Excessive Arbitrage Trading by Overconfidence[#]

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Keywords: Overconfidence, Ambiguity aversion, Excessive arbitrage trading, Market efficiency
JEL codes: G02, G12

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We investigate the effects of arbitrageurs' overconfidence on the performance of equity market neutral hedge portfolios. Our empirical results show that the profits of these trading strategies are positively affected by overconfidence, the effects of which are not subsequently reversed. Further we discover that signals inconsistent with arbitrageurs' confidence are treated as of low quality and thus ambiguous. When these hedge portfolios are sorted according to arbitrageurs' overconfidence levels, the anomalous return difference between high and low overconfidence-sorted hedge portfolios (i.e., hedge portfolio of hedge portfolios) is on average 9.6% a year in the 2000s, and has increased over the past four decades. Arbitrage trading in the 2000s is excessive in the sense that it has not eroded away the profit opportunities of the hedge portfolios, but instead, create economically and statically significant anomalous temporal profits.

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1. Introduction

A number of studies show that experts (e.g., institutional investors) are more likely to be subject to behavioral biases such as overconfidence, compared to inexperienced investors: for example, see De Long et al. (1991), Griffin and Tversky (1992) and Odean (1998). The effects of their behavioral biases on financial markets are likely to increase even more during the last decade as trading initiated by institutional investors have increased dramatically (Chan, Getmansky, Haas, and Lo, 2007; Lo, 2008; Hendershott, Jones, and Menkveld, 2011; Dichev, Huang, and Zhou, 2011). However, empirical studies in the effects of behavioral biases on financial markets are scarce due to the lack of well-defined implications or difficulties in finding the right variables that represent behavioral biases.

In this study we investigate the effects of hedge fund managers' overconfidence on the performance of equity market neutral trading strategies. If experts' judgment and decision making is affected by their overconfidence, then the trading where these arbitrageurs predominate is also affected by their overconfidence. Arbitrageurs' overconfidence would instigate more serious problems in the 2000s when their trading was active with fewer restrictions, e.g., lower transaction costs and more stocks available for short-sales, in comparison to the less arbitrage trading period of the 1970s and 1980s.[1] The effects of overconfidence, boosted by the active trading in the 2000s, may cause excessive arbitrage trading: overconfident hedge fund managers without the knowledge of how much of arbitrage opportunities can be exploitable may take too much positions in these hedge portfolios. Arbitrage trading expected to improve market efficiency could create another anomaly due to arbitrageurs' own overconfidence. This is what we investigate in this study.

For our analysis based on the Bayesian framework as in DHS (1998), the two key variables, i.e., signals and overconfidence, are defined for each of the equity market neutral strategies as follows. First, signals that arbitrageurs receive consist of fundamental payoffs and noise as in the DHS (1998, 2001), Gervais and Odean (2001), and Epstein and Schneider (2008). The unobserved fundamental payoffs for arbitrageurs (DHS, 1998, 2001) or what arbitrageurs want to know (Epstein and Schneider, 2008) is

[1] Some of the strategies might have been known before the 1990s. However, the total size of hedge funds is relatively small before 1990: for example, the estimated hedge fund industry size is only $38 billion in 1990, whereas the US equity market was $3.1 trillion in the same year.

represented by alphas (from CAPM) of their trading strategies. On the other hand, idiosyncratic errors of the strategies serve as noise.[2] The sum of alpha (payoff) and idiosyncratic error (temporal profit) is equivalent to realized profit for arbitrageurs; alpha alone is an unbiased estimate of the realized profit if the temporal profit is not affected by behavioral biases. The decomposition of the two components also makes it possible to investigate other behavioral biases such as ambiguity aversion (Epstein and Schneider, 2008).

Second, arbitrageurs' overconfidence is about their own expertise on each of their trading strategies. We construct two such measures of overconfidence from the theories proposed in the literature: the probability of successful predictability in the past (Odean, 1998; Gervais and Odean, 2001), and the change in the past payoffs (Kyle and Wang, 1997; Gervais and Odean, 2001; Statman, Thorley, and Vorkink, 2006; Chuang and Lee, 2006). Other popular measures such as trading volume or volatility do not necessarily represent arbitrageurs' overconfidence although they have been used to estimate overall levels of overconfidence in the literature (DHS, 1998, 2001; Chuang and Lee, 2006; Barone-Adesi, Mancini, Shefrin, 2013).

