicating either all individual hedge funds or broad hedge fund indexes without regard to the fact that some hedge fund strategies are, in fact, non-reproducible.

In this paper, we address the two issues above by following the methodology detailed in Duanmu, Li, and Malakhov (2016) (DLM thereafter). First, the DLM methodology spans the space of potential risk factors with all available ETFs, thus it greatly expands the coverage of tradable risk factors available for hedge fund replication. Second, the focus of DLM is on replicating *cloneable* hedge funds, namely, funds whose returns mostly reflect exposures to latent risk factors. Concentrating on *cloneable* hedge funds is the key to successful hedge fund replication, as it allows identifying a homogeneous group of hedge funds suitable for replication, i.e. the ones whose returns are driven by risk factor exposures.

While the DLM methodology allows identifying and successfully cloning beta-driven hedge fund returns, it does not offer a great deal of insight on the overall quality of beta-driven fund management. On the other hand, the efficacy of beta active hedge fund management is quantified in Duanmu, Malakhov, and McCumber (2016) (DMM thereafter) by way of introducing a measure of the overall beta activity, *BA*. Portfolios comprised of the most beta active hedge funds produce outstanding long-term risk-adjusted performance, outperforming portfolios comprised of the most alpha active hedge funds.

In this paper we combine approaches from DLM and DMM by focusing replication efforts only on portfolios of hedge funds that are *cloneable* and also display a high degree of overall beta activity, *BA*. The resulting high beta active *clonenable* hedge fund portfolios deliver outstanding long-term risk-adjusted performance, and their returns can be successfully replicated

[42] The number of tradable factors varies from six in Hasanhodzic and Lo (2007) to thirty in Weber and Peres (2013).

out-of-sample with ETF portfolios. Importantly, the replicating ETF portfolios deliver marginally better[43] long-term risk-adjusted performance than the portfolios of beta active *clonenable* hedge funds. Further, the ETF portfolios only need to be rebalanced annually, and maintain the same portfolio composition throughout the year, minimizing the effect of trading costs.

Our results are consistent with the relatively long-term nature of beta active management. Hedge fund managers take positions considering a wide range of possible macroeconomic scenarios. Because it is impossible to precisely time when a particular macroeconomic scenario will unfold, managers may not profit from their positions for extended periods of time,[44] which enable gains from efficaciously matching the risk factor exposures of hedge funds.

We conclude that our strategy of replicating top beta active *cloneable* hedge funds with ETFs successfully captures beta exposures of risk factors that would deliver superior payoff in the future. Our approach provides a transparent and liquid alternative to investors who may want to get access to returns generated by factor risk exposures of top beta active hedge funds.

C. Data Description

This study utilizes hedge fund data from Bloomberg[45] from 1994-2012 on 18,135 unique hedge funds.[46] The compiled data is comprehensive with information on fund returns net of management and performance fees, assets under management, manager information, and fund

[43] Although not at a statistically significant level.
[44] For example, Michael Burry's bets against subprime mortgage backed securities taken in 2005 were not profitable for two years until 2007 (see "The Big Short" (2010) by Michael Lewis).
[45] Bloomberg is the most common platform used by both hedge funds, who utilize news, analysis, research, and trading tools, and accredited investors, who use Bloomberg data to research hedge funds, private equity firms, and other alternative investment vehicles. Bloomberg aggregates data on live and dead funds inclusive of fund and parent company descriptions, manager and contact information, total assets under management, fees, past performance, and management style.
[46] We do not include funds of hedge funds in our sample.

characteristics for live as well as dead hedge funds that were acquired, liquidated, or simply ceased to report. We mitigate the effects of backfill bias by eliminating the first 24 months of reported returns.[47] Additionally, since four years of data are required to calculate the DMM measure of beta activity, *BA*, [48] only funds with inception dates prior to 2007 are considered. which leaves us with 8,530 unique funds. Finally, in the sample of the 8,530 funds that remain, only 2,014 unique hedge funds, of which 963 are active and 1,051 are inactive, have sufficient longevity to enable our methodology.

Panel A of Table 1 reports summary statistics on fund returns, fees, investor liquidity, and fund longevity. The typical hedge fund has a median 1.5% management fee, a median 20% incentive fee on all profits over an investor's high water mark,[49] a $250,000 minimum initial investment, and a thirty day redemption period. Not surprisingly, active funds exhibit higher median monthly excess returns, larger median assets under management, and greater longevity compared to inactive hedge funds. Inactive funds have longer median redemption and lockup periods. Panels B and C of Table 1 report the distribution of characteristics and declared styles across hedge funds. 88% of all funds have a high water mark provision, and only 6% impose hurdle rates in addition to high water marks. 69% of funds are non-U.S. domiciled. The most common declared style is long-short equity, which accounts 28% of all funds, while capital structure arbitrage is the least common style, accounting for 1% of hedge funds.

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[47] The 24 month backfill correction is in line with results in Jagannathan, Malakhov, and Novikov (2010) and Titman and Tiu (2011) suggesting dropping the first 25 and 27 months of returns.

[48] See Duanmu, Malakhov, and McCumber (2016) for the details of the *BA* methodology.

[49] High water marks are investor relevant, that is, an investor will not be charged incentive fees until profits accrue over a previous high, net of flows. Thus, not all investors are charged incentive fees in any given year; it is partially determined by when the investor capital was employed by the fund manager. An investor whose fund shares are worth more this year than last will be charged incentive fees. An investor who suffered a loss previously will not pay incentive fees until previous losses are regained.

We obtain ETF data from Morningstar over the period 1994-2012 on 1,484 unique U.S. listed ETF funds. We manually check the description of each ETF, and exclude all ETFs that are not passively managed index tracking funds,[50] as well as ETFs that track hedge fund style indexes; this leaves us with 1,387 unique ETFs. Additionally, we require ETFs to have at least 24 monthly observations starting from January each year, and eliminate ETFs with missing information on management fees. Further, since fewer than five ETFs were available prior to 1997, we excluded these years from the analysis. The 1,313 unique passively managed ETFs over the period 1997-2012 that remain are used in the study.

Figure 1 reports the number of ETFs available each year in our sample period. As shown, ETFs experienced significant growth over the sample period; from 19 ETFs in 1997 to 1,313 ETFs in 2012. The increase in the number of ETFs available expands the investment opportunity set dramatically, and consequently, our hedge fund replicating process achieves more precision towards the later years in our sample period.

Following the DLM methodology, we utilize two years of monthly ETF returns in order to identify the number of latent risk factors and ETFs that provide best proxies for latent risk factors.[51] Figure 2 reports the actual number of ETFs used for each two year window. In the early years, relatively few ETFs make the replication procedure less accurate. Following DLM, we restrict our out-of-sample analysis to the period 2005-2012, where more than 100 ETFs per year are available for the replication procedure.[52]

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[50] Benchmark indexes that retained ETFs track may not be publicly available. Some funds track in-house indexes.

[51] See Duanmu, Li, and Malakhov (2016) for the details of the methodology used to replicate hedge fund returns with ETFs.

[52] Specifically, for our in-sample analysis, we employ hedge fund data going back to 1999 and ETF data going back to 2003.

D. Research Methodology

In our study we rely on the methodology of hedge fund cloning with ETFs developed in DLM and on quantifying overall beta activity, *BA*, introduced in DMM.

Our study relies on the methodologies for replicating hedge fund returns with ETFs detailed in DLM and for quantifying beta activity in DMM. First, we use monthly returns over two-year estimation periods to construct a smart beta ETF portfolio, rebalanced on January 1 of each year, that replicates each hedge fund. A measure of beta activity, *BA*, for each hedge fund is also computed on January 1 of each year in the 2005 to 2012 sample period. Second, we rank all the hedge funds according to their in-sample R^2 and beta activity values. Following DLM, hedge funds in the top R^2 quartile (tercile) of in-sample matching regressions of hedge fund returns on ETFs are defined as *cloneable*; hedge funds in the bottom in-sample R^2 quartile (tercile) are defined as *non-cloneable.*

Our analysis relies on out-of-sample portfolio tests for the following reasons. First, the portfolio approach allows for out-of-sample risk-adjusted performance evaluation of hedge funds and their replicating ETF portfolios over long periods of time. Second, it allows us to explore the impact of hedge fund survivorship bias on replicating ETF portfolios by either immediately rebalancing an ETF clone portfolio after a matched hedge fund disappears from the database, or leaving the ETF clone portfolio unchanged until January 1 of the next year.

Portfolios of *cloneable* and beta active hedge funds as well as their replicating smart beta ETF portfolios are initially formed on January 1, 2005 and rebalanced on January 1 of each subsequent year based on the results from re-estimations of replicating ETF regressions. The same dollar amount is invested in each hedge fund with each annual rebalancing, and returns net-of-fees are computed each month until the sample period ends on December 31, 2012. When a hedge fund disappears, the remaining capital is redistributed equally among the surviving hedge funds in the portfolio. Moreover, when a hedge fund disappears, adjustments to the replicating ETF portfolio are made in one of two ways. In a 'matched' clone ETF portfolio, investments in the replicating ETFs are liquidated and redistributed among the surviving ETFs. In a 'static' clone ETF portfolio, no changes are made until the end of the year.

Over our sample period, the above procedure produces a time series of 96 monthly returns for hedge fund and replicating ETF portfolios, which is then used to evaluate long-term portfolio performance across diverse economic conditions including the most recent financial crisis of 2008 - 2009. We calculate end dollar values based upon a $1 initial investment, mean excess monthly returns, Sharpe ratios, Fung and Hsieh (2004) alphas, [53] information ratios, and attrition rates for each time series of monthly portfolio returns from January 2005 until December 2012.

E. Empirical Results

1. Hedge Funds and Smart Beta ETF Portfolios

Panel A of Table 2 reports the performance over the period 2005 to 2012 of *cloneable* hedge funds, namely, funds in the top in-sample R^2 quartile of in-sample regressions of hedge fund returns on ETFs, compared to their replicating smart beta ETF portfolio. Panel B of Table 2 reports the performance over the period 2005 to 2012 of top beta active hedge funds, namely funds that rank in the top quartile of beta activity defined by DMM, compared to their replicating smart beta ETF portfolio. The results confirm the overall efficacy of the DLM methodology in constructing replicating smart beta ETF portfolios whose returns are not statistically significantly different from the returns on their associated beta active hedge fund portfolios.

[53] See DLM for details on Fung and Hsieh (2004) alpha calculation.

2. Beta Active Cloneable Hedge Funds and Smart Beta ETF Portfolios

While the DLM cloning methodology works very well for the portfolio of *cloneable* hedge funds, these might not be the funds whose risk-adjusted performance is desirable for most investors. On the other hand, given the results Panel B of Table 2, cloning the risk-adjusted performance of top beta active hedge funds seems like a more desirable objective.

Now consider hedge funds that are both beta active and *cloneable*, namely, funds that rank in the top quartile of beta activity defined by DMM that are also in the top in-sample R^2 quartile of regressions of hedge fund returns on ETFs. In other words, we now consider a portfolio that is an intersection of the *cloneable* and the top *BA* portfolios. Following the methodology described in section 3, we consider two approaches to maintain clone ETF portfolios following a hedge fund dropping out of the database. In a 'matched' clone portfolio, the ETF clone is liquidated and its capital is redistributed equally among remaining ETF clones in the clone portfolio. In a 'static' clone portfolio, no changes are made until the end of the year. The 'static' clone portfolio approach could be more desirable from the investor perspective, as it does not require monthly tracking of hedge funds and potential portfolio rebalancing, only relying on annual hedge fund beta exposures.[54]

The results for top quartile beta active hedge funds that also belong to top quartile *cloneable* funds are presented in Table 3. Both 'matched' and 'static' clone ETF portfolios yield slightly higher absolute and risk-adjusted performance compared to the portfolio of beta active *cloneable* hedge funds. Moreover, the 'static' clone ETF portfolio produces slightly higher risk-adjusted performance compared to the 'matched' clone ETF portfolio. Figure 3 compares

[54] In fact, with the static clone portfolio approach, it suffices to only check the hedge fund data once a year prior to annual portfolio rebalancing.

cumulative performance of the portfolio of top beta active *cloneable* funds vs. its 'static' ETF clone portfolio.

As a robustness check, and also to increase the number of funds in the hedge fund portfolio, we considered an alternative specification of *cloneable* hedge funds, as the top tercile of in-sample R^2 matches. The results are presented in Table 4, and are consistent with results in Table 3. Despite the increased number of hedge funds, the smart beta ETF clone portfolios perform as well as the hedge fund portfolios; with the 'static' clone portfolio delivering slightly better risk-adjusted performance than the 'matched' clone portfolio.

We summarize our findings in Table 5 along with the benchmark comparison against a portfolio of Bloomberg peers, i.e. all hedge funds from our data that have long enough history to be included in our analysis.[55] All our hedge fund and smart beta ETF clone portfolios outperform the portfolio of Bloomberg peer hedge funds across all absolute and risk-adjusted performance measures. Figure 4 shows performance comparison of the 'static' ETF clone portfolio against Bloomberg peers, as well as the S&P 500 index, and also the Credit Suisse and HFR hedge indexes.

3. Smart Beta ETF Portfolio Weights

As we noted in the introduction, the underlying investment strategies of beta active hedge funds are reflected in their risk factor loadings. The success of such strategies depends on specific macroeconomic scenarios that may take time to unfold. Since our ETF cloning algorithm replicates beta exposures of the best beta active hedge funds as a group, high weights in smart beta ETF clone portfolios indicate specific risk factors that will be most profitable in the future as macroeconomic conditions change.

[55] In the DMM methodology, it is necessary for a hedge fund to have at least four years of history in order to calculate its measure of beta activity, *BA*.

With a benefit of hindsight we now examine the dynamics of ETF clone factor loadings across our sample period. Table 6 presents the top ten ETFs and their weights together with cumulative total, long, and short exposures of the smart beta ETF clone portfolios over the period 2005 to 2012. The results are very intuitive. Top beta active hedge funds scaled down their aggregate risk exposure as early as 2006, moving into pronounced defensive positions in 2007 marked by a long exposure to gold (GLD), a cumulative short exposure of -0.45, and an all-time low total aggregate exposure of 0.34. Interestingly, the top exposure in January 2011 was to ProShares Short S&P500 ETF (SH), which was prescient since the S&P 500 index declined in 2011. This shows a great deal of foresight on behalf of top beta active hedge fund managers.

F. Conclusion

By combining the methodologies developed in DLM and DMM we develop an algorithm for creating smart beta ETF portfolios that replicate the risk factor exposures taken by the best beta active hedge funds. The resulting smart beta ETF portfolios either match or exceed the risk-adjusted performance of their corresponding portfolios of hedge funds. Most important, the smart beta ETF portfolios only rely on annual rebalancing, and are constructed with a transparent approach.[56]

[56] See "smart beta" definition on the Research Affiliates web site at http://www.researchaffiliates.com/Our Ideas/Insights/Smart Beta/Pages/Home.aspx.

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Figure 1: Number of ETFs Available, 1999-2012

Number of ETFs available each year from 1999 to 2012 is reported. ETF data is collected from Morningstar.

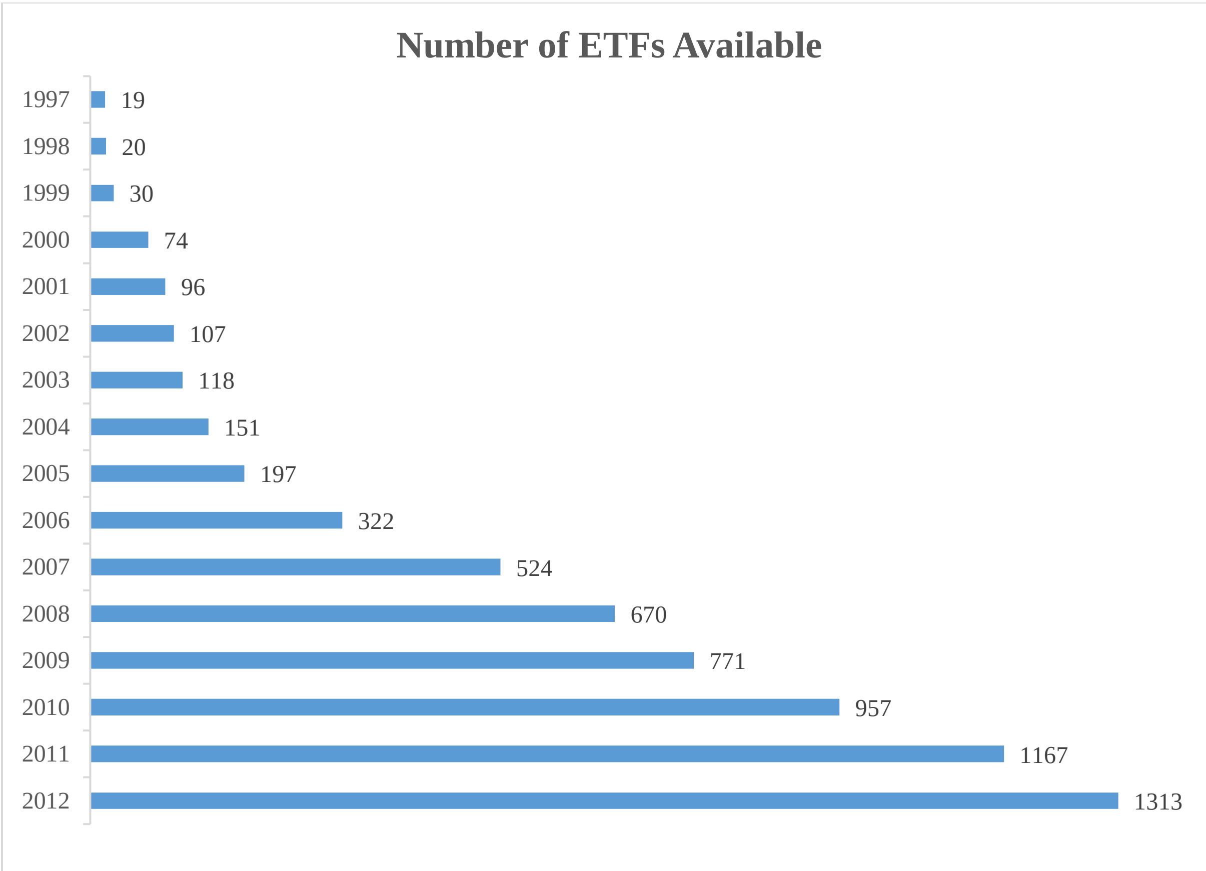

Figure 2: Number of ETFs Used

Number of ETFs used in LASSO matching regressions is reported. ETF data is collected from Morningstar.

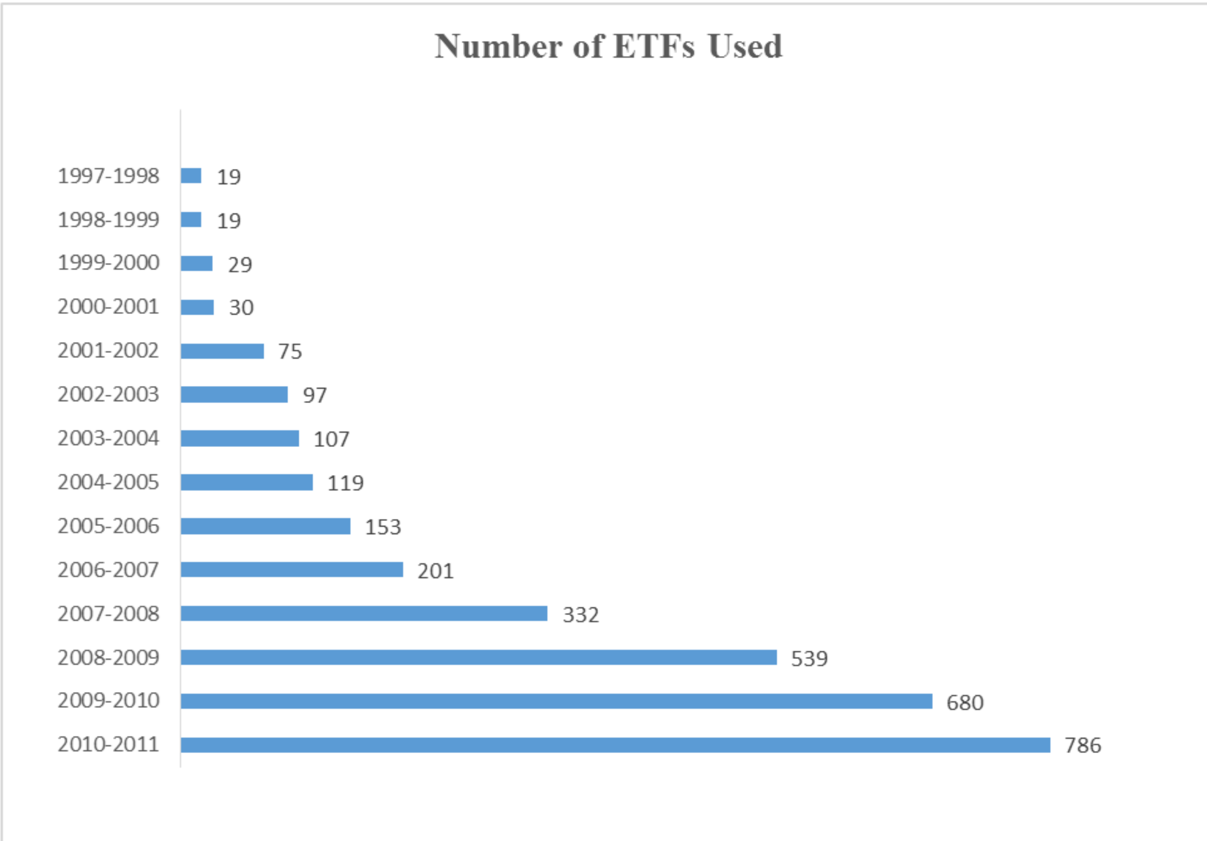

Figure 3: Beta Active Cloneable Hedge Fund Portfolio vs. Static ETF Clone Portfolio

Cumulative performance of the top beta active cloneable hedge fund portfolio vs. its 'static' ETF clone portfolio from January 1, 2005 to December 31, 2012.

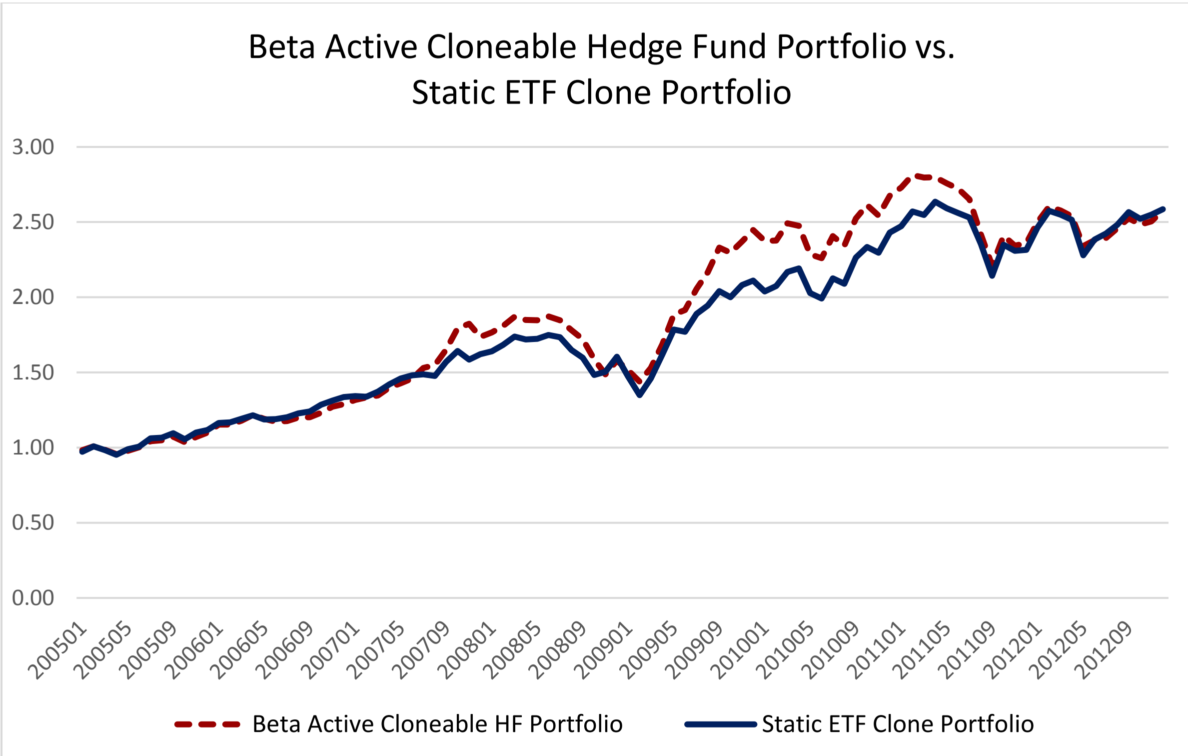

Figure 4: Performance Comparison

Static ETF clone portfolio performance comparison against Credit Suisse Hedge Index, HFRI, Bloomberg Peers, and S&P 500 from January 1, 2005 to December 31, 2012.

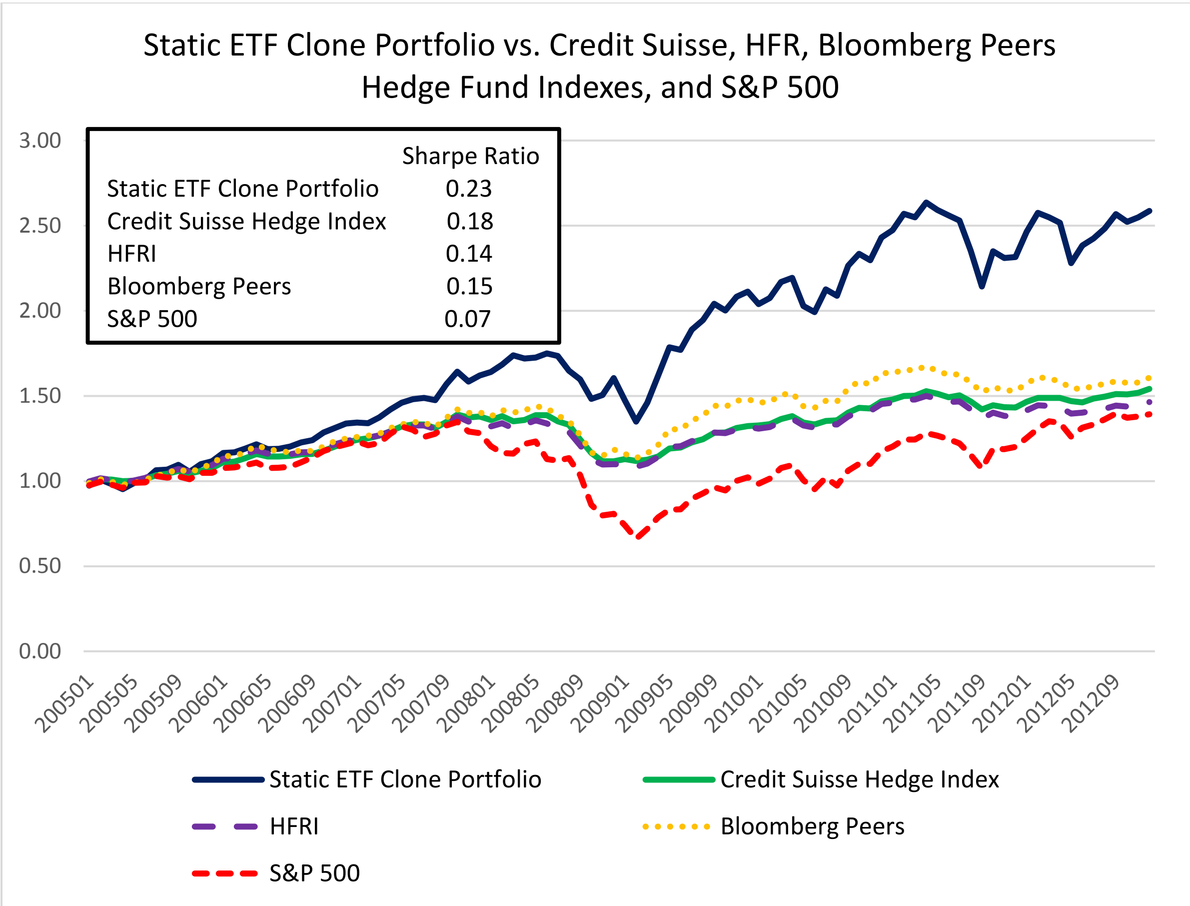

Table 1: Summary Statistics

Summary statistics of all hedge funds 1994-2012. Panel A reports returns, fees, investor liquidity measures, and fund longevity. Panel B reports means of indicator variables for fund characteristics while panel C reports self-declared fund styles.

Panel A	Full Sample (2,014 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly excess return	0.70	0.58	-4.38	5.95	5.46
Assets ($M)	279.39	34.63	2.50	394.50	2,365.85
Min Invest ($M)	1.08	0.25	0.02	1	12.50
Mgmt Fee (%)	1.47	1.5	0.75	2	0.76
Perf Fee (%)	17.48	20	5	20	6.75
Hurdle Rate (%)	0.37	0	0	0	1.73
Lockup Period (days)	79.80	0	0	360	189.20
Redemption Notice (days)	6.84	0	0	30	17.92
Redemption Period (days)	62.66	30	30	90	65.09
Total Redemption (days)	69.76	40	30	120	68.74
Longevity (months)	146.27	139	102	206	38.42
	Active Funds (963 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly excess return	0.85	0.68	-4.72	6.58	5.81
Assets ($M)	359.24	51.80	3.92	634.00	2,454.73
Min Invest ($M)	0.60	0.25	0.02	1	1.91
Mgmt Fee (%)	1.44	1.5	0.8	2	0.71
Perf Fee (%)	17.55	20	7.5	20	6.55
Hurdle Rate (%)	0.41	0	0	0	1.74
Lockup Period (days)	66.53	0	0	360	176.17
Redemption Notice (days)	9.74	0	0	30	20.74
Redemption Period (days)	56.57	30	15	90	55.58
Total Redemption (days)	66.37	40	15	120	61.21
Longevity (months)	153.11	144	103	227	42.02
	Inactive Funds (1,051 unique funds)				
	Mean	Median	10th pct	90th pct	Std
Monthly excess return	0.58	0.51	-4.11	5.44	5.15
Assets ($M)	187.82	24.55	1.29	247.94	2,256.17
Min Invest ($M)	1.63	0.25	0.015	1	18.23
Mgmt Fee (%)	1.50	1.5	0.75	2	0.82
Perf Fee (%)	17.39	20	4	20	6.98
Hurdle Rate (%)	0.33	0	0	0	1.71
Lockup Period (days)	96.23	0	0	360	203.00
Redemption Notice (days)	3.48	0	0	0	13.17
Redemption Period (days)	70.23	30	30	90	74.56
Total Redemption (days)	73.98	40	30	120	76.88
Longevity (months)	139.48	132	102	191	33.11

Table 1: Summary Statistics (Cont.)

Panel B - Indicator	Full Sample	% of Funds Active Funds	Inactive Funds
High Water Mark	0.88	0.87	0.89
Hurdle Rate	0.06	0.07	0.04
Offshore (non-US)	0.69	0.65	0.73
Closed to New Inv	0.07	0.07	0.07
Liquidated	0.19	0.00	0.37
Acquired	0.02	0.00	0.03

Panel C - Fund Styles	Full Sample	% of Funds Active Funds	Inactive Funds
Long Short Equity	0.28	0.34	0.22
Managed Futures	0.14	0.18	0.10
Multi-Style	0.11	0.09	0.13
Macro	0.09	0.08	0.11
Undisclosed	0.08	0.01	0.16
Equity Fundamental Neutral	0.06	0.05	0.07
Long Bias Equity	0.06	0.06	0.05
Emerging Markets	0.05	0.07	0.04
Distressed Securities	0.04	0.02	0.05
Merger Arbitrage	0.02	0.03	0.02
Fixed Income Arbitrage	0.02	0.03	0.02
Convertible Arbitrage	0.02	0.01	0.03
Fixed Income	0.02	0.02	0.02
Equity Statistical Arbitrage	0.01	0.01	0.02
Capital Structure Arbitrage	0.01	0.01	0.01

Table 2: Cloneable vs. Beta Active Hedge Funds and their Smart Beta ETFs

Annual returns and cumulative risk-adjusted performances of portfolios formed on the basis of in-sample LASSO matching regression R^2 or BA (Beta Activity measure, proposed by DMM). Portfolios of hedge funds and clones are formed on January 1, 2005, and rebalanced annually for funds in the top quartile of in-sample R^2 or BA. End value is as of December 31, 2012. Attrition rate is the average annual rate at which hedge funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio hedge funds. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

Panel A — Cloneable Hedge Funds, Top Quartile of In-Sample R^2 | **Panel B** — Beta Active Hedge Funds, Top Quartile of BA Measure

	Panel A: Cloneable Hedge Funds, Top Quartile of In-Sample R^2							Panel B: Beta Active Hedge Funds, Top Quartile of BA Measure						
		Hedge Fund Porftfolio			Clone Portfolio				Hedge Fund Porftfolio			Clone Portfolio		
Year	In-Sample R^2	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	In-Sample R^2	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds
2005	0.83	11.86	135	127	12.42	135	127	0.55	8.30	135	125	10.07	135	125
2006	0.83	16.17	180	164	19.36	180	164	0.48	13.05	180	171	17.11	180	171
2007	0.83	17.52	219	202	14.76	219	202	0.37	13.34	219	195	9.11	219	195
2008	0.86	-27.13	260	216	-26.88	260	216	0.46	-3.71	260	204	-6.68	260	204
2009	0.93	41.03	264	225	31.92	264	225	0.66	31.75	264	222	20.12	264	222
2010	0.89	11.83	286	257	18.29	286	257	0.53	10.81	286	229	6.72	286	229
2011	0.92	-9.73	278	233	-7.60	278	233	0.49	-7.32	278	235	-1.30	278	235
2012	0.85	9.55	246	220	13.07	246	220	0.54	2.74	246	222	8.52	246	222
End Value			1.74			1.84				1.86			1.80	
Mean Return			0.51			0.59				0.53**			0.50**	
(t-stat)			(1.28)			(1.29)				(2.16)			(2.14)	
Sharpe Ratio			0.13			0.13				0.22			0.22	
α			0.06			0.10				0.35**			0.22	
(t-stat)			(0.43)			(0.65)				(2.20)			(1.47)	
Info Ratio			0.05			0.08				0.25			0.19	
Mean R^2				0.87							0.51			
Attrition rate				11.40%							13.21%			

Table 3: Comparisons of the Top Beta Active Cloneable Hedge Fund Portfolio and its Matched and Static Clone Portfolios, Quartiles

Annual returns and cumulative risk-adjusted performances of portfolios formed on the basis of in-sample LASSO matching regression R^2 and BA (Beta Activity measure, proposed by DMM). Portfolios of hedge funds and clones are formed on January 1, 2005, and rebalanced annually to include funds that belong to top quartiles of both in-sample R^2 and BA. End value is as of December 31, 2012. Attrition rate is the average annual rate at which hedge funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio hedge funds. In the matched clone portfolio, the ETF clone matched to the disappeared hedge fund is liquidated and its capital is redistributed equally among remaining ETF clones in the clone portfolio. In the static clone portfolio no changes are made throughout the year until the complete rebalancing next January. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

		Hedge Fund Portfolio			Matched Clone Portfolio			Static Clone Portfolio		
Year	In-Sample R^2	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds
2005	0.84	10.07	43	42	11.67	43	42	11.68	43	43
2006	0.81	17.08	28	28	19.72	28	28	19.72	28	28
2007	0.81	34.74	10	10	21.22	10	10	21.22	10	10
2008	0.89	-9.07	28	19	-2.26	28	19	-0.95	28	28
2009	0.93	55.04	73	64	33.93	73	64	31.55	73	73
2010	0.89	9.32	44	39	16.36	44	39	15.05	44	44
2011	0.91	-11.79	16	14	-6.07	16	14	-4.71	16	16
2012	0.86	9.19	57	54	11.95	57	54	11.71	57	57
End Value			2.58			2.60			2.59	
Mean Return			0.93**			0.94**			0.93**	
(t-stat)			(2.23)			(2.16)			(2.23)	
Sharpe Ratio			0.23			0.22			0.23	
α			0.40			0.45*			0.46*	
(t-stat)			(1.58)			(1.67)			(1.72)	
Info Ratio			0.18			0.21			0.22	
Mean R^2			0.87			-			-	
Attrition rate			9.49%			9.49%			-	

Table 4: Comparisons of the Top Beta Active Cloneable Hedge Fund Portfolio and its Matched and Static Clone Portfolios, Terciles