Fifteen popular equity market neutral hedge portfolios are formed with the equities that hedge fund managers are likely to include in their universe. Our empirical results with the signal and overconfidence of each of these fifteen portfolios can be summarized as follows. First, we find clear evidence of overconfidence in the equity market neutral trading strategies in the 2000s when arbitrage trading is active. The positive effects of overconfidence on the temporal profits of equity market neutral portfolios are far stronger in the 2000s than in the 1970s and 1980s. When arbitrageurs become overconfident of the profitability of hedge portfolios, they attempt to exploit the opportunities too much by increasing their positions, which in turn positively affects the temporal profits. However, contrary to the previous studies in the literature (Odean, 1998; DHS, 1998, 2001; Gervais and Odean, 2001; Chuang and Lee, 2006), we do not find evidence that arbitrageurs' overconfidence affects trading volume or volatility of

[2] In most previous empirical studies, trading volume has been used as proxy for private information because it should increase on private information, not on public information (Kyle, 1985; Campbell, Grossman, and Wang, 1993; Chuang and Lee, 2006). However, trading volume may also increase on public information when investors interpret public information heterogeneously (Kandel and Pearson, 1995). The obscurity of trading volume as private information can be avoided by identifying the fundamental payoffs and noise.

the equity market neutral hedge portfolios. The results can be explained by the different roles of arbitrageurs in financial markets: we focus on how the zero investment hedge portfolios are affected by arbitrageurs' overconfidence whereas other studies investigate how asset prices are initially distorted by traders' overconfidence (DHS, 1998, 2001; Gervais and Odean, 2001; Chuang and Lee, 2006).

Second, contrary to the expectation in the theoretical models, e.g., DHS (1998) and Odean (1998), the effects of overconfidence on equity market neutral portfolios are not subsequently reversed. The main reason for this unexpected result is periodic rebalances of these portfolios together with changes in the universe. When the universe is updated annually as in this study for new or delisted equities or when the top and bottom portfolios are rebalanced on a monthly or annual basis, the hedge portfolios do not necessarily include the same individual equities over time. Therefore, although the effects of overconfidence on individual equities are subsequently reversed (e.g., De Bondt and Thaler, 1985, 1987; DHS, 1998; Chuang and Lee, 2006), the effects of overconfidence on the performance of hedge portfolios appear to be permanent rather than temporal to arbitrageurs.

Third, strong evidence of overconfidence does not suggest that arbitrageurs are not ambiguity averse. Contrary to the experimental results of Brenner, Izhakian, and Sade (2011), we find evidence of ambiguity aversion in these experts: positive (negative) signals are more weighted when confidence is low (high) than when confidence is high (low). When the signs of signals are not consistent with their confidence levels, arbitrageurs perceive these signals imprecise and thus respond more to these signals. As argued by Epstein and Schneider (2008), overconfidence and ambiguity aversion are not mutually exclusive.

Finally and more importantly, arbitrage trading was pervasive in the 2000s but it has not eroded away the profit opportunities of the hedge portfolios. Our out-of-sample forecasting tests indicate that alphas of the equity market neutral hedge portfolios decreased in the 2000s as reported by Chan, Getmansky, Haas, and Lo (2007) and Lo (2008), but the average alphas were still greater than 0.5% per month, regardless of forecasting methods. On the other hand, when the equity market neutral hedge portfolios are sorted according to arbitrageurs' overconfidence levels on these hedge portfolios, the difference in temporal profits between high and low overconfidence-sorted hedge portfolios was on average 9.6% per year in the 2000s, which is statistically and economically significant. Moreover, these anomalous profits increased from 4.5% per year in the 1970s and 1980s. These results suggest that arbitrage opportunities are excessively exploited by overconfident investors despite the cost or risk of arbitrage trading (Barberis and Thaler, 2005; Shleifer and Vishny, 1997).

The effects of overconfidence on trading profits are predicted differently in the literature: the models of DHS (1998, 2001) and Gervais and Odean (2001) suggest that overconfident traders have lower gains on average, whereas Kyle and Wang (1997) argue that a higher profit is possible. Our results are consistent with Kyle and Wang (1997) in the sense that overconfident arbitrageurs can make higher profits, but with a different reason: overconfidence creates anomalous profit opportunities that are not reversed subsequently. Arbitrage trading expected to exploit mispricing and thus improve market efficiency creates another anomaly due to arbitrageurs' own overconfidence.

Our study differs from previous studies in several ways. We investigate if the performance of equity market neutral trading strategies is affected by arbitrageurs' behavioral biases, given that these anomalies exist and are exploited by profit seeking arbitrageurs. We do not intend to explain the anomalies of various equity market neutral trading strategies using investors' behavioral biases as many previous studies do.

We investigate multiple equity market neutral trading strategies to investigate the effects of the behavioral biases of arbitrageurs on cross-sectional asset prices. Other empirical studies investigate the effects of overconfidence on trading volume and volatility (Statman, Thorley, and Vorkink, 2006; Darrat, Zhong, and Cheng, 2007; Chuang and Lee, 2006) as well as diversification (Goetzmann and Kumar, 2008; Merkle, 2013), or try to explain the premia of various hedge portfolios using behavioral biases (Lakonishok, Shleifer, and Vishny, 1994; DHS, 1998, 2001). Our study differs from those of fund flows by performance-sensitive investors (Shleifer and Vishny, 1997; Frazzini and Lamont, 2008) because we focus on the behavioral biases of market experts.