Annual returns and cumulative risk-adjusted performances of portfolios formed on the basis of in-sample LASSO matching regression R^2 and BA (Beta Activity measure, proposed by DMM). Portfolios of hedge funds and clones are formed on January 1, 2005, and rebalanced annually to include funds that belong to top terciles of both in-sample R^2 and BA. End value is as of December 31, 2012. Attrition rate is the average annual rate at which hedge funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio hedge funds. In the matched clone portfolio, the ETF clone matched to the disappeared hedge fund is liquidated and its capital is redistributed equally among remaining ETF clones in the clone portfolio. In the static clone portfolio no changes are made throughout the year until the complete rebalancing next January. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

		Hedge Fund Portfolio			Matched Clone Portfolio			Static Clone Portfolio		
Year	In-Sample R^2	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds	Return	Starting Funds	Ending Funds
2005	0.81	9.50	55	52	11.84	55	52	11.87	55	55
2006	0.78	17.82	38	38	20.71	38	38	20.71	38	38
2007	0.76	24.18	17	15	16.32	17	15	15.63	17	17
2008	0.85	-12.17	39	27	-6.63	39	27	-5.68	39	39
2009	0.91	52.92	96	84	36.52	96	84	34.00	96	96
2010	0.86	9.67	66	56	15.09	66	56	14.02	66	66
2011	0.86	-9.11	32	27	-2.91	32	27	-1.62	32	32
2012	0.83	9.22	76	73	11.86	76	73	11.67	76	76
End Value			2.34			2.50			2.47	
Mean Return			0.82**			0.89**			0.88**	
(t-stat)			(2.13)			(2.18)			(2.22)	
Sharpe Ratio			0.22			0.22			0.23	
α			0.32			0.43*			0.43*	
(t-stat)			(1.49)			(1.79)			(1.82)	
Info Ratio			0.17			0.23			0.23	
Mean R^2			0.83			-			-	
Attrition rate			11.90%			11.90%			-	

Table 5: Summarized Comparisons of Bloomberg Peers Portfolio, Top Beta Active Cloneable Hedge Fund Portfolio, and its Matched and Static Clone Portfolios

Annual returns and cumulative risk-adjusted performances of portfolios formed on the basis of in-sample LASSO matching regression R^2 and BA (Beta Activity measure, proposed by DMM). Portfolios of hedge funds and clones are formed on January 1, 2005, and rebalanced annually to include funds that belong to the top of both in-sample R^2 and BA rankings. End value is as of December 31, 2012. Attrition rate is the average annual rate at which hedge funds disappear from the database; resultant capital is assumed to be equally invested in remaining portfolio hedge funds. In the matched clone portfolio, the ETF clone matched to the disappeared hedge fund is liquidated and its capital is redistributed equally among remaining ETF clones in the clone portfolio. In the static clone portfolio no changes are made throughout the year until the complete rebalancing next January. Significance at the 10%, 5%, and 1% levels are designated by *, **, and ***, respectively.

	End Value	Attrition Rate	Mean Return (t-stat)	Sharpe Ratio	α (t-stat)	Information Ratio
Bloomberg Peers	1.61	13.55%	0.40 (1.52)	0.15	0.15 (1.36)	0.15
Hedge Fund Portfolio, Quartile	2.58	9.49%	0.93** (2.23)	0.23	0.40 (1.58)	0.18
Matched Clone Portfolio, Quartile	2.60	9.49%	0.94** (2.16)	0.22	0.45* (1.67)	0.21
Static Clone Portfolio, Quartile	2.59	-	0.93** (2.23)	0.23	0.46* (1.72)	0.22
Hedge Fund Portfolio, Tercile	2.34	11.90%	0.82** (2.13)	0.22	0.32 (1.49)	0.17
Matched Clone Portfolio, Tercile	2.50	11.90%	0.89** (2.18)	0.22	0.43* (1.79)	0.23
Static Clone Portfolio, Tercile	2.47	-	0.88** (2.22)	0.23	0.43* (1.82)	0.23

Table 6: Ten ETFs with Highest Weights in the ETF Clone Portfolio

List of ten ETFs with highest weights used to construct the clone portfolio for each vintage. ETF tickers and the corresponding portfolio weights are reported. Aggregate Positive Weight is the sum of betas of ETFs with positive weights selected for portfolio construction. Negative Aggregate Weight is the aggregation of ETF betas with negative weights. Total Portfolio Weight is the sum of betas of all ETFs used for portfolio constructions.

Year	Ten ETFs with Highest Weights in the ETF Clone Portfolio										Aggregate Postive Weights	Aggregate Negative Weights	Total Portfolio Weights
2005	MDY	IWW	VTI	IGM	IBB	IVV	IYE	ITF	VXF	IJR	1.06	-0.02	1.04
	0.093	0.084	0.073	0.062	0.058	0.054	0.048	0.041	0.040	0.035			
2006	IEV	IBB	IXP	EWU	IWD	XLV	EWO	AGG	RSP	EWK	0.83	-0.06	0.77
	0.265	0.084	0.068	0.048	0.041	0.037	0.035	0.031	0.029	0.023			
2007	GLD	VDE	ADRU	EWC	EWO	IYH	IGE	EWA	EWZ	SPY	0.78	-0.45	0.34
	0.115	0.072	0.070	0.066	0.066	0.065	0.063	0.062	0.060	0.037			
2008	FXE	IYJ	IWS	IAU	EPP	TIP	VDC	EWM	VGT	EWU	0.90	-0.11	0.80
	0.760	0.031	0.016	0.013	0.012	0.010	0.010	0.010	0.008	0.006			
2009	FXE	RSP	DWM	RGI	GSP	DXJ	RYE	AGG	IWP	JPP	1.20	-0.03	1.17
	0.328	0.095	0.046	0.046	0.043	0.042	0.038	0.036	0.035	0.034			
2010	VTI	TOK	GBF	BWX	SDS	DWM	INY	GML	GBB	GMM	1.22	-0.04	1.18
	0.157	0.112	0.108	0.084	0.054	0.052	0.049	0.047	0.037	0.036			
2011	SH	IEV	JYN	IWR	JPP	ACWI	RYE	GMM	IFNA	FXO	1.31	-0.22	1.09
	0.242	0.164	0.150	0.147	0.141	0.109	0.088	0.049	0.049	0.048			
2012	ACWI	DWM	ITR	XLE	DLN	RSP	HGI	GLD	IGE	EEM	0.80	-0.24	0.56
	0.118	0.067	0.059	0.048	0.043	0.039	0.038	0.036	0.030	0.030			

IV. Essay 3: On the Market Timing and Feedback Effect of "Hedging": Evidence from U.S. Oil and Gas Producers[57]

Yongjia Li and Kangzhen Xie

A. Abstract

Using a hand-collected data, we provide evidence that U.S. oil and gas producers generate profits on average from their use of derivatives in hedging, indicating that it is a positive NPV project. The profits are positively related to the intensity of hedging. Further decomposition shows that the profits are strongly and positively related to the market timing component in hedging. The hedging profits reveal some feedback effects on the hedge ratio in the subsequent period. Losers hedge more when they lose more. Winners hedge more when they gain more, but the effect is less strong.

JEL Classification: G32, G11, G14

Keywords: risk management, hedging, derivative, market timing, feedback effect

B. Introduction

Corporate risk management is an important part of corporate finance. With the growing popularity of financial derivatives on the markets, firms are increasing their use of financial derivatives for hedging. While many studies have focused on whether hedging affects shareholder value and why firm hedge [58], we know little about the actual impact of hedging on

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[58] The literature has proposed several channels for hedging to affect shareholder value including reducing cost of financial distress (e.g., Stulz (1984)), tax saving (e.g., Smith and Stulz (1985), Graham and Smith (2001)), alleviating under-investment (e.g., Froot, Scharfstein and Stein

the corporate earnings due to the lack of data. A related and widely debated issue is whether firms should take a view on the timing of their use of derivatives in hedging and its consequence (e.g., Stulz (1996), Faulkender (2005), Adam and Fernando (2006), Brown et al. (2006), Geczy et al. (2007), Chernenko and Faulkender (2011))[59]. Also, an unexplored issue is whether and how the results of hedging affect subsequent hedging decisions. Drawing on a hand-collected data, we are able to provide new insights into these issues.

Recent accounting rules allow us to take a closer look at the consequence of corporate hedging. FASB 133 requires firms to disclose the details of their hedging activities. FASB 161 further requires firms to disclose the purpose of using derivatives and the outcome. We focus on the U.S. oil and gas producers in the sample period from 2007 to 2011[60] and hand-collect the gains and losses from the use of derivatives for risk management. Firms can choose to record the hedging activities and profits on hedge account and/or non-hedge account. While most users of non-hedge account claim that their derivatives positions are for hedging, the fact that they elect to use non-hedge account indicates that their derivative transactions don't fully match the real production. The deviation from pure hedging makes it harder to comply with the requirement of hedge accounting.[61] We use the information in the two accounts to further identify the effects of hedging.

(1993)), and product market competition (e.g., Zhu (2011)). Smith (2008) provides a survey on corporate risk management. However, the empirical evidence is mixed. (e.g., see a review paper by Aretz and Bartram (2010)). Bodnar et al (2014) use survey data and find that managerial risk aversion plays a role in the decision to hedge.

[59] Since the literature also uses terms such as selective hedging and speculation for market timing hedging, we use these terms interchangeably in our paper.

[60] Although the effective date for FASB 161 is for the fiscal years beginning after Nov 15, 2008, most firms in our sample also reported the profits of the use of derivatives in 2007.

[61] We don't claim that all firms use non-hedge accounting for market timing activities as Demarzo andDuffie (1995) suggest that the choice of hedge accounting may also be affected by career concern. The association between the use of non-hedge accounting and market timing activities is an empirical question, which we provide some evidence.

We find that U.S. oil and gas producers on average generate profits on their use of derivatives for hedging during our sample period. The average hedging profit is a gain of 1.78% of assets, which contrasts to an average 3.48% loss of return on assets. Thus, the hedging outcome has a significant impact on corporate earnings. The mean and median of raw hedging profits are $74.9 million and $5.92 million respectively. We further investigate the outcome of hedging in each year in the sample. The hedging activities produce positive profits on average almost in every year except 2007. The mean and median of cumulative profits over the five-year window are $ 283.19 million and $30.18 million respectively. The result is surprising. As we know that the use of derivatives is a zero-sum game, we should expect the hedgers to make zero profit on average. The finding indicates that the use of derivatives in hedging can be a positive NPV activity in oil and gas industry.

The question then arises: are the profits driven by favorable market condition or by market timing? Adam and Fernando (2006) find that gold mining firms earn profit in the use of derivatives due to the persistent positive risk premia in the gold futures market, so could firms in our sample also happen to gain for the same reason? To address this issue, we follow Jin and Jorion (2006)'s method to calculate the hedging portfolio delta and normalize it by the total production to obtain *Relative Delta Production* as the measure for hedge ratio. Our regressions show that the hedging profits are positively related to the hedge ratio and the risk premia in oil futures contracts. We then adopt three approaches to decompose the hedging activities into two parts: the true hedging component and the market timing component. We first use the industry mean hedge ratio each year as the true hedging component and the deviation from the industry mean as the market timing component. We allow variation of industry mean over time to reflect the impact of unknown market changes on hedging demand. Since each firm may have firm-specific hedging demand, the second approach regresses the hedge ratio on firm characteristics and risk premia. It then uses each firm's predicted hedge ratio as the true hedging component and the residual as the market timing component. There can be unknown firm factor that causes a firm to hedge differently from others persistently. Hence, the third approach uses the firm fixed effect regression to further control the unknown factor. We find that the total profits and the profits recorded on non-hedge account are positively related to the market timing component in all three decompositions while the profits recorded on hedge account are not. Hence, the positive profits are likely to be generated by the market timing activities of the firms in our sample.

To further investigate this issue, we also try to separate the market timing profits from hedging profits. Assuming a firm doesn't change hedging portfolio actively, then the profits which the firm would obtain should be roughly equal to the hedging portfolio delta multiplied by the change of commodity prices during the year. The estimated profits should capture the outcome from true hedging component and favorable market condition. We then obtain the market timing profits as the difference between the actual profits and the estimated profits. Both the mean and median of the difference are positive and large relative to firms' reported profits. We then regress the difference on the two components of hedge ratio. If the firm adjusts the hedging portfolio to time the market, then the difference will reflect the gains or losses generated from these activities. We find that the difference is positively related to the market timing component of hedge ratio. Thus, evidence again shows that firms are able to generate profits through the market timing activities.

Lastly, we find that the hedging activities are affected by the hedging profits in the preceding period. A closer look reveals that the feedback has opposite effects for winners and losers. When a firm gains from the previous hedging, it tends to hedge more. On the other hand, there is a negative feedback effect when a firm suffers a loss from the previous hedging. It appears that the more the firm loses, the more it will hedge in the subsequent period. When a firm only uses financial derivatives to hedge and sticks to the optimal hedge ratio, the gains or losses of hedging should be closely related to the change of market prices in the current period and should not be affected by the gains or losses of preceding hedging activities. Also, the net income should not be impacted much by the result of hedging activities because any losses or gains on the revenue of production will be offset by those from the hedging positions. However, if a firm uses financial derivatives for market timing and deviates from the optimal hedge ratio, the net income will then be impacted by the outcome of the derivatives contracts. For this reason, the firm will adjust its derivatives positions given the result of hedging in the preceding period. Therefore, the current use of derivatives will vary with the consequence of previous activities. Our findings on feedback effect provide further evidence that firms use derivatives for investment and even for speculation purpose.

Our paper contributes to the literature in three ways. First, the findings on hedging profits and the positive relationship between hedging profits and hedging activities suggest that the use of derivatives can be a positive NPV investment. To our knowledge, our data is the first sample which contains the information of both hedging activities and actual hedging profits. Allayannis and Weston (2001) and Carter et al. (2006) provide support that hedging increases shareholder wealth while Jin and Jorion (2006) find no evidence that hedging affects firm value in the oil and gas industry. Perez-Gonzalez and Yun (2013) also show that the use of weather derivatives in hedging increases the market-to-book ratios. Several studies (e.g., Adam and Fernando (2006), Brown et al. (2006)) use survey data on gold mining firms to estimate the cash flow outcome of derivatives contracts and show that firms on average gain from hedging. Our results in oil and gas industry are based on actual accounting data instead of estimated cash flows. Campello et al. (2011) argue that hedging can affect corporate outcome by reducing cost of borrowing and alleviating capital expenditure restriction. Our analysis provides direct evidence of hedging on corporate earnings.

Second, we are able to decompose the performance of hedging activities and find that the positive derivative outcome is associated with the market timing component of hedging. This finding is contrary to previous literature on hedging of interest rate risk and foreign exchange rate risk which states that firms (except financial firms) do not possess information advantage in general. Our research helps to resolve the debate on hedging and speculation (e.g., Faulkender (2006), Adam and Fernando (2006), Brown et al. (2006), Geczy et al. (2007), Chernenko and Faulkender (2011)). Stulz (1996) suggests that selective hedging can benefit firms which possess an information advantage relative to the market and firms which have the strength to bear additional risk from market timing activities. However, the previous research finds that the profits of selective hedging are trivial. Oil and gas producers collect information on the demand and supply of commodities and make production decision based on their predictions on the future market prices. This information can be transferred to their risk management teams to make hedging decisions. Hence, our study provides evidence for the hypothesis of information advantage. Not all firms which use selective hedging are successful. However, our results show that at least some firms are able to deliver good performance on the market timing activities consistently.

Third, our paper adds to the current research on learning and feedback effect in corporate finance. Feedback effect has been studied extensively in asset pricing. However, only recently researchers start to investigate how the market prices can affect corporate decisions[62]. For example, Luo (2005) shows that an acquisition can learn from the market's reaction to a merger announcement. Edmans, Goldstein and Jiang (2013) illustrate how market anticipation and stock price affect the probability of a firm being a takeover target. Our paper shows that the outcome of hedging matters for corporate hedging activities. The changes of oil and gas prices affect firms' hedging decision through the profits of hedging and the channel of firms' earnings. The losers learn to hedge more when their losses are more.

The remainder of the paper is organized as follows. Section 2 describes data sources, collection methods and summary statistics; section 3 discusses the empirical strategy and regression results; section 4 provides results of robustness tests, and section 5 concludes the paper.

C. Data and Sample Description

We focus on all oil and gas producers with SIC code of 1311 in the United States for which data is available from 2007 to 2011. The initial dataset contains 1029 firm-year observations. We then drop 60 firm-year records with missing asset values. We further remove 362 observations for firms whose assets are less than $100 million as small firms are often not required to provide disclosure on derivatives positions and don't actively use derivatives for hedging due to the lack of expertise. We also require that the data on hedging contracts, hedging profits and financial information should be available. Our final sample for regression consists of 105 firms and 397 firm-year observations.

[62] Please see a recent survey by Bond et al (2012).

1. Derivatives Contracts and Hedge Ratio

In order to study firms' use of derivatives, we hand-collect derivatives contracts from the annual 10-K reports. We write a PERL program to collect the entire text of 10-K for each firm from SEC Edgar database. Using the algorithm, we search for financial hedging keywords such as "hedg", "derivative", "financial instrument", "risk management", "item 7a", "market risk", "commodity risk", "price risk", "notional", "commodity contract", "commodity option", "option contract", "forwards", "forward contract", "forward exchange", "oil forwards", "natural gas forwards", "futures", "futures contract", "commodity futures", "oil futures", "natural gas futures", "swap", "collar" , "fixed price" and "volumetric production".

We then read through surrounding texts of each highlighted keyword and manually code the contracts data. We collect all derivatives contracts for firms' crude oil, natural gas and natural gas liquids (NGL) productions (Following Jin and Jorion (2006), NGL contracts are converted into standard crude oil contracts and treated as oil equivalent). The types of contracts include call options, put options, ceiling and floor contracts, fixed price swaps, forward and futures contracts, two-way collars and three-way collars. As in Jin and Jorion (2006), oil and gas basis contracts are not included in our data samples.

Table 1 presents the summary statistics of firms' derivatives contracts. Panel A shows that oil and gas related derivatives have balanced representation in our samples. The numbers and notional amounts of derivatives contracts in both commodities vary over years. Panel B summarizes the contracts for each type of derivatives. Swaps are the most popular derivative instruments used by oil and gas firms. Collars come next. Firms also use put options and floors substantially. Panel C and Panel D provides contract details for natural gas and crude oil respectively.

Following Jin and Jorion (2006), we employ Black and Scholes's derivative valuation model to calculate the delta for every contract. Out of our samples, there are 397 firm-years with delta in crude oil or gas contracts. We then aggregate individual delta to portfolio delta on the firm-year level and scale the firms' portfolio delta by their reported production for the year. The scaled delta represents the firm's hedge ratio in oil and gas production in that year (e.g., Tufano (1996), Jin and Jorion (2006)).[63]

$$Relative\ Delta\ Production\ = -\frac{Portfolio\ Delta}{Production}$$

As a robustness check, each firm-year's total notional amount of derivatives positions is calculated and scaled by annual production as another measure of hedge ratio.

$$Relative\ Notional\ Production\ = \frac{Total\ Notional\ Amount}{Production}$$

Panel A of Table 2 gives the summary statistics of firms' *Relative Delta Production* and *Relative Notional Production*. Our regression samples include 397 observations from 2007 to 2011. The mean and the median of hedge ratio are 84.48% and 62.57% every year. The value of *Relative Delta Production* appears to be greater than that in Jin and Jorion (2006) whose sample period ranges from 1998 to 2001. We use the delta calculation example in their paper and verify that our procedure obtains the same number for Relative Delta Production. The calculation example is presented in Appendix B. The difference may be driven by two reasons. First, firms in our sample are bigger. We only include firms with asset size at least $100 million while Jin and Jorion (2006) require asset size greater than $20 million. Large firms tend to use more

[63] For example, a firm lists its outstanding derivatives contracts which would be in effect from January 2010 in the 2009's annual report. These derivatives positions are actually scheduled to hedge the oil and gas production in fiscal year 2010 and forward and hence are used to calculate the portfolio delta in 2010. The portfolio delta is then scaled by the production in 2010.

derivatives. Also, we drop firms with no use of derivatives as our major interest is to investigate the profits of derivative transactions. If we include those firms, then the sample mean and median of Relative Delta Production are 57.56% and 38.93% respectively. The results could be found in Appendix C. Second, Jin and Jorion (2006)'s sample period is from 1998 to 2001. Oil prices were much higher and more volatile during our sample period from 2007 to 2011, which created more incentives to use derivatives in hedging. Moreover, the new accounting rules which became effective in 2008 could have improved the quality of firms' disclosure on derivative position. Third, we use all derivative positions including those with a maturity longer than one year. It is possible that firms also increase their long-term hedging given the high price and volatile market condition. If we exclude those long-term contracts, the mean and median of Relative Delta Production are 72.69% and 46.92% respectively.

2. Derivative Gains and Losses

To obtain the actual gains and losses from hedging activities, we use the same PERL algorithm to locate gains and losses information in 10-K and manually compile them into our database.

With FASB 133, firms are required to disclose the outcome of derivatives positions. If a firm designates the derivatives as cash flow hedges to be treated as the hedge account, then only realized gains or losses will impact earnings. The realized gains or losses are recorded as *Reported Realized Hedge Profit* in this paper. The unrealized gains or losses will be recorded in the other comprehensive income and accumulated until actualized. A firm can also elect not to designate its derivative instruments as cash flow hedges, but then the gains or losses are recorded on income statement immediately whether they are realized or unrealized. We record this type of profits as *Reported non-Hedge Profit*. For the cash flow hedge designated derivatives, part of them can become “ineffective” due to the change of market condition and firm’s production. The gains or losses of the ineffective portion of cash flow hedge will also be immediately reflected on earnings whether realized or unrealized and are recorded as *Reported Ineffective Hedge Profit*. The *Reported Total Profit* is the sum of *Reported Realized Hedge Profit*, *Reported non-Hedge Profit* and *Reported Ineffective Hedge Profit*. We hand-collect the gains and losses for the above items whenever they are available in 10-K files.

Panel A of Table 2 also provides the summary statistics of firms’ derivative profits normalized by total assets[64]. Overall, our results are similar to that in Manchiraju et al. (2012). The U.S. oil and gas firms generate profits in the use of derivatives on average, with the average total profits being 1.78% of total assets and the total median profits being 0.63% of total assets. (The mean of total raw profit before normalized by assets is $74.9 million and the median is $5.92 million[65]). T-tests show that the mean of *Reported Total Profit* and all of its components are significantly greater than zero. The 25th percentile of *Reported Total Profit* is -0.62% of assets. While the 75th percentile is 3.76%, about seven times larger than the 25th percentile in absolute value. Clearly, the gains from hedging far exceed the losses.

The finding of positive profits is surprising. According to hedging theory (e.g., Stulz (1984), Stulz (1990), Smith and Stulz (1985), Froot et al. (1993), Demarzo and Duffie (1995), Mello and Parsons (2000)), the expected return on hedging activities should be around zero since the use of derivatives is a zero-sum game. Further, Dewally et al. (2013) find that hedging profits are negative on average due to the hedging pressure and risk premia in futures contracts.

[64] Out of the 381 observations, several firms only report “net of tax gains or losses.” We address the tax issue by calculating the firm-year’s corporate income tax rate and adding back the taxes to its gains and losses.
[65] These numbers are not obtained by multiplying the mean and median of total profit in Panel A of Table 2 by the mean of asset in Panel B due to the normalization.

However, we find that firms gain from the use of derivatives on average with substantial economic value, which is contrary to the prediction of hedging theories. In section III, we further investigate the sources of gains using regression analysis.

3. Other Control Variables

The control variables include those identified by the literature as being determinants of the hedging activities: *Log Asset*, *Market to Book Ratio*, *Leverage Ratio, Cash*[66], *Dividend, S&P Rating Dummy* (e.g., Nance et al (1993), Haushalter (2000), Stulz (1996), Adam and Fernando (2006)). Besides, we include several other variables. We collect *Lifting Cost per Boe* (production cost per barrel of oil equivalent). Jin and Jorion (2006) use lifting cost as a control for Q ratio regression. We conjecture that the hedging demand is likely to be positively related to the lifting cost. The higher the lifting cost, the greater the incentive to hedge the production. Similarly, the *Cost of Goods Sold* and *Inventory* are used as control variables. We also include *Revenue* (revenue from oil and gas production), which is a direct measure of the demand for hedging, and *ROA* (return on assets), which measures the performance of the firm. We assume that capable firms are more likely to hedge. Lastly, we include the annual *Oil Price Volatility, Gas Price Volatility, Oil Futures Risk Premia and Gas Futures Risk Premia*. Since *Oil Price Volatility* and *Gas Price Volatility* are highly correlated, we only use *Oil Price Volatility*. The more volatile the oil (or gas) prices, the higher the demand for hedging. Also, we expect that the hedging demands are positively related to risk premia, which are the spreads between contracted futures prices and realized spot prices (e.g., Adam and Fernando (2006)).

The data on oil and gas production and reserve, lifting cost per barrel of oil equivalent and total revenues from oil and gas production are collected from Bloomberg Financial Market

[66] We use cash ratio instead of liquidity because we find cash has a stronger effect.

Platform. We manually check and correct the values and complement the missing values if we can find them from 10-Ks. Companies' fundamental data are collected from COMPUSTAT.

Panel B of Table 2 presents the summary statistics of the control variables included in regressions. We winsorize the ratio variables at the 1% level. The *Oil Futures Risk Premia* is slightly negative and *Gas Futures Risk Premia* is positive on average. The mean of annual *Oil Price Volatility* is 0.4153, which is high relative to the whole economy. *Cash*, *Inventory*, *Cost of Goods Sold*, *ROA*, *Revenue* and *Capital Expenditure* are normalized by total assets. The *Dividend* is normalized by the number of shares outstanding.

Panel C and Panel D of Table 2 display the yearly distribution of hedge ratio and hedging profits variables. U.S. oil and gas producers hedge a significant amount of oil and gas production while the mean and median of hedge ratio vary over years. U.S. oil and gas producers experienced a small loss only in 2007 and made profits in all other years in our samples. Panel D also provides the summary of profits on hedge account and non-hedge account. Mean and median profits on both accounts are positive. The standard deviation of profits on the non-hedge account is larger (hence more volatile) than that on the hedge account, indicating that the profits on non-hedge account are more closely related to the market timing activities than those on hedge account.

Panel E presents the yearly distribution of *Oil Futures Risk Premia* and *Gas Futures Risk Premia*. Since most of the hedging positions cover the productions spreading out in the year, we calculate the risk premia for each business day every year and then use the annual mean in the regressions. The risk premia are lagged values. For example, the mean of *Oil Futures Risk Premia* in 2009 is 38.871, which means the average difference between the 1-year contracted oil futures price in 2008 and the realized oil spot price in 2009 is $38.871. We match the mean risk premia to the derivative profits in 2009 and the outstanding derivative positions at the end of 2008.

Panel F investigates whether there are some firms which can consistently generate more profits on their hedging activities. If a firm can make positive profits in at least 4 years, we call it a Good Hedger. Otherwise, we call it a Mediocre Hedger. We find 27 firms are Good Hedgers with 133 firm-year observations, and 78 firms are Mediocre Hedgers with 264 firm-year observations. We then compare their hedge ratios and profits. The Good Hedgers are able to deliver three times profits as much as the Mediocre Firms do while the hedge ratios for both groups are not much different. The finding indicates that there are some firms which have some skills in their use of derivatives and the profits are likely to be related to not only how much firms hedge but also how firms hedge.

Table 3 gives Pearson correlation of our key variables and control variables. Our two proxies for hedge ratio (Relative Delta Production and Relative Notional Production) are positively correlated with firms' Leverage Ratio and negatively correlated with firms' financial strength (Cash and S&P Rating Dummy). They are also positively correlated with Lag Oil Price Volatility. This reflects that firms hedge according to the hedging demand. However, they are also positively correlated to the Oil and Gas Futures Risk Premia. The three measures of hedging profits are highly and positively correlated to the hedge ratio. The Reported Total Profit is slightly positively correlated to the Oil and Gas Futures Risk Premia. However, the Reported Realized Hedge Profit is strongly and positively correlated with the risk premia while the Reported non-Hedge Profit is negatively correlated with the risk premia.

D. Empirical Design and Results

We focus on the U.S. oil and gas producers for several reasons: First, previous studies show that the industry is exposed to oil and gas price risks and uses financial derivatives to hedge the risks extensively. Second, the firms in this industry have their business concentrated in the oil and gas production and are not diversified. Therefore, we don't need to consider the effect of diversification and natural hedge. Third, the products are quite homogeneous and hence are exposed to the same market price risks.[67]

Being able to observe both the hedging activities and the actual hedging profits allows us to investigate two issues which intrigue both researchers and practitioners. The first issue is about the extent of market timing hedging (or called selective hedging) and its effectiveness. The second issue is the feedback effect of hedging outcome on future hedging activities. The following subsections discuss the empirical methods designed to address these issues and the empirical findings.

1. Hedging Profits and Decomposition of Hedge Ratio

In previous section, we show that hedging activities generate profits. However, it is not clear how the hedging gains are linked to hedging activities. Consequently, our first step is to investigate whether the positive profits are driven by hedging activities. We employ the following regression model.

$$Profit_{it} = \alpha + \beta \times Hedge_{i,t} + \gamma \times Risk\ Premia_t + \eta_t + \mu_i + \varepsilon_{i,t} \qquad (1)$$

where subscript i refers to the firm, subscript t refers to the time in years, η_t refers to time fixed effects, and μ_i refers to firm fixed effects.

[67] Some recent papers using data from this industry include Bakke et al. (2013), Kumar and Rabinnovitch (2013), Manchiraju et al. (2013) and Ranasinghe et al. (2013).

In the regression model, *Hedge* is the measure of hedge ratio. The primary proxy for hedge ratio is *Relative Delta Production* which follows Jin and Jorion (2006) and is the portfolio delta in year t divided by total production for the year. In case there is measurement error in calculating delta, a second proxy is used: *Relative Notional Production,* which is the total notional amount of outstanding derivatives positions in year t divided by total production for the year.

If firms hedge according to the exact amount and date of future production without market timing, then profits generated from hedging activities should be around zero since derivative trading is a zero-sum game, and hence we should not expect any significant relationship between hedge ratio and hedging profits. The coefficient β for *Hedge* should not be significantly different from zero. However, if the oil and gas producers indeed possess superior information and/or skills in hedging (e.g., Stulz (1996)), firms are able to generate positive expected return from hedging. Then, we should observe a positive relationship between hedging and profits.

One concern is that with hedge accounting the profits from a derivative position designated as a cash flow hedge are recognized in earnings when the transaction being hedged is realized, not necessary when the profits from the derivative positions are realized. If, however, the derivative position is classified as a fair value hedge, profits will be recognized in earnings when the profits occur. Since fair value hedges are typically applied to commodity inventories and are rare in the energy industry, we find that almost all hedges in our sample are cash flow hedges. Thus, one may argue that the association between a firm’s derivatives position and profits from derivatives is hard to interpret due to the delay in the timing of when profits from derivatives are recognized in earnings. To address such concern, we conduct regressions using

Reported Realized Hedge Profit and *Reported non-Hedge Profit* separately. The results of Reported Non-Hedge Profit should help to reduce the timing problem.

We include three measures of derivative profits in the regressions. As illustrated in Table 2, we are able to obtain the total profits of derivatives and the individual profit components in firms' current earnings. The *Reported Total Profit* is the sum of realized cash flow hedge profits, realized and unrealized profits from non-hedge designated derivatives and the realized and unrealized profits from ineffective portion of cash flow hedge. The measure *Reported Realized Hedge Profit* represents the outcome of the use of derivatives that a firm designated as hedge account. Generally, this item should be closely related to the true hedging activities. The third measure *Reported non-Hedge Profit* is the sum of realized and unrealized gains or losses on non-hedge designated derivatives. Although firms typically claim that the use of derivative is for hedging, it is likely for firms to conduct selective hedging since this type of hedging activities and results are not recorded on hedge account.

Adam and Fernando (2006) argue that a persistent upward biased risk premia in oil and gas futures can generate profits for short hedgers. Hence, the hedging profits may be driven by the positive risk premia instead of firms' efforts in selective hedging. To account for this possibility, we include the annual mean oil and gas futures risk premia in regressions. If the hedging profits are caused by positive risk premia, then these two variables should have positive coefficients.

Table 4 presents estimation results for equation (1). The dependent variable in model 1, 2 and 3 is the *Reported Total Profit* on derivatives. We use the *Reported Realized Hedge Profit* for model 4, 5 and 6, and the *Reported non-Hedge Profit* for model 7, 8 and 9. We use *Relative Delta Production* as the proxy for hedge ratio.

We find a positive relationship between profits and hedging activities. The regression coefficients in model 1, 2 and 3 are significant at the 1% level. For example, in column 1, the coefficient for *Relative Delta Production* is 0.018. A one standard deviation increase in *Relative Delta Production* would yield a 0.014 increase in *Reported Total Profit* on derivatives, which is greater than 70% of the average total profits.

To control for unobserved market factors which might drive firms' use of derivatives in a specific year, we add year fixed effects in model 2, 5 and 8. In model 3, 6, and 9, we add firm fixed effects in addition to year fixed effects to control for unobserved firm-level characteristics which may affect firms' demand for hedging.

The differences between the coefficients for *Relative Delta Production* of column 4, 5, 6 and that of column 7, 8, 9 reveal that firms' derivatives positions create a greater impact on non-hedge designated profits than on hedge designated profits. The difference indicates that a proportion of total profits is the result of market timing activities.

The *Oil Futures Risk Premia* are significant in most regressions. Consistent with the finding in Adam and Fernando (2006), the hedging outcome is positively related to *Oil Futures Risk Premia*. Thus a fraction of the hedging profits is likely to be driven by the risk premia in the futures market. The *Gas Futures Risk Premia* are dropped from the regressions once we include the year fixed effect. The *Gas Futures Risk Premia* appear to have a negative sign, but this is due to the high collinearity with *Oil Futures Risk Premia*. The correlation coefficient is 0.93 in Table 3. If we drop *Oil Futures Risk Premia*, then the sign for *Gas Futures Risk Premia* are all positive and significant. Also, if we only use *Gas Futures Risk Premia* in the regressions for the other tables, the results are virtually the same.

1.1 Decomposition using Industry Mean

While the model above can help us examine the relationship between hedging and the outcome of hedging, another issue remains to be addressed: do profits come from true hedging activities or market timing activities? We adopt three approaches to decompose the hedge ratio and obtain the component which is likely related to market timing.

The first approach measures the deviation of a firm's hedge ratio from the industry's average hedge ratio. Since there exist market-level factors that cause the general shift of hedging demand for the whole industry, the hedging profits may be positively related to the hedging demand driven by these factors. The industry-level hedge ratio can help absorb this effect of hedging. The deviation from this ratio is likely to be driven by individual firm's own market timing decision in hedging. For each year, we first calculate the industry average *Relative Delta Production*. We then subtract each firm's *Relative Delta Production* by industry average *Relative Delta Production* to obtain the firm's *Relative Delta Production Deviation*. The deviation corresponds to market timing hedging activities and the industry-level hedge ratio reflects true hedging activities.

Specifically, we estimate the following model:

$$Profit_{it} = \alpha + \beta_1 \times Hedge\ Deviated_{i,t} + \beta_2 \times Industry\ Mean\ Hedge_{i,t} \qquad (2)$$

$$+ \gamma \times Risk\ Premia_t + \eta_t + \mu_i + \varepsilon_{i,t}$$

Similarly, we use the three measures of hedging profits in our estimation starting with the raw model, and then models with year fixed effects and models with both year and firm fixed effects. From column 1 to column 3 of Table 5, the coefficients of the deviated hedge ratio are all positive and significant at the 1% level. The industry average hedge ratio gets omitted in column

2 and 3 due to the collinearity with fixed effects. The coefficient for industry average hedge ratio in column 1 is positive at 0.123 and also significant at the 1% level.

Interestingly, when using *Reported Realized Hedge Profit* as the dependent variable in column 4, 5 and 6, the market timing effects become insignificant as we expected, and the hedging effects become significant at the 5% level in model 4. This is consistent with the hypothesis that the industry average *Relative Delta Production* represents true hedging activities, while the deviation from industry average *Relative Delta Production* proxies for market timing activities.

The results using *Reported non-Hedge Profit* provide further evidence for market timing. The coefficient for *Delta Deviated from Mean* is significant at the 1% level even after controlling for *Industry Mean Delta*.