Although this paper is closely related with studies in the effects of sentiment on asset prices (Baker and Wurgler, 2006), we focus on overconfidence of market experts rather than market-wide sentiment. In order to do so, we form hedge portfolios using liquid and shortable equities that could be included in the universe of hedge fund managers, and thus our results are not directly comparable with those of Stambaugh, Yu, and Yuan (2011). Moreover, both sentiment and overconfidence are context specific: overconfidence in this study is defined with respect to experts' expertise (Griffin and Tversky, 1992) whereas sentiment represents market participants' expectations relative to fundamentals. With this definition we show that expert's overconfidence matters in the equity market neutral trading strategies but sentiment does not.

This paper is organized as follows. In the following section, we describe the basic setting used in this study, and then propose the hypotheses for overconfidence, ambiguity and biased self-attribution. In section 3, we explain how we decompose hedge portfolio returns into alpha, beta and idiosyncratic error in the conditional CAPM. In the empirical tests, from sections 4 and 5, we first explain how hedge portfolios are constructed and then report the empirical results for overconfidence, ambiguity and biased self-attribution. We then show in section 6 the performance of the hedge portfolios in out-of-sample forecasting and suggest consequences of excessive arbitrage trading. Section 7 offers the conclusions.

2. Implication of Overconfidence and Ambiguity Bias on Arbitrage Trading

Arbitrageurs' behavioral biases need to be investigated with care because signals of arbitrage trading are not necessarily the same as those of individual assets. The signals that arbitrageurs receive for their arbitrage trading strategies are rather restricted due to the confidentiality of the hedge fund industry. Moreover, arbitrageurs' overconfidence is not likely to be measured in the same way as that of the other traders in the market, because arbitrageurs trade against price distortion created by other traders' anomalous trading.

We first explain the return process for hedge portfolios, and then describe signals that arbitrageurs receive and two measures of overconfidence. A series of hypotheses for the effects of behavioral biases on the performance of equity market neutral trading strategies follow.

2.1 Return process of hedge portfolios

Assume that a hedge portfolio p is neutral to the market by hedging out the systematic risk.[3] Its return at time t can be presented as

$$r_{pt}=\alpha_{pt}+\eta_{pt}, \tag{1}$$

where α_{pt} is the payoff that arbitrageurs try to optimize by constructing the hedge portfolio, and $\eta_{pt}=\sigma_{pt}\varepsilon_{pt}$ represents an idiosyncratic shock and $\varepsilon_{pt}\sim N(0{,}1)$. Alpha follows a stochastic process as in Epstein and Schneider (2008): [4]

$$\alpha_{pt}=\mu_p+\phi_p\left(\alpha_{pt-1}-\mu_p\right)+\epsilon_{pt}, \tag{2}$$

where $\mu_p=E(\alpha_{pt})$ is the unconditional (long-run) expected return of the hedge portfolio, ϕ_p measures the persistence of alpha, and ϵ_{pt} follows $N\left(0,\sigma_{\epsilon p}^2\right)$. The idiosyncratic volatility, σ_{pt}, is assumed to follow a stochastic volatility process:

$$\ln(\sigma_{pt}^2)=\gamma_0+\gamma_1\ln(\sigma_{pt-1}^2)+\upsilon_{p\sigma t}, \tag{3}$$

where $\upsilon_{p\sigma t}\sim N\left(0,\sigma_{p\sigma}^2\right)$. The volatility process models the time-varying uncertainty of hedge portfolio returns. [5] As commonly assumed in the theoretical models (DHS, 2001), α_{pt+1} (or ϵ_{pt+1}) and η_{pt} are uncorrelated.

2.2 Signals of hedge portfolios

A noisy signal at time t, s_{pt}, received by arbitrageurs consists of future innovation in the payoff at t+1 and noise at t:

$$s_{pt}=\epsilon_{pt+1}+\eta_{pt}, \tag{4}$$

which is conditionally independent of α_{pt} as in Epstein and Schneider (2008). This assumption about the noisy signal reflects the practice in hedge funds, where signals come, in most cases, from the past performance of their own trading strategies rather than exogenously, mainly due to their confidentiality. Therefore, as in Gervais and Odean (2001), arbitrageurs learn from the performance of their past trading.

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[3] Simple long-short hedge portfolios are not likely to be market neutral in practice; however, the market risk can be hedged out by taking positions in the market portfolio.

[4] Alphas are often explained in regime switching models which have an advantage in the identification of sudden change points in alphas or other parameters. For example, see Perez-Quiros and Timmermann (2000), Guidolin and Timmermann (2008), Gulen, Xing, and Zhang (2011), and Hwang and Rubesam (2013). In general, the change points are infrequent and alphas are highly persistent.