1.2 Decomposition using Regression Predicted Hedge and Residual

While the deviation from industry mean hedge ratio can be a good proxy for market timing, it can still contain the effect driven by each firm's own demand. Therefore, the second approach of decomposition uses the residual from the regression of firm's hedge ratio on factors that are likely related to hedging demand. We first estimate the following model to obtain the residual:

$$Hedge_{it} = \alpha + \beta \times Industry\ Mean\ Hedge_{i,t} + \gamma \times X_{i,t} + \varepsilon_{i,t} \qquad (3)$$

$X_{i,t}$ are the control variables including *Lifting Cost per Boe, Market to Book Ratio, Leverage Ratio, Log Asset, Cash, ROA, Revenue, S&P Rating Dummy, Capital Expenditure, Dividend, Lag Oil Price Volatility, Oil Futures Risk Premia and Gas Futures Risk Premia.*

Because these firm-specific characteristics determine firms' regular demand for derivatives, the regression predicted value is considered to be firms' true hedging activities.

Similarly, the regression residual would be the proxy for firms' market timing activities. We then use these two variables as independent variables in the following regression model:

$$Profit_{it} = \alpha + \beta_1 \times Residual\ Hedge_{i,t} + \beta_2 \times Predicted\ Hedge_{i,t} \qquad (4)$$

$$+ \gamma \times Risk\ Premia_t + \eta_t + \mu_i + \varepsilon_{i,t}$$

The results are reported in Table 6. As we expected, the market timing component still plays an important role in determining hedging profits. For example, in column 1, the coefficient of residual (market timing component) is 0.024 and is significant at the 1% level. The result remains if we add year and firm fixed effects. The predicted value (true hedging component) also has a positive impact on the profits. However, once we include both of year fixed effects and firm fixed effects, it is no longer significant. It is possible that the firm fixed effects absorb the persistent profits generated by the predicted hedge ratio.

In model 4, 5 and 6, we find that the market timing component is also positively significant. It indicates that firms' profits on hedge designated derivatives positions also include market timing effect, even though firms assert that these derivatives positions are designed as cash flow hedge.

The regressions of *Reported non-Hedge Profit* yield a similar picture as previous tables. The market timing component has a strong effect in predicting the profits even with both fixed effects. The true hedging component represented by predicted hedge ratio has no effect after controlling for the firm fixed effects.

1.3 Decomposition using Fixed Effect Regression Predicted Hedge and Residual

The third approach is an extension of the methods described above. We employ a stricter examination on the decomposition of hedge ratio. We regress firms' *Relative Delta Production* (or *Relative Notional Production*) on firm characteristics which might affect their derivatives positions as in equation (3). Importantly, we also include firm fixed effects in the regressions. We then obtain the regression predicted value as a proxy for true hedging component, and the regression residual as a proxy for market timing component. The firm fixed effects can absorb part of individual firm's market timing effect if a firm conducts persistent market timing activities. For example, if a firm keeps more short positions each year during our sample period, then it will show up in the intercept of the regression and be recognized as hedging activity. Therefore, this is a quite stringent rule which leaves only the time varying speculation behavior in the residual. We use these two proxies in the regression and report the results in Table 7.

In column 1, the coefficient of residual (market timing component) is 0.021 and is positively significant at the 1% level. The coefficients are also positively significant for model 2 with year fixed effects, and model 3 with both year and firm fixed effects. Specifically, the coefficient of market timing component is stronger than that of true hedging component in model 3. The coefficient of true hedging component becomes insignificant because the fixed effects in model 3 absorb the consistent hedging profits. When we use the *Reported Realized Hedge Profit* in model 4, 5 and 6, the coefficients of market timing component are weaker. However, the coefficients then get stronger for the *Reported non-Hedge Profit* in the regressions of 7, 8 and 9. Overall, with a stricter rule, the results are still in support of our finding that firms are market timers and achieve a large amount of derivative gains from market timing activities.

1.4 Decomposing the Profits with Estimated Profits

Lastly, we measure the difference between the reported profits from 10-K and an estimated profit and use it as a proxy for market timing profits. The estimated profit is the predicted year-end profit calculated by multiplying the portfolio delta of a firm's outstanding derivatives contracts in the end of the previous year by the change of year-end commodity prices, and is then normalized by total assets. If a firm maintains its outstanding portfolio to the end of the year, then the estimated profit should be a good proxy for the natural market impact on hedging profits due to the change of year-end prices. We consider the difference between reported profits and estimated profits as the market timing profits. The mean and median of the market timing profits are 1.53% and 0.52% of total assets, which are large relative to the mean and median of total profits.

We first use the same regression specification in equation (2) and replace the dependent variable with the market timing profits. The regressions outputs are provided in Table 8. Overall, the market timing component of hedging is strongly related to the market timing profits. In model 1, 2, 3, 7, 8 and 9, the coefficients of residual (market timing component) are significant at the 1% level. In regard to profits designated as hedge, the coefficients of market timing component are still significant in model 4, 5 and 6.

We then use the market timing profits as the dependent variable in equation (4) and the independent variables remain the same. The regressions outputs are in Table 9. The market timing component of hedging is consistently significant in model 3 and 9 with both year and firm fixed effects. Hence, the market timing activities generate profits for the firms. Interestingly, the negative coefficients of predicted hedge ratio in model 3 and 9 indicate that the more firm hedges according to its demand, the lower the market timing profits will be. Thus, the difference between reported profits and estimated profits is a good proxy for market timing profits.

2. **Feedback Effect on Hedging Activities**

Our results have implied that firms are timing the market and holding corresponding derivatives contracts. Now, we turn into another issue about whether firms' current derivatives positions are affected by the outcome of the previous experience. Feedback effect is defined as the impact transmitted from the change of prices to corporate decisions. The issue is part of the current topic of the real effects of financial markets (e.g., Bond et al. (2012)). The empirical findings shed light on the debate in extant literature about whether firms are indeed hedging their future production, or are using derivatives as investment (or speculation) tools and seeking for positive returns. In this section, the key question of interest is: how current gains or losses on derivatives contracts affect firms' future hedging decisions?

We run the following regression:

$$Hedge_{it} = \alpha + \beta \times Profit_{i,t-1} + \gamma \times X_{i,t\ or\ t-1} + \eta_t + \mu_i + \varepsilon_{i,t} \qquad (5)$$

where subscript i refers to the firm, subscript t refers to the time in years, η_t refers to time fixed effects, and μ_i refers to firm fixed effects. Again, we use two proxies for hedge ratio and the three measures of hedging profits as discussed above.

It is in our interest to examine the significance and sign of the coefficient β. If hedging activities are solely driven by hedging demand, then the coefficient on hedging gains should be zero. However, if current period's hedging is influenced by the hedging outcome of the previous period, then the coefficient β should be significantly different from zero.

Table 10 examines the feedback effect on hedging activities using *Relative Delta Production* as the dependent variable. Model 1 studies the determinant of *Relative Delta Production* without looking at previous derivative profits. The independent variables in column 1 are firm specific characteristics. Consistent with the literature, we find that the coefficient on previous year's *Oil Price Volatility* is positively significant at the 1% level (*Oil Price Volatility* and *Gas Price Volatility* are collinear variables so we only include *Oil Price Volatility*). *Dividend*, which is a commitment on future payments, is positively significant at the 1% level, suggesting that the greater amount of committed future payments, the more likely for the firm to hedge. *Cash*, which proxies for liquidity, is negatively significant at the 1% level. Firm size is negatively correlated with *Relative Delta Production*. Interestingly, the *Leverage Ratio*, which is related to financial constraints, exhibits a positive and significant relationship with hedge ratio.

We then introduce *Lag Reported Total Profit* in model 2 and 3, *Lag Reported Realized Hedge Profit* in model 4 and 5, and *Lag Reported non-Hedge Profit* in model 6 and 7. Model 3, 5 and 7 includes both year fixed effects and firm fixed effects.

As given in column 2, 3, 4, 5, 6 and 7, in spite of the types of profits (total profit, realized hedge profit, or non-hedge profit), firms' current *Relative Delta Production* is positively correlated with previous profits on derivatives contracts. For instance, in column 2, the coefficient of preceding year's *Reported Total Profit* is significant at the 10% level. The result suggests the feedback effect on hedging activities. However, the results are not significant in most of other models when year fixed effects and firm fixed effects are included.

Would previous gains on derivatives contracts affect firms' current hedging activities differently than previous losses? This is a reasonable assumption because winners and losers are likely to hedge differently. When a firm has large hedging gains, it may reduce its position if it believes that the prices are mean reverting. Or the positive outcome may encourage the firm to hedge more. When a firm suffers large hedging losses, it may increase its position if it believes that the prices are mean reverting, or it may scale back its hedging position due to internal pressure. To answer this question, we divide our samples into two groups and repeat the regressions with year and firm fixed effects. In Table 11, model 1 and 2 are based on firms with gains on derivatives during the past year, and model 3 and 4 are based on firms with losses on derivatives during the past year. We do not include models with Lag Reported Realized Hedge

Profit because of collinearity. As expected, we discover different feedback effects for the two groups.

For firms with positive derivative profits, the feedback effect is positive, suggesting that firms benefit from past year's derivatives positions tend to hold more derivatives relative to production in the current year. However, the coefficients are not significant.

For firms with derivative losses, the feedback effect is in the opposite direction. For these firms, the losses on preceding year's derivatives positions lead to greater hedge ratio in the current year. For example, the coefficient of *Lag Reported Total Profit* in column 3 is -7.782 and is significant at the 5% level, and a one standard deviation decrease in previous *Reported Total Profit* leads to a 0.3006 (30.06%) increase in current *Relative Delta Production*. The coefficient of *Lag Reported non-Hedge Profit* in column 4 is -9.352 and significant at the 1% level. It indicates a gambling behavior when firms bear a large loss from previous derivatives positions. They anticipate that the price will fall after the loss due to the price increase. This result strongly contradicts traditional views on corporate hedging. It further strengthens our findings that some oil and gas firms behave as investors, and they are timing the market, holding a large amount of derivatives positions as a speculation.

E. Robustness Tests

1. Change of Profits and Change of Hedge Ratio

To capture the dynamics of hedging profits and hedging activities, we modify equation (1) and run the following model:

$$\Delta\ Profit_{it} = \alpha + \beta \times \Delta\ Hedge_{i,t} + \gamma \times Risk\ Premia_t + \eta_t + \mu_i + \varepsilon_{i,t} \qquad (6)$$

where subscript i refers to the firm, subscript t refers to the time in years, η_t refers to time fixed effects, and μ_i refers to firm fixed effects. We use the change of profits, which is the difference between current year's profits and last year's profits, as the dependent variable. The independent variables include the change of hedge ratio, risk premia and fixed effects.

As noted in Table 12, the positive relationship between hedging profits and hedging activities is still noteworthy. Firms' change of hedging activities has a greater impact on non-hedge designated profits than on hedge designated profits. Furthermore, for hedge designated profits, the coefficients of risk premia are all significant at the 1% level, with and without fixed effects, showing that regular hedging profits are closely linked to market risk premia.

2. **Decomposition of Hedge Ratio using Industry Median Hedge ratio**

In section 3, based on industry average hedge ratio, we conduct various tests to decompose hedge ratio into market timing and true hedging components. In the event that the industry mean is affected by outliers, we use industry median hedge ratio as a proxy for general hedging demand and get similar results in unreported tables. The market timing effect remains considerable.

3. **Upstream Oil and Gas Producers**

To identify firms in the upstream oil and gas sector and not to include midstream and downstream oil and gas firms, Doshi et al. (2014) utilize four different industry classification codes from Compustat: National American Industry Classification System (NAICS), Standard Industry Classification (SIC), S&P Industry Sector Code (SPCINDCD) and Global Industry Classification Sector Code (GSECTOR).

We add NACIS and SPCINDCD as additional filtering criteria. In addition, we use GSUBIND (the fourth level in the hierarchy of the Global Industry Classification Standard) instead of GSECTOR (the first level in the hierarchy of the Global Industry Classification Standard). Specifically, we require that each firm included in our regression samples must fulfill the following standards: SIC equals 1311 (Crude Petroleum and Natural Gas), NAICS equals 211111 (Crude Petroleum and Natural Gas Extraction), SPCINDCD equals 380 (Oil & Gas Exploration & Production), GSUBIND equals 10102020 (Oil & Gas Exploration & Production). Since there are many missing values for SPCINDCD, to avoid accidentally excluding qualified oil and gas producers, we also allow SPCINDCD to be null if a firm meet all the other three criteria.

By applying these criteria, 13 firms are excluded from our original samples, and the filtered samples include 88 unique firms. We rerun all the regressions in section 3 and get robust and consistent results.

4. Contracts Mature in the Succeeding Year

At the end of each fiscal year, oil and gas firms report their derivatives positions scheduled for the following years. The derivatives positions could be matured in different years in the future. In this test, we only consider firms' derivatives contracts scheduled for the following one year. To get firms' hedge ratio, we then aggregate the delta (or notional amount) of these outstanding contracts and normalize it by annual production for the following year.

The results are similar to those in the key regressions of predicting profits in section 3. All of the regressions in Table 13 include both of year fixed effects and firm fixed effects. The coefficients of hedge ratio and market timing activities are still positively correlated with *Reported Total Profit* and economically significant.

The findings in Table 14 are also consistent with previous regressions evaluating feedback effect. All of the regressions include both of year fixed effects and firm fixed effects. Column 1 and 4 examine the feedback effect on hedging activities. The coefficient on *Lag Reported Total Profit* in model 4 is significant. Moreover, after dividing the samples into two sub-groups base on the sign of their profits, we find similar feedback effects as that in section 3. Column 2 and 5 include firms with positive profits in the previous year. The greater the profit they gained in the past year, the greater the hedge ratio they maintain in the current year. Column 3 and 6 include firms with negative profits in the previous year. The coefficients in model 3 and 6 are both negatively significant. The greater the loss they suffered in the previous year, the greater the hedge ratio they maintain in the current year. The conflicting direction of feedback effects for these two groups suggests that firms behave as market timers and speculators in the derivatives market.

5. Sub-period from 2008 to 2011

We also revisit the feedback effect of hedging by using a sub-period from 2008 to 2011. The reason we exclude the 2007 samples is that crude oil price rose sharply during 2007, and firms' derivatives positions generated a loss on average. This brings us to the question about how firms changed their hedging strategies after the initial price shock in our sample period. As displayed in Panel D of Table 2, the average total loss on derivatives in 2007 is 1.30% of total assets. The reported total gains or losses then become positive during all years afterward, even if oil price rose again in 2009. Do firms react differently to the abrupt price movement? As seen from Table 2 of Panel C, firms indeed increase their hedge ratio after 2007. To further answer this question, we reexamine the feedback effect of hedging by focusing on the 2008-2011 sub-period.

Table 15 reports the feedback effect of hedging for 2008-2011 and the results are quite consistent with Table 10.

Table 16 investigates the feedback effect on hedging for winners and losers respectively during 2008-2011. Past gains impact current hedging activities significantly, and previous losses still motivate losers to increase hedge ratio as we found before. The positive correlations between risk premia and hedge ratio for winners in model 1 and 2 indicate that winners successfully predict the direction of risk premia after 2007 and adjust their hedge ratio accordingly. Current hedge ratio is also positively correlated with past reported total profits. On the other hand, the coefficients of risk premia for losers are negative in model 3 and 4, showing that losers fail to bet on the right direction of risk premia for their short positions. In addition, despite the past losses, they still raise hedge ratio. The coefficients of profit variables in model 3 and 4 are both negative and are significant.

F. Conclusion

Recent literature studies how companies use market-timing in corporate financing and payout decisions (e.g., Bolton et al. (2013)). However, the literature has been debating whether management should incorporate their view of the market in risk management. Hedging the price exposure to product market risk is quite different from hedging interest rate risk and foreign exchange risk. Due to the investment on the information of product market, firms may possess information advantage on hedging the market risk of their products (e.g., Stulz (1996)). Cheng and Xiong (2013) find that commodity hedgers act like speculators and trade actively on derivatives markets. Altogether, the practice warrants more investigations.

While the U.S. oil and gas producers have been extensively studied by researchers, we provide new evidence on hedging in the industry. Based on our samples and sample period from 2007 to 2011, we show that the U.S. oil and gas producers on average gain from their hedging activities. Such gains are positively related to the hedge ratio and the market timing activities. Gains in previous period will also have an impact on the hedging decision next period. Overall, our findings show that the new data on hedging profits can help us understand more about corporate hedging.

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Table 1: Summary Statistics of Natural Gas and Crude Oil Contracts

The table presents the summary statistics of natural gas and crude oil contracts. Panel A gives the number and the notional amount of contracts. The notional amount is in Bcf (billion cubic feet) for natural gas contracts and in Mmbbl (million barrels) for crude oil contracts. Panel B summarizes the types of contracts, which include call options, put options, ceilings, floors, collars, three-way collars, forwards and swaps contracts. The notional amount is in Mmboe (million barrels of oil equivalent). Panel C and Panel D provides contracts information for natural gas and crude oil respectively.

Panel A - Commodity Contracts

	Gas Contracts		Oil Contracts	
Year	Number	Notional (Bcf)	Number	Notional (Mmbbl)
2006	522	3201.59	474	386.43
2007	659	5838.64	625	510.63
2008	646	6405.47	516	440.46
2009	714	7447.16	590	565.44
2010	484	7226.55	652	648.74
2011	402	7323.74	660	658.19

Panel B - Contract Types (notional amount in Mmboe)

		Call	Put	Ceiling	Floor	Collar	Three	Forward	Swap
2006	N	31	33	0	25	417	35	24	431
	Notional	4.54	49.30	0.00	16.45	280.84	116.65	5.72	446.54
2007	N	29	54	10	86	441	26	20	618
	Notional	90.20	74.38	2.42	38.83	397.45	171.38	19.89	689.19
2008	N	34	57	8	54	453	35	7	514
	Notional	130.43	96.03	1.94	24.92	418.99	129.58	4.13	702.02
2009	N	20	65	18	38	432	37	7	687
	Notional	187.39	56.39	26.00	49.46	368.17	278.09	1.98	839.17
2010	N	44	58	7	17	329	68	3	610
	Notional	359.94	84.98	1.93	5.79	347.43	265.53	1.07	786.49
2011	N	45	52	0	5	253	96	2	610
	Notional	495.25	62.23	0.00	0.29	327.85	202.26	0.30	790.64

Table 1: Summary Statistics of Natural Gas and Crude Oil Contracts (Cont.)

Panel C - Natural Gas Contracts (notional amount in Bcf)

		Call	Put	Ceiling	Floor	Collar	Three	Forward	Swap
2006	N	18	5	0	16	224	16	14	229
	Notional	18.14	3.23	0.00	41.98	973.39	229.07	31.80	1903.98
2007	N	12	26	4	26	212	13	10	356
	Notional	382.56	76.72	4.10	27.54	1455.91	633.98	51.63	3206.20
2008	N	13	24	4	22	253	25	2	303
	Notional	571.95	206.09	4.39	20.08	1684.12	614.76	8.60	3295.48
2009	N	8	43	6	14	221	21	4	397
	Notional	1000.39	193.63	7.16	40.05	1188.04	1187.37	6.46	3824.07
2010	N	8	19	3	5	124	18	3	304
	Notional	1658.80	268.74	6.59	7.39	992.57	827.72	6.43	3458.31
2011	N	25	19	0	1	91	19	1	246
	Notional	2344.55	242.47	0.00	0.60	1127.41	505.29	1.37	3102.04

Panel D - Crude Oil Contracts (notional amount in Mmbbl)

		Call	Put	Ceiling	Floor	Collar	Three	Forward	Swap
2006	N	13	28	0	9	193	19	10	202
	Notional	1.52	48.76	0.00	9.46	118.61	78.47	0.42	129.21
2007	N	17	28	6	60	227	13	10	259
	Notional	26.44	61.59	1.74	34.24	154.58	65.72	11.28	154.80
2008	N	21	33	4	32	200	10	5	211
	Notional	35.10	61.69	1.21	21.58	138.30	27.12	2.70	152.77
2009	N	12	22	12	24	211	16	3	290
	Notional	20.66	24.12	24.81	42.78	170.16	80.19	0.90	201.82
2010	N	36	39	4	12	205	50	0	306
	Notional	83.47	40.19	0.83	4.56	182.00	127.58	0.00	210.11
2011	N	19	33	0	4	162	77	1	364
	Notional	104.49	17.36421.	0.00	0.19	139.95	118.04	0.07	273.63

Table 2: Summary Statistics of Key Variables and Control Variables

This table provides summary statistics of key variables and control variables. Panel A reports the summary statistics for key dependent variables including hedge ratio variables and reported profits variables. Reported profits variables are normalized by total assets. The p-values of t-test of means are reported in the last column. Panel B lists the summary statistics for major control variables. Number of observations, mean, standard deviation, 25 percentile, median, and 75 percentile are reported. Cash, Inventory, Cost of Goods Sold, ROA, Revenue and Capital Expenditure are normalized by total assets. Dividend is normalized by number of shares outstanding. Panel C provides summary statistics of Relative Delta Production and Relative Notional Production during sample period from 2007 to 2011. Panel D provides summary statistics of Reported Total Profit, Reported Realized Hedge Profit and Reported non-Hedge Profit during sample period from 2007 to 2011. Panel E reports the annual mean of Oil and Gas Futures Risk Premia. Panel F reports the comparison of hedge results. If a firm is able to generate positive hedge profits in at least 4 years, then we can call it a Good Hedger, otherwise we call it a Mediocre Hedger.

Panel A - Key Variables

	N	Mean	SD	P25	Median	P75	p-value
Relative Delta Production	397	0.8448	0.7711	0.2915	0.6257	1.1370	0.0000
Relative Notional Production	397	1.0412	0.9002	0.4094	0.7862	1.4235	0.0000
Reported Total Profit	397	0.0178	0.0507	-0.0062	0.0063	0.0376	0.0000
Reported Realized Hedge Profit	178	0.0153	0.0404	-0.0049	0.0014	0.0212	0.0000
Reported non-Hedge Profit	322	0.0134	0.0487	-0.0067	0.0046	0.0312	0.0000
Reported Ineffective Hedge Profit	76	0.0000	0.0023	-0.0004	0.0000	0.0005	0.4270
Reported Raw Profit ($Million)	397	74.8980	337.5571	-4.4000	5.9190	48.4250	0.0000
Accumulate Raw Profit ($Million)	105	283.1857	1056.7660	0.0000	30.1820	171.0000	0.0036

Panel B - Control Variables

	N	Mean	SD	P25	Median	P75
Oil Futures Risk Premia	397	-2.3005	22.2269	-10.3318	-8.8114	-1.3862
Gas Futures Risk Premia	397	1.9426	1.8944	1.2635	1.7179	2.1531
Lag Oil Price Volatility	397	0.4153	0.1154	0.2902	0.4281	0.4572
Lifting Cost per Boe	366	14.1586	9.4407	9.0963	12.1416	16.9344
Market to Book Ratio	381	2.0622	5.8924	1.0771	1.8270	2.7813
Leverage Ratio	397	0.3578	0.2194	0.2226	0.3256	0.4551
Log Asset	397	7.3188	1.5094	6.1880	7.2613	8.2405
Cash	397	0.0354	0.0521	0.0030	0.0156	0.0460
Inventory	374	0.0059	0.0107	0.0000	0.0010	0.0078
Cost of Goods Sold	397	0.1810	0.2456	0.0600	0.0933	0.1674
ROA	397	-0.0348	0.2423	-0.0544	0.0184	0.0604
Revenue	397	0.2991	0.1707	0.1989	0.2680	0.3573
Dividend	397	0.0123	0.0352	0.0000	0.0000	0.0048
Capital Expenditure	397	0.2351	0.1418	0.1306	0.2188	0.3225
S&P Rating Dummy	397	0.5365	0.4993	0.0000	1.0000	1.0000

Table 2: Summary Statistics of Key Variables (Cont.)

Panel C – Relative Delta Production and Relative Notional Production, 2007 to 2011

		Relative Delta Production						Relative Notional Production				
Year	N	Mean	SD	P25	Median	P75	N	Mean	SD	P25	Median	P75
2007	70	0.6518	0.7537	0.1933	0.4388	0.8826	70	0.8490	0.9227	0.2656	0.6149	1.1771
2008	87	0.8645	0.8621	0.2813	0.5098	1.1803	87	1.1020	1.0165	0.3930	0.7766	1.4399
2009	79	0.9517	0.7835	0.3409	0.7683	1.3995	79	1.1161	0.9218	0.4241	0.8462	1.4918
2010	83	0.9450	0.7371	0.3866	0.8410	1.3182	83	1.1521	0.8404	0.5048	0.9939	1.6656
2011	78	0.7813	0.6763	0.2977	0.6132	1.0034	78	0.9519	0.7567	0.4249	0.7816	1.2593
Total	**397**	**0.8448**	**0.7711**	**0.2915**	**0.6257**	**1.1370**	**397**	**1.0412**	**0.9002**	**0.4094**	**0.7862**	**1.4235**

Panel D – Reported Total Profit, Reported Realized Hedge Profit and Reported non-Hedge Profit, 2007 to 2011

		Reported Total Profit						Reported Realized Hedge Profit				
Year	N	Mean	SD	P25	Median	P75	N	Mean	SD	P25	Median	P75
2007	70	-0.0130	0.0358	-0.0219	-0.0045	0.0068	40	0.0066	0.0156	-0.0030	0.0016	0.0152
2008	87	0.0316	0.0614	-0.0072	0.0119	0.0668	41	-0.0120	0.0168	-0.0221	-0.0091	-0.0005
2009	79	0.0255	0.0599	-0.0155	0.0158	0.0556	36	0.0573	0.0551	0.0139	0.0463	0.0903
2010	83	0.0229	0.0446	-0.0015	0.0103	0.0418	31	0.0181	0.0387	-0.0018	0.0057	0.0399
2011	78	0.0169	0.0305	-0.0019	0.0074	0.0319	30	0.0106	0.0258	-0.0026	0.0014	0.0199
Total	**397**	**0.0178**	**0.0507**	**-0.0062**	**0.0063**	**0.0376**	**178**	**0.0153**	**0.0404**	**-0.0049**	**0.0014**	**0.0212**

		Reported non-Hedge Profit				
Year	N	Mean	SD	P25	Median	P75
2007	45	-0.0259	0.0365	-0.0329	-0.0103	-0.0020
2008	68	0.0463	0.0587	0.0017	0.0331	0.0807
2009	66	0.0002	0.0487	-0.0250	-0.0011	0.0205
2010	74	0.0177	0.0374	-0.0030	0.0051	0.0271
2011	69	0.0145	0.0298	-0.0003	0.0074	0.0279
Total	**322**	**0.0134**	**0.0487**	**-0.0067**	**0.0046**	**0.0312**

Panel E – Oil and Gas Futures Risk Premia, 2007 to 2011

Year	Oil	Gas
2007	-1.386	2.153
2008	-27.010	-0.441
2009	38.871	5.287
2010	-8.811	1.718
2011	-10.332	1.264
Total	**-2.301**	**1.943**

Panel F – Comparison of Hedge Results

	Good Hedger		Mediocre Hedger		Difference of Mean	p-value
	N	Mean	N	Mean		
Relative Delta Production	133	0.893	264	0.820	0.073	0.1871
Reported Total Profit	133	0.034	264	0.010	0.024	0.0000

Table 3: Correlation Matrix

This table provides the correlation among key variables and control variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) Relative Delta Production	1																			
(2) Relative Notional Production	0.910	1																		
(3) Reported Total Profit	0.673	0.537	1																	
(4) Reported Realized Hedge Profit	0.422	0.317	0.571	1																
(5) Reported non-Hedge Profit	0.416	0.349	0.613	-0.277	1															
(6) Oil Futures Risk Premia	0.060	0.016	0.143	0.509	-0.336	1														
(7) Gas Futures Risk Premia	0.065	0.031	0.147	0.522	-0.347	0.9939	1													
(8) Lag Oil Price Volatility	0.152	0.206	0.242	0.224	0.069	0.1105	0.1498	1												
(9) Lifting Cost per Boe	-0.117	-0.001	-0.205	-0.162	-0.075	-0.155	-0.149	-0.141	1											
(10) Market to Book Ratio	0.053	0.315	-0.149	0.059	-0.230	0.030	0.068	0.1844	0.396	1										
(11) Leverage Ratio	0.294	0.355	0.290	0.047	0.311	-0.016	-0.031	0.070	0.0525	-0.009	1									
(12) Log Asset	-0.551	-0.484	-0.297	-0.313	-0.086	0.031	0.015	-0.033	-0.090	-0.137	-0.175	1								
(13) Cash	-0.134	-0.149	-0.148	-0.154	-0.032	-0.050	-0.034	0.152	-0.135	-0.010	-0.275	-0.041	1							
(14) Inventory	-0.293	-0.263	-0.128	-0.119	-0.037	-0.079	-0.090	0.012	-0.081	-0.065	-0.162	0.468	0.023	1						
(15) Cost of Goods Sold	-0.076	0.039	-0.009	-0.010	-0.004	-0.046	-0.069	0.030	0.177	0.115	0.065	0.128	-0.102	0.6651	1					
(16) ROA	-0.183	-0.211	-0.260	0.082	-0.405	-0.195	-0.195	-0.192	0.085	0.157	-0.405	0.151	-0.003	0.1353	-0.125	1				
(17) Revenue	0.009	0.025	0.016	0.145	-0.090	-0.182	-0.192	-0.024	0.187	0.158	-0.180	0.055	-0.137	0.662	0.7961	0.2269	1			
(18) Dividend	0.387	0.308	0.170	0.552	-0.260	0.025	0.026	0.015	0.114	0.175	-0.081	-0.361	-0.114	-0.012	0.050	0.4109	0.3634	1		
(19) Capital Expenditure	-0.097	-0.064	-0.159	-0.229	0.007	-0.349	-0.358	-0.285	-0.273	-0.152	0.133	-0.206	0.110	-0.221	-0.076	-0.005	-0.197	-0.150	1	
(20) S&P Rating Dummy	-0.343	-0.326	-0.210	-0.157	-0.128	0.084	0.086	-0.073	-0.209	-0.143	0.045	0.659	-0.073	0.270	-0.023	0.126	-0.010	-0.266	-0.098	1

Table 4: Hedging Profits and Hedging Activities

The dependent variables include Reported Total Profit, Reported Realized Hedge Profit and Reported non-Hedge Profit. The key independent variable is Relative Delta Production. Oil Risk Premia and Gas Risk Premia are also included. Please see Appendix A for detailed definition of the variables. We control for year fixed effect in column 2, 5 and 8. We control for both year and firm fixed effect in column 3, 6 and 9. We report t-statistics in parentheses. ***, ** and * represents 1%, 5% and 10% significant levels.

Hedging Profits and Relative Delta Production

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Reported Total Profit	Reported Total Profit	Reported Total Profit	Reported Realized Hedge Profit	Reported Realized Hedge Profit	Reported Realized Hedge Profit	Reported non-Hedge Profit	Reported non-Hedge Profit	Reported non-Hedge Profit
Relative Delta Production	0.018***	0.016***	0.019***	0.006*	0.005	0.008	0.017***	0.015***	0.020***
	(5.55)	(5.00)	(3.09)	(1.71)	(1.41)	(1.63)	(5.45)	(5.19)	(3.38)
Oil Futures Risk Premia	0.002***	0.001***	0.001***	0.000	0.001***	0.001***	0.003***	0.001***	0.001**
	(2.60)	(4.33)	(3.67)	(0.21)	(6.41)	(7.88)	(3.24)	(2.74)	(2.34)
Gas Futures Risk Premia	-0.030***			0.009			-0.044***		
	(-2.70)			(0.81)			(-3.93)		
Observations	397	397	397	178	178	178	322	322	322
R-squared	0.089	0.143	0.412	0.328	0.346	0.793	0.189	0.267	0.527

Table 5: Hedging Profits, Hedging Activities and Market Timing Activities – Deviated from Industry Mean

The dependent variables include Reported Total Profit, Reported Realized Hedge Profit and Reported non-Hedge Profit. The independent variables are Industry Mean Delta and Delta Deviated from Industry Mean. Oil Risk Premia and Gas Risk Premia are also included. Please see Appendix A for detailed definition of the variables. We control for year fixed effect in column 2, 5 and 8. We control for both year and firm fixed effect in column 3, 6 and 9. We report t-statistics in parentheses. ***, ** and * represents 1%, 5% and 10% significant levels.

Hedging Profits and Market Timing Activities Based on Industry Mean Relative Delta Production

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Reported Total Profit	Reported Total Profit	Reported Total Profit	Reported Realized Hedge Profit	Reported Realized Hedge Profit	Reported Realized Hedge Profit	Reported non-Hedge Profit	Reported non-Hedge Profit	Reported non-Hedge Profit
Delta Deviated from Mean	0.013***	0.013***	0.019***	0.004	0.004	0.008	0.013***	0.013***	0.019***
	(4.70)	(4.72)	(3.36)	(1.31)	(1.31)	(1.62)	(4.78)	(4.83)	(3.57)
Industry Mean Delta	0.123***			0.048**			0.145***		
	(5.42)			(2.09)			(6.14)		
Oil Futures Risk Premia	0.002	0.001***	0.001***	-0.000	0.001***	0.001***	0.002**	0.001***	0.001***
	(1.60)	(4.94)	(4.45)	(-0.35)	(6.65)	(8.56)	(2.51)	(3.29)	(3.04)
Gas Futures Risk Premia	-0.020*			0.016			-0.036***		
	(-1.77)			(1.30)			(-3.33)		
Observations	397	397	397	178	178	178	322	322	322
R-squared	0.132	0.137	0.416	0.340	0.345	0.793	0.252	0.259	0.530

Table 6: Hedging Profits, Hedging Activities and Market Timing Activities – from Residual Perspective on Industry Mean

The dependent variables include Reported Total Profit, Reported Realized Hedge Profit and Reported non-Hedge Profit. The independent variables are regression Residuals representing market timing activities, and Predicted values representing hedging activities (we regress firm's Relative Delta Production on industry mean, firm characteristics, and risk premia to get the Residual and Predicted value). Please see Appendix A for detailed definition of the variables. We control for year fixed effect in column 2, 5 and 8. We control for both year and firm fixed effect in column 3, 6 and 9. We report t-statistics in parentheses. ***, ** and * represents 1%, 5% and 10% significant levels.

Hedging Profits and Market Timing Activities Based on Industry Mean Relative Delta Production

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Reported Total Profit	Reported Total Profit	Reported Total Profit	Reported Realized Hedge Profit	Reported Realized Hedge Profit	Reported Realized Hedge Profit	Reported non-Hedge Profit	Reported non-Hedge Profit	Reported non-Hedge Profit
Residual from Industry Mean Delta	0.024***	0.024***	0.028***	0.012**	0.012**	0.011*	0.021***	0.021***	0.025***
	(5.40)	(5.46)	(4.09)	(2.47)	(2.39)	(1.89)	(4.72)	(4.86)	(3.89)
Predicted from Industry Mean Delta	0.030***	0.022***	0.016	0.025***	0.022***	0.013	0.026***	0.017**	0.011
	(4.63)	(3.22)	(0.86)	(3.57)	(2.89)	(0.82)	(3.85)	(2.51)	(0.59)
Oil Futures Risk Premia	0.002**	0.001***	0.001**	0.000	0.001***	0.001***	0.003***	0.000*	0.001*
	(2.35)	(2.81)	(2.48)	(0.03)	(5.15)	(5.60)	(2.93)	(1.68)	(1.73)
Gas Futures Risk Premia	-0.029**			0.012			-0.043***		
	(-2.47)			(0.94)			(-3.59)		
Observations	350	350	350	151	151	151	279	279	279
R-squared	0.141	0.167	0.425	0.397	0.404	0.798	0.215	0.261	0.533

Table 7: Hedging Profits, Hedging Activities and Market Timing Activities – with Residual Fixed Effect

The dependent variables include Reported Total Profit, Reported Realized Hedge Profit and Reported non-Hedge Profit. The key independent variables are regression Residuals representing market timing activities, and Predicted values representing hedging activities (we regress firm's Relative Delta Production on industry average, risk premia, firm characteristics and firm fixed effect to get the Residual and Predicted value). Please see Appendix A for detailed definition of the variables. We control for year fixed effect in column 2, 5 and 8. We control for both year and firm fixed effect in column 3, 6 and 9. We report t-statistics in parentheses. ***, ** and * represents 1%, 5% and 10% significant levels.