[5] Note that we assume ϵ_{pt} to be homoskedastic for simplicity. In a complicated model, where the innovation of alpha (ϵ_{pt+1}) is also heteroskesdastic, we would have a similar result because it is the ratio of $\sigma_{p\sigma}^2$ to $\sigma_{\epsilon p}^2$ that matters.

For hedge fund managers, the alpha at time t+1 (α_{pt+1}) represents the fundamental payoff for their trading strategies (DHS, 1998, 2001; Gervais and Odean, 2001).[6] The future realized return (r_{pt+1}) neither represents the *ex ante* payoff nor the one that these investors would like to learn about (Epstein and Schneider, 2008). Hedge fund managers would seek a significant positive alpha, because it represents sustainable payoff for their trading strategies and also a future source of profits due to its high level of persistence.

The idiosyncratic shock η_{pt} represents noise for the trading strategy because a fortuitous positive realized return driven by η_{pt} would not attract the interests of the experts who seek viable profit opportunities in the future. As in Grossman and Stiglitz (1980), Kyle (1985), and DHS (1998), noise is defined as the variability of realized profits from trading, which is not related to alpha. The volatility, σ_{pt}, which we refer to as 'noise volatility', also represents the quality of information as in Epstein and Schneider (2008): an asset with large noise volatility needs to be compensated with higher returns because investors try to avoid ambiguity of the low quality information of that asset. In this study, $\mathrm{r}_{\mathrm{pt+1}}$ and $\eta_{\mathrm{pt+1}}$ are referred to as realized profit and temporal profit, respectively, in order to differentiate them from the payoff (alpha).

2.3 Overconfidence of arbitrageurs

It is well documented in psychology and finance that experts are more overconfident than novice. Theories and models that these experts develop for their trading strategies would make them even more overconfident (De Long et al., 1991; Griffin and Tversky, 1992; Odean, 1998). However, there is no definite answer to the question of how to measure overconfidence.

Overconfidence has been measured in various ways in different contexts. For example, the timing of option exercises is used to identify overconfidence of CEOs (Malmendier and Tate, 2005). Others use trading volume (Chuang and Lee, 2006), profits (Gervais and Odean, 2001; Statman, Thorley, Vorkink, 2006; Chuang and Lee, 2006), psychological profile (Grinblatt and Keloharju, 2009), survey data (Deaves,

[6] The shock on the payoff at time t+1, ϵ_{pt+1}, together with $\mu_p + \phi_p(\alpha_{pt} - \mu_p)$, provides the full information for α_{pt+1}.

Lüders, and Schröder, 2010; Merkle, 2013), or bias in expected volatility of returns (Barone-Adesi, Mancini, Shefrin, 2013). These are context-specific and may not be appropriate to measure overconfidence of arbitrageurs for each of their trading strategies.

Theoretically overconfidence increases upon signals that confirm traders' prior belief (DHS, 1998) or successful predictions in the past (Gervais and Odean, 1998). We propose two such overconfidence measures. The first overconfidence measure is calculated on odds of success and failure of trading strategies as in Gervais and Odean (2001). According to Odean (1998) and Gervais and Odean (2001), an investor's overconfidence grows with the probability of successful predictability in the past or favorable feedback from gains:

$$c_{pt}^{p} = \frac{1}{12}\sum_{h=0}^{11} I_{\alpha_{pt-h}^{+}},$$

where $I_{\alpha_{pt}^{+}} = 1$ when $\alpha_{pt} \geq \mu_p + \phi_p(\alpha_{pt-1} - \mu_p)$, and zero otherwise. The prior $\mu_p + \phi_p(\alpha_{pt-1} - \mu_p)$ is a predictor for α_{pt} free from behavioral biases and thus, c_{pt}^{p} measures the successful predictions in the past. The second overconfidence measure is constructed on past profits as in Gervais and Odean (2001), Statman, Thorley, Vorkink (2006), and Chuang and Lee (2006). If confidence increases when past payoffs increase, we can use the changes in alpha over the past 12 months as follows:

$$c_{pt}^{\alpha} = \frac{1}{12}\sum_{h=0}^{11} \Delta\alpha_{pt-h}.$$

These overconfidence measures are calculated with alphas. Temporal profits are not appropriate for measuring confidence. They may be affected by other transitory biases, for example, fund flows by performance-chasing investors (Shleifer and Vishny, 1997). On the other hand, alpha is less likely to be affected by these biases, and a significant increase in alpha would boost overconfidence of arbitrageurs on their trading strategies. Nonetheless, our overconfidence measures may be confused with profitability represented by the level of alpha, and thus we use alpha as a control variable.[7]

We investigate if other overconfidence measures such as trading volume and volatility (Chuang and Lee, 2006; Goetzmann and Kumar, 2008) can represent

[7] See section 5. We find that the presence of alpha does not change our results.

arbitrageurs' overconfidence. However, they may not necessarily increase with arbitrageurs' overconfidence, because they are also under influence of other traders in the market (Statman, Thorley, Vorkink, 2006; Chuang and Lee, 2006). For example, when a profitable arbitrage opportunity initially created by other traders in the market is exploited by arbitrageurs, arbitrageurs' overconfidence alone does not necessarily increase the trading volume and volatility of the hedge portfolio. A detailed explanation together with empirical results follows in subsection 5.2. The bottom line is that volatility or trading volume is not a proper measure of arbitrageurs' overconfidence.

In all cases, we assume that arbitrageurs use the past 12-month data to engender overconfidence in order to reflect the dynamic trading of hedge funds. We have used longer periods, but the results do not change our story. These two overconfidence measures are standardized to have zero mean and unit variance.

2.4 Hypotheses on the Effects of Behavioral Biases on Hedge Portfolios

When posterior means of trading strategies are upward biased as in DHS (1998, 2001), arbitrageurs tend to increase their investment (i.e., long and short positions) in the strategies in order to exploit these profit opportunities. An increase in portfolio positions affects equity prices (Wermers, 2004; Coval and Stafford, 2007; Frazzini and Lamont, 2008), such that the performance of these strategies may appear to be improved. These effects, however, are not likely to be permanent (DHS, 1998, 2001; Gervais and Odean, 2001; Epstein and Schneider, 2008), although they may be persistent: the behavioral biases are more likely to affect temporal profits than fundamental payoffs (alphas).[8]

Therefore, using signal (s_{pt}) and overconfidence (c_{pt}), we propose the testable hypotheses as follows.

Hypothesis 1*: Overconfidence positively affects temporal profits of arbitrage trading strategies.*

As predicted by many previous studies, if overconfidence affects equity market neutral trading strategies, we have

[8] It is likely that behavioral biases affect alphas. However, the effects of behavioral biases on temporal profits are far larger than those on alphas. The effects are compared later in the empirical results.

$$\eta_{pt}^{b} = \gamma_{\eta} c_{pt} + \eta_{pt}, \tag{5}$$

where $\gamma_{\eta} > 0$ and superscript b indicates that the temporal profits are biased because of overconfidence. Overconfident arbitrageurs would increase their long and short positions because of the upward bias in the posterior expectation of the hedge portfolio return, which in turn could temporally affect the performance of the hedge portfolio.

Hypothesis 2*: Positive signals affect arbitrageurs' confidence more than negative signals.*

Overconfidence appears in an asymmetric form – it increases when investors' beliefs are confirmed by signals (Lord, Ross, and Lepper, 1979; Nisbett and Ross, 1980; Fiske and Taylor, 1991; DHS, 1998; Gervais and Odean, 2001), but does not decrease commensurately upon signals that contradict their beliefs. In order to test the asymmetry to positive and negative signals, we have the following equation:

$$c_{pt} = \gamma_{sc}^{+} s_{pt} I_{s_{pt}^{+}} + \gamma_{sc}^{-} s_{pt} (1 - I_{s_{pt}^{+}}) + \zeta_{ct}, \tag{6}$$

where $I_{s_{pt}^{+}}$ is an indicator variable that equals one when $s_{pt} \geq 0$ and zero otherwise. As trading strategies are perceived to be profitable, positive signals would increase arbitrageurs' overconfidence more than negative signals, and thus $\gamma_{sc}^{+} > \gamma_{sc}^{-}$ is expected.

Hypothesis 3*: Ambiguity-averse arbitrageurs react more strongly to unfavorable signals than to favorable signals when signals appear imprecise.*

According to Epstein and Schneider (2008), when the signals are ambiguous, these investors may respond more to unfavorable signals than to favorable signals because they tend to optimize under a worst-case scenario. For arbitrageurs, a signal may appear informative if it is consistent with their confidence, whereas a signal inconsistent with their confidence may be viewed as imprecise. In order to test arbitrageurs' ambiguity aversion, we divide signals depending on arbitrageurs' confidence levels and the signs of signals as follows:

$$\begin{aligned} \eta_{pt}^{b} = {} & \gamma_{\eta}^{++} s_{pt} I_{c_{pt}^{+}} I_{s_{pt}^{+}} + \gamma_{\eta}^{--} s_{pt} \left(1 - I_{c_{pt}^{+}}\right)\left(1 - I_{s_{pt}^{+}}\right) \\ & + \gamma_{\eta}^{-+} s_{pt} \left(1 - I_{c_{pt}^{+}}\right) I_{s_{pt}^{+}} + \gamma_{\eta}^{+-} s_{pt} I_{c_{pt}^{+}} (1 - I_{s_{pt}^{+}}) + \eta_{pt}, \end{aligned} \tag{7}$$

where $I_{s_{pt}^{+}}$ and $I_{c_{pt}^{+}}$ are indicator variables which equal one when $s_{pt} \geq 0$ and $c_{pt} \geq 0$, respectively, and zero otherwise. Here, signals with $I_{c_{pt}^{+}} I_{s_{pt}^{+}}$ and $\left(1 - I_{c_{pt}^{+}}\right)\left(1 - I_{s_{pt}^{+}}\right)$ are unambiguous whereas those with $\left(1 - I_{c_{pt}^{+}}\right) I_{s_{pt}^{+}}$ and $I_{c_{pt}^{+}}(1 - I_{s_{pt}^{+}})$ are ambiguous.