Hedging Profits and Market Timing Activities Based on Relative Delta Production

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Reported Total Profit	Reported Total Profit	Reported Total Profit	Reported Realized Hedge Profit	Reported Realized Hedge Profit	Reported Realized Hedge Profit	Reported non-Hedge Profit	Reported non-Hedge Profit	Reported non-Hedge Profit
Residual Delta Fixed Effect	0.021***	0.021***	0.021***	0.010	0.011	0.011*	0.021***	0.019***	0.016***
	(2.70)	(2.70)	(3.09)	(1.03)	(1.15)	(1.81)	(2.84)	(2.64)	(2.61)
Predicted Delta Fixed Effect	0.026***	0.023***	-0.016	0.023***	0.021***	-0.024	0.015***	0.012***	-0.035*
	(5.40)	(4.68)	(-0.78)	(4.46)	(3.89)	(-1.47)	(3.24)	(2.67)	(-1.70)
Oil Futures Risk Premia	0.002	0.001***	0.001***	-0.000	0.001***	0.002***	0.002*	0.000	0.001***
	(1.54)	(2.60)	(3.91)	(-0.04)	(5.67)	(7.48)	(1.84)	(0.99)	(2.89)
Gas Futures Risk Premia	-0.019			0.014			-0.031**		
	(-1.58)			(1.08)			(-2.54)		
Log Asset	-0.000	-0.000	0.017	-0.002	-0.003	0.037***	0.001	0.001	0.002
	(-0.02)	(-0.17)	(1.62)	(-1.26)	(-1.37)	(3.44)	(0.67)	(0.47)	(0.16)
ROA	0.014	0.020	0.046***	0.019	0.021	0.015	-0.008	0.000	0.037*
	(0.93)	(1.26)	(2.75)	(1.31)	(1.39)	(1.34)	(-0.46)	(0.02)	(1.81)
leverage	0.038**	0.038***	0.047	0.007	0.007	0.003	0.058***	0.058***	0.062*
	(2.58)	(2.61)	(1.46)	(0.39)	(0.40)	(0.13)	(3.74)	(3.88)	(1.75)
Revenue	0.061***	0.055***	0.282***	0.064***	0.062***	0.255***	0.021	0.014	0.194***
	(3.76)	(3.41)	(6.91)	(3.79)	(3.64)	(5.61)	(1.39)	(0.90)	(4.86)
Observations	327	327	327	139	139	139	256	256	256
R-squared	0.200	0.221	0.569	0.509	0.515	0.869	0.295	0.338	0.651

Table 8: Estimated Profits, Hedging Activities and Market Timing Activities – from Residual Perspective on Industry Mean

The dependent variables include the differences between reported profits and estimated profits. The independent variables are regression Residuals representing market timing activities, and Predicted values representing hedging activities (we regress firm's Relative Delta Production on industry mean, firm characteristics, and risk premia to get the Residual and Predicted value). Please see Appendix A for detailed definition of the variables. We control for year fixed effect in column 2, 5 and 8. We control for both year and firm fixed effect in column 3, 6 and 9. We report t-statistics in parentheses. ***, ** and * represents 1%, 5% and 10% significant levels.

Market Timing Profits and Market Timing Activities Based on Industry Mean Relative Delta Production

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	(Reported - Estimated) Total Profit	(Reported - Estimated) Total Profit	(Reported - Estimated) Total Profit	(Reported - Estimated) Realized Hedge Profit	(Reported - Estimated) Realized Hedge Profit	(Reported - Estimated) Realized Hedge Profit	(Reported - Estimated) non-Hedge Profit	(Reported - Estimated) non-Hedge Profit	(Reported - Estimated) non-Hedge Profit
Residual from Industry Mean Delta	0.036***	0.036***	0.050***	0.028**	0.027**	0.041**	0.036***	0.036***	0.053***
	(3.77)	(3.81)	(3.15)	(2.52)	(2.49)	(2.03)	(3.44)	(3.49)	(3.05)
Predicted from Industry Mean Delta	0.019	0.006	-0.017	0.017	0.010	-0.008	0.013	-0.001	-0.017
	(1.38)	(0.43)	(-0.38)	(1.08)	(0.61)	(-0.16)	(0.84)	(-0.09)	(-0.33)
Oil Futures Risk Premia	0.008***	-0.000	0.000	0.003	0.001	0.001	0.010***	-0.000	0.000
	(3.68)	(-0.15)	(0.65)	(1.36)	(1.19)	(1.32)	(4.01)	(-0.18)	(0.27)
Gas Futures Risk Premia	-0.110***			-0.038			-0.140***		
	(-4.49)			(-1.39)			(-4.99)		
Observations	350	350	350	151	151	151	279	279	279
R-squared	0.185	0.204	0.326	0.056	0.066	0.261	0.272	0.301	0.429

Table 9: Estimated Profits, Hedging Activities and Market Timing Activities – with Residual Fixed Effect

The dependent variables include the differences between reported profits and estimated profits. The key independent variables are regression Residuals representing market timing activities, and Predicted values representing hedging activities (we regress firm's Relative Delta Production on industry average, risk premia, firm characteristics and firm fixed effect to get the Residual and Predicted value). Please see Appendix A for detailed definition of the variables. We control for year fixed effect in column 2, 5 and 8. We control for both year and firm fixed effect in column 3, 6 and 9. We report t-statistics in parentheses. ***, ** and * represents 1%, 5% and 10% significant levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	(Reported - Estimated) Total Profit	(Reported - Estimated) Total Profit	(Reported - Estimated) Total Profit	(Reported - Estimated) Realized Hedge Profit	(Reported - Estimated) Realized Hedge Profit	(Reported - Estimated) Realized Hedge Profit	(Reported - Estimated) non-Hedge Profit	(Reported - Estimated) non-Hedge Profit	(Reported - Estimated) non-Hedge Profit
Residual Delta Fixed Effect	0.053***	0.053***	0.052***	0.027	0.028	0.025	0.062***	0.060***	0.052***
	(3.18)	(3.18)	(3.10)	(1.27)	(1.28)	(1.43)	(3.41)	(3.29)	(2.89)
Predicted Delta Fixed Effect	0.026**	0.022**	-0.035	0.037***	0.035***	0.143***	0.017	0.013	-0.147**
	(2.57)	(2.12)	(-0.67)	(3.22)	(2.93)	(3.28)	(1.47)	(1.09)	(-2.51)
Oil Futures Risk Premia	0.006***	-0.000	0.001	0.003	0.000	-0.000	0.007***	-0.001	0.001
	(2.60)	(-0.66)	(1.08)	(1.10)	(0.85)	(-0.35)	(2.86)	(-0.94)	(1.48)
Gas Futures Risk Premia	-0.086***			-0.031			-0.114***		
	(-3.27)			(-1.08)			(-3.77)		
Log Asset	0.003	0.003	0.052*	0.001	0.001	0.081***	0.005	0.004	0.034
	(0.86)	(0.81)	(1.94)	(0.34)	(0.30)	(2.77)	(1.03)	(0.95)	(1.16)
ROA	-0.032	-0.020	0.012	-0.020	-0.017	-0.030	-0.073*	-0.053	-0.023
	(-0.96)	(-0.59)	(0.28)	(-0.59)	(-0.51)	(-0.98)	(-1.68)	(-1.22)	(-0.41)
leverage	0.054*	0.056*	0.085	0.055	0.054	-0.022	0.067*	0.070*	0.078
	(1.70)	(1.76)	(1.04)	(1.45)	(1.42)	(-0.30)	(1.73)	(1.83)	(0.77)
Revenue	0.070**	0.060*	0.419***	0.017	0.016	0.273**	0.030	0.016	0.370***
	(2.00)	(1.70)	(4.08)	(0.46)	(0.42)	(2.21)	(0.78)	(0.40)	(3.26)
Observations	327	327	327	139	139	139	256	256	256
R-squared	0.210	0.219	0.420	0.135	0.137	0.660	0.301	0.317	0.556

Table 10: Feedback Effect on Hedging Activities

The dependent variable is Relative Delta Production. The key independent variables are Lag Reported Total Profit, Lag Reported Realized Hedge Profit and Lag Reported non-Hedge Profit. Risk premia and firm characteristics are also included as control variables. We control for both of year and firm fixed effect in column 3, 5 and 7. Please see Appendix A for detailed definition of the variables. We report t-statistics in parentheses. ***, ** and * represents 1%, 5% and 10% significant levels.

Dependent Variable: Relative Delta Production

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lag Reported Total Profit		1.318*	0.488				
		(1.70)	(0.82)				
Lag Reported Realized Hedge Profit				2.124	1.218		
				(1.31)	(0.67)		
Lag Reported non-Hedge Profit						0.824	0.414
						(0.83)	(0.53)
Lag Oil Price Volatility	0.975***	0.638		0.137		0.804	
	(3.21)	(1.49)		(0.23)		(1.56)	
Oil Futures Risk Premia	0.012	-0.001	0.004**	-0.010	0.005*	0.002	0.004*
	(0.85)	(-0.04)	(2.17)	(-0.34)	(1.86)	(0.10)	(1.78)
Gas Futures Risk Premia	-0.138	-0.004		0.116		-0.026	
	(-0.83)	(-0.02)		(0.33)		(-0.10)	
Lifting Cost per Boe	0.002	0.002	-0.002	-0.013**	-0.005	-0.001	0.004
	(0.40)	(0.29)	(-0.35)	(-2.20)	(-0.49)	(-0.19)	(0.50)
Market to Book Ratio	-0.002	-0.004	-0.004	-0.110**	-0.026	-0.003	-0.004
	(-0.44)	(-0.75)	(-1.22)	(-2.60)	(-0.81)	(-0.47)	(-1.07)
Leverage Ratio	1.033***	0.908***	-0.457	0.198	-0.203	1.079***	-0.511
	(5.53)	(4.18)	(-1.28)	(0.63)	(-0.41)	(3.89)	(-1.01)
Log Asset	-0.017	-0.017	0.050	-0.043	-0.110	-0.031	0.014
	(-0.55)	(-0.44)	(0.32)	(-0.80)	(-0.37)	(-0.65)	(0.08)
Cash	-2.429***	-2.644***	-1.040	-3.930**	1.250	-2.386***	-1.416
	(-3.83)	(-3.59)	(-1.29)	(-2.61)	(0.70)	(-2.83)	(-1.50)
Inventory	-2.311	-0.958	3.773	0.822	5.075	-5.639	2.027
	(-0.61)	(-0.22)	(0.61)	(0.13)	(0.49)	(-1.07)	(0.26)
Cost of Goods Sold	-0.245	-0.066	-0.141	-0.920	0.004	-0.206	-0.242
	(-0.78)	(-0.19)	(-0.45)	(-1.50)	(0.01)	(-0.53)	(-0.68)
ROA	0.151	0.308	0.054	-0.800	0.018	0.293	0.039
	(0.44)	(0.80)	(0.16)	(-1.45)	(0.04)	(0.64)	(0.10)
Revenue	-0.377	-0.649*	0.562	0.004	0.822	-0.140	0.528
	(-1.16)	(-1.73)	(1.20)	(0.01)	(1.20)	(-0.32)	(0.95)
Dividend	5.448***	7.212***	-7.562*	7.941***	-4.725	7.157***	-7.421*
	(5.53)	(5.77)	(-1.88)	(4.32)	(-0.72)	(4.78)	(-1.72)
Capital Expenditure	-0.173	-0.004	0.600*	-0.349	0.753	-0.143	0.476
	(-0.66)	(-0.01)	(1.75)	(-0.55)	(1.16)	(-0.35)	(1.15)
S&P Rating	-0.084	-0.110	0.013	-0.144	-0.159	-0.069	0.222
	(-0.91)	(-0.95)	(0.09)	(-1.02)	(-0.89)	(-0.47)	(1.22)
Observations	327	260	260	110	110	203	203
R-squared	0.304	0.343	0.848	0.449	0.890	0.343	0.858

Table 11: Feedback Effect on Hedging Activities – Gain or Loss Status

The dependent variable is Relative Delta Production. The key independent variables are Lag Reported Total Profit, Lag Reported Realized Hedge Profit and Lag Reported non-Hedge Profit. Risk premia and firm characteristics are also included as control variables. Column 1 and 2 include firm-years with positive profits only. Column 3 and 4 include firm-years with negative profits only. We control for both of year and firm fixed effect in all regressions. Please see Appendix A for detailed definition of the variables. We report t-statistics in parentheses. ***, ** and * represents 1%, 5% and 10% significant levels.

Dependent Variable: Relative Delta Production

	(1)	(2)	(3)	(4)
Lag Reported Total Profit	0.693		-7.782**	
	(0.65)		(-2.50)	
Lag Reported non-Hedge Profit		0.420		-9.352***
		(0.22)		(-3.93)
Oil Futures Risk Premia	0.002	0.003	-0.006	-0.004
	(1.07)	(0.66)	(-1.06)	(-0.82)
Lifting Cost per Boe	0.011	0.017	-0.044	-0.006
	(0.88)	(1.09)	(-1.34)	(-0.16)
Market to Book Ratio	-0.002	-0.002	0.001	-0.002
	(-0.61)	(-0.38)	(0.04)	(-0.19)
Leverage Ratio	-0.151	0.149	-2.585	-1.497
	(-0.33)	(0.23)	(-1.63)	(-1.21)
Log Asset	0.012	-0.053	0.396	0.028
	(0.06)	(-0.21)	(0.89)	(0.08)
Cash	-2.588**	-3.574**	-0.441	-0.103
	(-2.04)	(-2.17)	(-0.34)	(-0.09)
Inventory	-4.649	-5.650	24.124	1.502
	(-0.57)	(-0.47)	(1.21)	(0.09)
Cost of Goods Sold	-0.417	-0.602	0.548	0.598
	(-1.33)	(-1.63)	(0.46)	(0.59)
ROA	-0.432	-0.592	0.953	0.966
	(-1.25)	(-1.27)	(0.81)	(0.95)
Revenue	-0.273	-1.082	-1.562	-0.934
	(-0.32)	(-0.84)	(-0.95)	(-0.73)
Dividend	-12.229**	-19.858	-1.213	0.814
	(-2.17)	(-1.27)	(-0.08)	(0.07)
Capital Expenditure	0.013	0.017	0.441	0.405
	(0.03)	(0.03)	(0.58)	(0.60)
S&P Rating	0.073	0.172	0.054	0.297
	(0.47)	(0.69)	(0.17)	(0.94)
Observations	150	107	110	96
R-squared	0.924	0.940	0.950	0.961

Table 12: Change of Hedging Profits and Change of Hedging Activities

The dependent variables include change of Reported Total Profit, change of Reported Realized Hedge Profit and change of Reported non-Hedge Profit. The key independent variable is change of Relative Delta Production. Oil Risk Premia and Gas Risk Premia are also included. Please see Appendix A for detailed definition of the variables. We control for year fixed effect in column 2, 5 and 8. We control for both year and firm fixed effect in column 3, 6 and 9. We report t-statistics in parentheses. ***, ** and * represents 1%, 5% and 10% significant levels.

Change of Hedging Profits and Change of Relative Delta Production

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Δ Reported Total Profit	Δ Reported Total Profit	Δ Reported Total Profit	Δ Reported Realized Hedge Profit	Δ Reported Realized Hedge Profit	Δ Reported Realized Hedge Profit	Δ Reported non-Hedge Profit	Δ Reported non-Hedge Profit	Δ Reported non-Hedge Profit
Δ Relative Delta Production	0.029***	0.026***	0.037***	0.008	0.008	0.017*	0.031***	0.026***	0.031***
	(3.92)	(3.44)	(3.21)	(1.32)	(1.40)	(1.87)	(4.12)	(3.42)	(2.78)
Oil Futures Risk Premia	0.002	-0.001***	-0.001***	0.008***	0.001***	0.001***	-0.000	-0.002***	-0.002***
	(1.01)	(-3.56)	(-2.87)	(6.00)	(10.35)	(9.06)	(-0.14)	(-8.92)	(-7.16)
Gas Futures Risk Premia	-0.028			-0.071***			-0.017		
	(-1.32)			(-4.77)			(-0.77)		
Observations	267	267	267	118	118	118	210	210	210
R-squared	0.101	0.115	0.203	0.600	0.602	0.680	0.305	0.343	0.420

Table 13: Regression on Reported Total Profit – Contracts for Next Year Only

For all models, the dependent variable is Reported Total Profit, and both year fixed effect and firm fixed effect are included. The independent variables in column 1, 2, 3 and 4 are delta related variables and replicate the key regressions to predict profits in Section 3. The independent variables in column 5, 6, 7 and 8 are notional amount related variables and replicate the key regressions to predict profits in Section 3. Please see Appendix A for detailed definition of variables. We report t-statistics in parentheses. ***, ** and * represents 1%, 5% and 10% significant levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Reported Total Profit	Reported Total Profit	Reported Total Profit	Reported Total Profit	Reported Total Profit	Reported Total Profit	Reported Total Profit	Reported Total Profit
Relative Delta Production	0.029***							
	(3.81)							
Delta Deviated from Mean		0.026***						
		(3.67)						
Residual from Industry Mean Delta			0.033***					
			(3.89)					
Predicted from Industry Mean Delta			0.017					
			(0.59)					
Residual Delta Fixed Effect				0.029***				
				(3.14)				
Predicted Delta Fixed Effect				0.058***				
				(2.62)				
Relative Notional Production					0.027***			
					(4.47)			
Notional Deviated from Mean						0.028***		
						(4.77)		
Residual from Industry Mean Notional							0.031***	
							(4.85)	
Predicted from Industry Mean Notional							0.008	
							(0.40)	
Residual Notional Fixed Effect								0.025***
								(3.54)
Predicted Notional Fixed Effect								0.053***
								(2.96)
Oil Futures Risk Premia	0.001***	0.001***	0.001***	0.000	0.001***	0.001***	0.001***	0.000
	(3.87)	(4.70)	(2.63)	(1.64)	(3.92)	(4.18)	(3.03)	(1.60)
Observations	353	353	317	295	353	353	317	295
R-squared	0.438	0.436	0.431	0.466	0.449	0.455	0.454	0.476