Our hypothesis is $\gamma_{\eta}^{+-} > \gamma_{\eta}^{-+}$ in equation (7) if ambiguity-averse arbitrageurs react more strongly to unfavorable signals than to favorable signals when signals appear imprecise. Moreover, ambiguity averse arbitrageurs would react to ambiguous signals more than to unambiguous signals, and thus we expect $\gamma_{\eta}^{-+} > \gamma_{\eta}^{++}$ and $\gamma_{\eta}^{+-} > \gamma_{\eta}^{--}$.

Finally, by observing the reactions of temporal profits to signals and overconfidence, equation (7) allows us to investigate if arbitrageurs asymmetrically response to favorable and unfavorable signals after controlling ambiguity aversion. Only using unambiguous signals, evidence of $\gamma_{\eta}^{++} > \gamma_{\eta}^{--}$ can be interpreted as asymmetric response of overconfident investors to favorable signals.

When asset prices increase (decrease) by overconfidence, these biases are not expected to be permanent, but are eventually corrected. Using simulations, DHS (1998) demonstrate that the price impact of short-term overreaction is reversed in the long-run. Baker and Wurgler (2006) show that the overreaction to sentiment is corrected slowly for certain types of stocks. However, it is unknown whether or not the effects of overconfidence on equity market neutral hedge portfolios are subsequently reversed, and if reversed, how quickly the reversals happen. This is an important issue for arbitrageurs because, as shown later in the empirical tests, the effects of overconfidence on the hedge portfolios are significant; therefore, the subsequent reversals may be critical in the performance of arbitrageurs. As in DHS (1998), we investigate the reversals using an autocorrelogram of temporal profits. For the impact of overconfidence and its reversals on the performance of arbitrageurs, we conduct a series of out-of-sample forecasts.

3. Estimation of Alpha and Idiosyncratic Volatility Processes

To test the hypotheses from the previous section, we need to obtain α_{pt} and η_{pt} for equity market neutral hedge portfolios, both of which time-vary. We use the conditional CAPM, as in Ang and Chen (2007).

3.1 Conditional CAPM model

We use the following conditional CAPM model to estimate α_{pt} and η_{pt}:

$$r_{pt}^{*} = \alpha_{pt} + \beta_{pt} r_{mt} + \sigma_{pt}\varepsilon_{pt}, \tag{8}$$

where $\varepsilon_{pt} \sim i.i.d.\ N(0,\ 1)$, r_{pt}^{*} represents the raw return on hedge portfolio *p* at time *t* and r_{mt} is the excess market return. The time-varying parameters, α_{pt} and β_{pt}, are portfolio *p*'s market risk-adjusted return and systematic risk at time *t*, respectively, and σ_{pt} is the idiosyncratic volatility. Note that equation (1) in the previous section, r_{pt}=$\alpha_{pt} + \eta_{pt}$, can be obtained by excluding $\beta_{pt} r_{mt}$ from equation (8).

For the latent processes, α_{pt}, β_{pt} and σ_{pt}, we use simple AR(1) processes, which minimize the problems associated with the choice of conditioning variables that may not represent the full set of state variables (Jostova and Philipov, 2005; Lewellen and Nagel, 2006):

$$\begin{aligned} \alpha_{pt} &= c_{p\alpha} + \phi_{p\alpha}\alpha_{pt-1} + \epsilon_{p\alpha t}, \\ \beta_{pt} &= c_{p\beta} + \phi_{p\beta}\beta_{pt-1} + \epsilon_{p\beta t}, \\ h_{pt} &= c_{ph} + \phi_{ph} h_{pt-1} + \upsilon_{pt}, \end{aligned} \tag{9}$$

where $h_{pt} = \ln(\sigma_{pt}^2)$, $\begin{pmatrix}\epsilon_{p\alpha t}\\ \epsilon_{p\beta t}\end{pmatrix} \sim i.i.d.\ N\left(\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}\sigma_\alpha^2 & \sigma_{\alpha\beta}\\ \sigma_{\alpha\beta} & \sigma_\beta^2\end{pmatrix}\right)$, and $\upsilon_{pt} \sim i.i.d.\ N(0, \sigma_{ph}^2)$.

3.2 Estimation method

We use Bayesian methods (Markov Chain Monte Carlo (MCMC) methods) to estimate the three latent processes, i.e., α_{pt}, β_{pt} and h_{pt}. The classical maximum likelihood is not appropriate because it has many local maxima, some of which may be in the improbable parameter space. The Bayesian MCMC approach updates the parameters using standard conjugate draws, conditional on the simulated series of time-varying parameters. In this section, we briefly explain the econometric techniques which we use to estimate the conditional CAPM. The detailed estimation procedure is described in Appendix A.

The elicitation of prior distribution is vital in the Bayesian estimation. Because our model allows all three parameters to time-vary, identification problems arise as in Ang and Chen (2007).[9] In order to minimize these problems, we use informative priors for the three AR coefficients, i.e., $\phi_{p\alpha}$, $\phi_{p\beta}$ and ϕ_{ph}, as explained in the following. For all the other parameters, diffuse priors are used.

For the prior means of the AR parameters, we calculate the 12th autocorrelations of α_{pt}, β_{pt} and h_{pt}, the series of which are calculated from using 12-month rolling OLS, and then take their 12th roots. We use a shorter window, i.e., 12 months, than that of Ang and Chen (2007), i.e., 60 months, because the estimates of the 60th autocorrelations are close to zero or even negative for some portfolios.[10] As expected, in most cases, the prior means of $\phi_{p\alpha}$ and $\phi_{p\beta}$ are close to 1, which is consistent with those suggested by the theory as well as by the empirical results (Gomes, Kogan, and Zhang, 2003; Ang and Chen, 2007).

For the variances of AR parameters, we use the following relationship between the variance of the 12th autocorrelation estimate and the variance of the first order autocorrelation: for example, for $\phi_{p\alpha}$, $\mathrm{var}(\phi_{p\alpha}) = \mathrm{var}(\phi_{12,p\alpha})\frac{1-\phi_{p\alpha}^2}{1-\phi_{p\alpha}^{24}}$ under the assumption that α_{pt} follows the AR(1) process, where $\phi_{p\alpha}$ and $\phi_{12,p\alpha}$ are the autocorrelation and 12th autocorrelation for α_{pt}, respectively. The estimated values of $\mathrm{var}(\phi_{p\alpha})$ lie between 0.0012 and 0.0025.[11] Considering the instability of the OLS estimates, we use twice of $\mathrm{var}(\phi_{p\alpha})$ as our prior variance.

Finally, the prior values of ϕ_{ph} lie between 0.9 and 0.95, which are slightly lower than those of $\phi_{p\alpha}$ and $\phi_{p\beta}$. However, these are higher than the value of 0.86, which Kim, Shephard, and Chib (1998) use as a prior mean for the estimation of stochastic volatility processes.

[9] Ang and Chen (2007) consider the time-variation in beta only.
[10] The autocorrelations are downward biased due to the measurement error from using the estimates of α_{pt}, β_{pt} and h_{pt}. We correct the bias by subtracting the average variance of the measurement error from the variance of the estimated autocorrelations. Any prior value of ϕ_{α} and ϕ_{β} larger than 0.99 is trimmed to 0.99 for the stationarity of α_{pt} and β_{pt}.
[11] These variances of the AR parameter are significantly larger than 0.003^2, a figure which Ang and Chen (2007) use for the estimation of time-varying beta of the book-to-market portfolio return.

We run a Gibbs sampler for 20,000 iterations, the first 10,000 of which is discarded. After confirming convergence using the Geweke (1992) diagnostic test, we use the last 10,000 draws to compute the posterior statistics.

4. Hedge Portfolios

In this section, we examine the properties of various equity market neutral portfolios documented in the finance literature. We then present the dynamics of alphas of these hedge portfolios. For this purpose, we calculate a total number of fifteen equity market neutral portfolios for the robustness of our results.

4.1 Data and the universe

In order to create hedge portfolios, we use the monthly data file from the merged Center for Research in Security Prices (CRSP) – Compustat database for common stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and NASDAQ. We exclude financial stocks (Standard Industrial Classification code from 6000 to 6999) because the accounting practice and variables of the financial sector are not compatible with those of the other sectors. Due to the restrictions on the various input variables in the 1960s, we calculate 492 monthly portfolio returns from July 1970 to June 2011 using data from 1967 to 2011.