Table 14: Regression on Feedback Effect – Contracts for Next Year Only

The dependent variable is Relative Delta Production in column 1, 2, and 3, and Relative Notional Production in column 4, 5 and 6. For all models, both year fixed effect and firm fixed effect are included. The independent variables are Lag Reported Total Profit and firm characteristics. These regressions replicate the key feedback effect regressions in Section 3. Column 1 and 4 examine the feedback effect on hedging activities without dividing the samples into sub-groups. Column 2 and 5 include firms with positive profit in previous year. Column 3 and 6 include firms with negative profit in previous year. Please see Appendix A for detailed definition of variables. We report t-statistics in parentheses. ***, ** and * represents 1%, 5% and 10% significant levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	Relative Delta Production	Relative Delta Production	Relative Delta Production	Relative Notional Production	Relative Notional Production	Relative Notional Production
Lag Reported Total Profit	0.352	0.683	-6.421***	1.191*	0.562	-5.721***
	(0.43)	(0.06)	(-3.55)	(1.69)	(0.02)	(-3.10)
Oil Futures Risk Premia	0.003*	0.003	-0.003	0.003	0.002	-0.005
	(1.73)	(1.14)	(-0.54)	(1.50)	(0.72)	(-0.51)
Lifting Cost per Boe	-0.007	-0.006	-0.015	-0.008	0.014	-0.039
	(-1.03)	(-0.45)	(-0.43)	(-0.96)	(0.93)	(-0.69)
Market to Book Ratio	-0.002	0.001	-0.006	-0.005	-0.003	-0.006
	(-0.74)	(0.20)	(-0.54)	(-1.31)	(-0.63)	(-0.33)
Leverage Ratio	-0.430	-0.412	-0.470	-0.333	-0.138	-3.686
	(-1.33)	(-0.90)	(-0.33)	(-0.80)	(-0.27)	(-1.63)
Log Asset	0.061	0.144	0.079	0.173	0.152	0.360
	(0.41)	(0.71)	(0.20)	(0.90)	(0.66)	(0.56)
Cash	-0.794	-1.493	-0.398	-0.997	-2.519	-1.353
	(-1.07)	(-1.11)	(-0.30)	(-1.05)	(-1.64)	(-0.64)
Inventory	1.844	-5.688	22.719	11.365	-4.336	30.726
	(0.30)	(-0.65)	(1.32)	(1.46)	(-0.44)	(1.13)
Cost of Goods Sold	-0.232	-0.367	1.836	-0.047	-0.279	1.905
	(-0.81)	(-1.19)	(1.27)	(-0.13)	(-0.79)	(0.83)
ROA	-0.023	-0.420	2.639	0.182	-0.313	2.546
	(-0.08)	(-1.22)	(1.72)	(0.47)	(-0.80)	(1.05)
Revenue	0.783*	0.529	-1.605	0.857	0.643	-2.417
	(1.71)	(0.62)	(-0.96)	(1.45)	(0.66)	(-0.91)
Dividend	-8.043**	-12.419**	6.251	-8.788*	-14.884**	-4.849
	(-2.22)	(-2.22)	(0.49)	(-1.88)	(-2.33)	(-0.24)
Capital Expenditure	0.423	-0.057	0.585	0.479	-0.527	1.087
	(1.35)	(-0.12)	(0.87)	(1.19)	(-1.00)	(1.02)
S&P Rating	-0.067	0.044	0.136	-0.038	0.109	-0.025
	(-0.52)	(0.29)	(0.52)	(-0.23)	(0.62)	(-0.06)
Observations	242	139	103	242	139	103
R-squared	0.869	0.922	0.967	0.842	0.925	0.940

Table 15: Feedback Effect on Hedging Activities – Sub-period 2008-2011

The models include data samples from 2008 to 2011 (data samples in year 2007 are not included). The dependent variable is Relative Delta Production. The key independent variables are Lag Reported Total Profit, Lag Reported Realized Hedge Profit and Lag Reported non-Hedge Profit. Risk premia and firm characteristics are also included as control variables. We control for both of year and firm fixed effect in column 3, 5 and 7. Please see Appendix A for detailed definition of the variables. We report t-statistics in parentheses. ***, ** and * represents 1%, 5% and 10% significant levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lag Reported Total Profit		1.462*	0.475				
		(1.79)	(0.73)				
Lag Reported Realized Hedge Profit				2.222	0.996		
				(1.38)	(0.52)		
Lag Reported non-Hedge Profit						1.433	0.518
						(1.28)	(0.58)
Lag Oil Price Volatility	0.443	0.799*		0.276		0.975*	
	(1.09)	(1.88)		(0.49)		(1.90)	
Oil Futures Risk Premia	-0.007	0.011	0.004**	0.011	0.004	0.008	0.005**
	(-0.41)	(0.56)	(2.06)	(0.40)	(1.39)	(0.33)	(2.33)
Gas Futures Risk Premia	0.093	-0.135		-0.106		-0.097	
	(0.46)	(-0.60)		(-0.33)		(-0.35)	
Lifting Cost per Boe	0.001	-0.001	-0.003	-0.009*	-0.006	-0.003	0.003
	(0.22)	(-0.18)	(-0.46)	(-1.76)	(-0.59)	(-0.63)	(0.33)
Market to Book Ratio	-0.002	-0.003	-0.004	-0.095**	-0.025	-0.002	-0.003
	(-0.37)	(-0.54)	(-1.10)	(-2.43)	(-0.77)	(-0.30)	(-0.95)
Leverage Ratio	0.969***	0.640***	-0.433	0.075	-0.366	0.714**	-0.685
	(4.71)	(2.79)	(-1.10)	(0.25)	(-0.70)	(2.35)	(-1.22)
Log Asset	-0.017	-0.049	-0.016	-0.047	-0.393	-0.066	0.031
	(-0.45)	(-1.23)	(-0.09)	(-0.91)	(-1.25)	(-1.35)	(0.16)
Cash	-2.656***	-3.032***	-1.075	-3.840***	0.383	-2.825***	-1.624
	(-3.70)	(-3.87)	(-1.26)	(-2.69)	(0.22)	(-3.11)	(-1.64)
Inventory	-1.877	-3.304	-1.043	-0.119	4.445	-7.578	-4.838
	(-0.44)	(-0.72)	(-0.15)	(-0.02)	(0.40)	(-1.34)	(-0.54)
Cost of Goods Sold	-0.189	-0.293	-0.354	-1.597**	-0.227	-0.416	-0.311
	(-0.56)	(-0.77)	(-1.06)	(-2.59)	(-0.45)	(-0.98)	(-0.86)
ROA	0.116	0.017	-0.322	-1.340**	-0.251	-0.090	-0.286
	(0.31)	(0.04)	(-0.89)	(-2.43)	(-0.55)	(-0.18)	(-0.65)
Revenue	-0.410	-0.491	0.864	0.183	1.122	0.085	0.891
	(-1.14)	(-1.16)	(1.51)	(0.29)	(1.22)	(0.17)	(1.33)
Dividend	5.799***	7.900***	-5.127	9.598***	0.746	7.061***	-5.118
	(5.19)	(5.92)	(-1.32)	(4.70)	(0.11)	(4.73)	(-1.26)
Capital Expenditure	0.003	-0.206	0.162	-0.041	0.452	-0.342	0.088
	(0.01)	(-0.57)	(0.45)	(-0.07)	(0.67)	(-0.78)	(0.20)
S&P Rating	-0.115	-0.034	-0.018	-0.146	-0.164	0.022	0.182
	(-1.03)	(-0.29)	(-0.12)	(-1.10)	(-0.82)	(0.14)	(0.95)
Observations	272	238	238	102	102	185	185
R-squared	0.298	0.346	0.851	0.470	0.883	0.341	0.864

Table 16: Feedback Effect on Hedging Activities – Gain or Loss Status, Sub-period 2008-2011

The models include data samples from 2008 to 2011 (data samples in year 2007 are not included). The dependent variable is Relative Delta Production. The key independent variables are Lag Reported Total Profit, Lag Reported Realized Hedge Profit and Lag Reported non-Hedge Profit. Risk premia and firm characteristics are also included as control variables. Column 1 and 2 include firm-years with positive profits only. Column 3 and 4 include firm-years with negative profits only. We control for both of year and firm fixed effect in all regressions. Please see Appendix A for detailed definition of the variables. We report t-statistics in parentheses. ***, ** and * represents 1%, 5% and 10% significant levels.

Dependent Variable: Relative Delta Production

	(1)	(2)	(3)	(4)
Lag Reported Total Profit	0.404		-6.726**	
	(0.34)		(-2.72)	
Lag Reported non-Hedge Profit		0.335		-5.099***
		(0.16)		(-3.62)
Oil Futures Risk Premia	0.003	0.005	-0.018	-0.001
	(1.40)	(1.24)	(-1.51)	(-0.20)
Lifting Cost per Boe	0.010	0.013	-0.096	0.022
	(0.77)	(0.84)	(-0.92)	(0.47)
Market to Book Ratio	-0.002	-0.001	0.022	0.010
	(-0.55)	(-0.35)	(1.30)	(0.66)
Leverage Ratio	-0.064	0.014	-4.159*	-2.511
	(-0.12)	(0.02)	(-2.04)	(-1.72)
Log Asset	0.060	0.026	-0.298	-0.155
	(0.29)	(0.10)	(-0.51)	(-0.37)
Cash	-2.289	-2.928	-1.953	0.056
	(-1.58)	(-1.47)	(-1.06)	(0.04)
Inventory	-5.237	-5.862	9.458	2.253
	(-0.60)	(-0.43)	(0.41)	(0.12)
Cost of Goods Sold	-0.505	-0.626	2.488	2.120
	(-1.52)	(-1.61)	(1.69)	(1.67)
ROA	-0.505	-0.587	2.107	2.575*
	(-1.38)	(-1.20)	(1.23)	(1.92)
Revenue	-0.007	-0.651	-6.166*	-1.795
	(-0.01)	(-0.46)	(-2.06)	(-0.85)
Dividend	-10.552*	-22.042	-15.805	4.008
	(-1.81)	(-1.36)	(-0.74)	(0.31)
Capital Expenditure	-0.038	0.171	-0.851	-0.244
	(-0.08)	(0.26)	(-0.73)	(-0.24)
S&P Rating	0.049	0.154	-0.643	0.092
	(0.31)	(0.60)	(-1.43)	(0.23)
Observations	142	99	94	81
R-squared	0.928	0.944	0.962	0.973

Appendix A: Glossary of Variables

Reported Total Profit

It is the sum of realized gain/loss of commodity cash flow hedge, realized and unrealized gain/loss of non-hedge designated commodity derivatives and realized and unrealized gain/loss of ineffective portion of commodity cash flow hedge.

Reported Realized Hedge Profit

It is the realized gain/loss of commodity cash flow hedge.

Reported non-Hedge Profit

It is the sum of realized and unrealized gain/loss of non-hedge designated commodity derivatives.

Reported Realized non-Hedge Profit

It is the realized gain/loss of non-hedge designated commodity derivatives.

Reported Ineffective Hedge Profit

Effectiveness is defined as the part of the gain (or loss) on the hedging instrument that offsets a loss (or gain) on the hedged item. For cash flow hedges, changes in the fair market value of a derivative are separated into an effective portion and an ineffective portion. The net gain or loss on the effective portion of the hedging instrument should be reported in OCI. The gain or loss on the ineffective portion is reported in current earnings (Baker & Lembke, Advanced Financial Accounting).

Relative Delta Production

It is the total delta of derivatives scaled by annual production.

Relative Notional Production

It is the total notional amount of derivatives scaled by annual production.

Industry Mean Delta

It is the average value of all sample firms' relative delta production in a year.

Industry Median Delta

It is the median value of all sample firms' relative delta production in a year.

Industry Mean Notional

It is the average value of all sample firms' relative notional production in a year.

Industry Median Notional

It is the median value of all sample firms' relative delta production in a year.

Delta Deviated from Mean

It is the difference between a firm's relative delta production and the average value of all sample firms' relative delta production in a year.

Delta Deviated from Median

It is the difference between a firm's relative delta production and the median value of all sample firms' relative delta production in a year.

Notional Deviated from Mean

It is the difference between a firm's relative notional production and the average value of all sample firms' relative notional production in a year.

Notional Deviated from Median

It is the difference between a firm's relative notional production and the median value of all sample firms' relative notional production in a year.

Residual from Industry Mean Delta

It is the regression residual value calculated by regressing a firm's relative delta production on the average value of all sample firms' relative delta production.

Residual from Industry Median Delta

It is the regression residual value calculated by regressing a firm's relative delta production on the median value of all sample firms' relative delta production.

Residual from Industry Mean Notional

It is the regression residual value calculated by regressing a firm's relative notional production on the average value of all sample firms' relative notional production.

Residual from Industry Median Notional

It is the regression residual value calculated by regressing a firm's relative notional production on the median value of all sample firms' relative notional production.

Predicted from Industry Mean Delta

It is the regression predicted value calculated by regressing a firm's relative delta production on the average value of industry relative delta production.

Predicted from Industry Median Delta

It is the regression predicted value calculated by regressing a firm's relative delta production on the median value of all sample firms' relative delta production.

Predicted from Industry Mean Notional

It is the regression predicted value calculated by regressing a firm's relative notional production on the average value of all sample firms' relative notional production.

Predicted from Industry Median Notional

It is the regression predicted value calculated by regressing a firm's relative notional production on the median value of all sample firms' relative notional production.

Residual Delta Fixed Effect

It is the regression residual value calculated by regressing a firm's relative delta production on firm fixed effects and other key control variables.

Predicted Delta Fixed Effect

It is the regression predicted value calculated by regressing a firm's relative delta production on firm fixed effects and other key control variables.

Residual Notional Fixed Effect

It is the regression residual value calculated by regressing a firm's relative notional production on firm fixed effects and other key control variables.

Predicted Notional Fixed Effect

It is the regression predicted value calculated by regressing a firm's relative notional production on firm fixed effects and other key control variables.

Oil Futures Risk Premia

It is the spread between the 1-year contracted oil futures price at year t-1, denoted by F(t-1), and the realized spot price at year t, denoted by S(t). We calculate the oil futures risk premia for every business during the year t and then use the mean of each year in the regression.

Gas Futures Risk Premia

It is the spread between the 1-year contracted gas futures price at year t-1, denoted by F(t-1), and the realized spot price at year t, denoted by S(t). We calculate the oil futures risk premia for every business during the year t and then use the mean of each year in the regression.

Lag Oil Price Volatility

It is the average of annualized volatility of past year's oil futures prices.

Lag Gas Price Volatility

It is the average of annualized volatility of past year's gas futures prices.

Lifting Cost per Boe

It is the average cost to produce one barrel of oil equivalent (BOE). It is calculated as production costs divided by oil and gas production for the year.

Market to Book Ratio

It is a firm's total market value (product of shares outstanding and fiscal year closing price) scaled by total common equity.

Leverage Ratio

It is a firm's total debt (sum of total debt in current liabilities and total long-term debt) scaled by total assets.

Log Asset

It is the log value of a firm's total assets.

Cash

It is a firm's cash and cash equivalents.

Inventory

It is the merchandise bought for resale and materials and supplies purchased for use in production of revenue.

Cost of Goods Sold

All costs directly allocated by the company to production, such as material, labor and overhead.

ROA

Return on assets. It is a firm’s net income scaled by total assets.

Revenue

It is the gross income received from all divisions of the company.

Dividend

It is the total amount of dividends (other than stock dividends) declared on the common/ordinary capital of the company, based on the current year's net income.

Capital Expenditure

The funds used for additions to property, plant, and equipment, excluding amounts arising from acquisitions.

S&P Rating Dummy

It is a dummy variable indicating whether a firm has a debt rating from Standard & Poor’s.

Appendix B: Delta Calculation

We find that U.S. oil and gas firms, on average, use a significant amount of derivatives. Our average hedge ratio is greater than that in prior research. To verify our calculation of delta, we use Jin and Jorion (2006)'s computation of delta as benchmark and examine the accuracy of our delta.

The Appendix B of Jin and Jorion (2006) demonstrates the computation of delta for Devon, an oil producing firm. According to Devon's 2001 annual report, the firm uses swaps, collars and fixed-price contracts. The annual report also discloses the volume, exercise price and maturity of each contract. As of December 2001, the firm has an outstanding swap contract of 22,000 Bbls/day, a swap contract of 4,350 Bbls/day, a collar contract of 20,000 Bbls/day and a fixed-price contract of 10,032 Bbls/day.

The swaps and fixed-price contracts exhibit linear payoff so the delta per unit of volume is -1. We focus on the computation of delta of collar. Utilizing Black and Scholes option pricing model, we plug in the contract specific variables, the interest rate and the historical volatility to solve for the delta of put and call component of the collar. We then aggregate the two delta components to get the total delta of the collar contract.

Our computation of delta for the collar contract is -0.81, which is almost the same as Jin and Jorion (2006)'s delta, -0.80. The small difference could be due to slight differences in interest rate and volatility used in delta calculation. In addition, Jin and Jorion (2006) use 61 million barrels as the production over the period of 2002 in the calculation of relative delta production. We obtain the production data from Bloomberg and also find a quite similar number of 61.466 million barrels.

Overall, compared to the computation in Jin and Jorion (2006), our model generates almost the same delta and relative delta production. The results verify the accuracy and quality of our calculation of Relative Delta Production variable.

Appendix C: Summary Statistics of Key Variables, Including Firms with No Use of Derivatives

As a robustness check, we include firms with no use of derivatives and re-calculate the summary statistics for key variables. The sample mean and median of Relative Delta Production are 57.56% and 38.93% respectively.

	N	Mean	SD	P25	Median	P75
Relative Delta Production	510	0.5756	0.6387	0.0001	0.3893	0.9092
Relative Notional Production	510	0.7046	0.7320	0.0005	0.5082	1.1300
Reported Total Profit	510	0.0134	0.0401	-0.0011	0.0000	0.0227
Reported Realized Hedge Profit	303	0.0089	0.0312	0.0000	0.0000	0.0057
Reported non-Hedge Profit	441	0.0093	0.0378	-0.0014	0.0000	0.0139
Reported Ineffective Hedge Profit	207	0.0000	0.0014	0.0000	0.0000	0.0000

V. Conclusion

In the first essay, I use ETF returns as proxies for tradable risk factors in hedge fund performance evaluation and identify contemporaneously relevant risk factors from the entire universe of ETFs. The model provides more informative estimates of alpha and beta coefficients for predicting hedge fund out-of-sample performance compared with other widely used hedge fund factor models. Portfolios of top alpha hedge funds selected by the model generate statistically significant out-of-sample performance that is substantially higher compared with portfolios selected by other models. In addition, the beta-weighted clone portfolios exhibit substantially higher out-of-sample correlations with underlying hedge funds than clone portfolios formed using alternative models.

The second essay shows that only hedge funds whose returns are driven by beta management of exposures to latent risk factors could be successfully replicated. I develop a methodology for creating a portfolio of ETFs that replicates risk factor exposures taken by successful beta active cloneable hedge funds. The methodology allows any investor to access active factor strategies employed by hedge funds. It could be interpreted as cloning beta exposures of the best beta active hedge funds, delivering outstanding long-term risk-adjusted performance. The active factor ETF portfolio only requires annual rebalancing, and is constructed with a transparent algorithmic approach, which conforms to a definition of a smart beta strategy.

The third essay investigates the use of derivatives among firms. A careful study of hedging motives and hedging effectiveness is critical to understanding the financial impact of derivative use by firms. I examine the use of commodity derivatives by oil and gas producers and show that, on average, these firms report gains from their derivative positions. The profits from derivatives, particularly non-hedge profits, are positively associated with the extent of hedging that is classified as market timing activities.