A delicate but an important issue in this study is to decide the universe, i.e., which stocks should be included to form hedge portfolios. As our purpose is to investigate arbitrageurs' behavioral biases on equity market neutral hedge portfolios, our universe should resemble those of actively managed hedge funds in practice.[12] We first select stocks as in the academic literature by excluding stocks whose prices are less than a certain level, i.e., $1, at the portfolio formation time, in order to avoid the extreme returns associated with microstructure biases and thin trading of penny stocks. These non-penny stocks should have past three years' accounting as well as market

[12] The choice of the universe has significant impacts on the performance of hedge portfolios. For example, small stocks show higher returns in momentum (Jegadeesh and Titman, 2001) or asset growth (Cooper, Gulen, and Schill, 2008) than large stocks. Including these stocks would certainly improve the performance of these hedge portfolios; however, many small stocks are too illiquid to trade or are difficult to short. For the effects of short-sale constraints on asset pricing, see Duffie, Garleanu, and Pedersen (2002), Jones and Lamont (2002), Scheinkman and Xiong (2003), Nagel (2005), and Stambaugh, Yu, and Yuan (2012).

information which is required for the formation of hedge portfolios. This universe typically used in many empirical academic studies includes many stocks that hedge fund managers do not trade. In practice, the fund managers consider many other aspects, such as trading strategies, costs of trading, and inventories of the prime broker for short-selling. However, these aspects can vary widely and are difficult to consider in this study. Instead, we shrink the universe so that it includes only liquid and shortable stocks, in addition to the above academic universe; more specifically, excluding stocks whose sizes (number of shares outstanding times share price) and monthly average turnovers (the number of shares traded divided by shares outstanding) for the past two years belong to the bottom 10%.

At the first portfolio formation, June 1970, the number of stocks in the universe is 1,113, and the minimum size and past 24-month average turnover are $2.7 million and 2.5% per month, respectively. At the last formation, June 2010, the total number of stocks is 2,268, and the minimum size and turnover are $22.9 million and 19.6% per month, respectively. As in Dichev, Huang, and Zhou (2011), the trading volume has increased significantly since 1970.[13]

4.2 Construction of hedge portfolios

Depending on the rebalancing frequency, we have seven annually rebalanced portfolios formed on the annual accounting variables and eight monthly rebalanced portfolios formed on the quarterly accounting variables or daily and monthly market information. Ten equally weighted portfolios are formed for each trading strategy; then, a hedge portfolio is calculated by the difference between the highest and the lowest decile portfolios.[14] The detailed explanations on the construction of hedge portfolios can be found in Appendix B.

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[13] Our universe is not excessively small for moderate sized hedge funds. For a hedge fund which invests in market neutral strategies with an AUM of one hundred million dollars and a gross leverage of two (the sum of long and short exposure divided by AUM) (Ang, Gorovyy, and Inwegen, 2011), an equal investment weight on the top and bottom 10% of 2,000 stocks is equivalent to 0.5 million dollars in long or short positions in individual stocks. This means that the positions taken by a trading strategy would not be larger than 2.2% of market size at the end of the sample period even for the smallest firm (i.e., $22.9 million) in the universe.

[14] We also calculate quintile portfolios or tertile portfolios (top and bottom 30%), and use value weights for these portfolios. We find similar results to those we report with equally weighted decile portfolios. The results other than we report in this study are available upon request.

The seven annually rebalanced portfolios include accruals (Acc) (Sloan, 1996), asset growth (AG) (Cooper, Gulen, and Schill, 2008), book-to-market ratio (BEME) (Rosenberg, Reid and Lanstein, 1985; Fama and French, 1992, 1993), gross profitability (GP) (Novy-Marx, 2010), investment to assets (IA) (Chen and Zhang, 2010), net operating assets (NOA) (Hirshleifer, Hou, Teoh, and Zhang, 2004), and net stocks issues (NSI) (Fama and French, 2008). The eight monthly rebalanced portfolios are O-score distress (Osc) (Ohlson, 1980), return on assets (ROA) (Chen and Zhang, 2010) and failure probability (FP) (Campbell, Hilscher, and Szilagyi, 2008), earnings surprises (ESur) (Chan, Jegadeesh, and Lakonishok, 1996), liquidity (Liq) (Amihud, 2002), size (ME) (Banz, 1980; Fama and French, 1992, 1993), momentum (Mom) (Jegadeesh and Titman, 1993, 2001), and idiosyncratic volatility (IVol) (Ang, Hodrick, Xing and Zhang, 2006; George and Hwang, 2011).[15] These hedge portfolios may represent risk or anomalies; further discussions on these hedge portfolios are beyond the scope of this study.

The monthly rebalanced portfolios, i.e., Liq, ME, Mom, and IVol, are formed at the end of every month using the data of the previous months (skipping one month), and are held from three months from the formation month (six months for Mom). We skip one month in order to avoid any interference from a short-term reversal, as in Jegadeesh and Titman (2001). As these portfolios are formed every month, we have three portfolios overlapped at any time. Overlapping would contribute to the reduction of volatility and turnover that arises from the monthly rebalancing. The three overlapping portfolios are then averaged with equal weights in order to calculate the portfolio returns.[16] For the other monthly rebalanced portfolios which use quarterly accounting variables, i.e., Osc, FP, ESur, and ROA, the holding period is one month and we do not form overlapping portfolios, as in Ohlson (1980), Campbell, Hilscher, and Szilagyi, (2008), and Chen and Zhang (2010). As in the previous studies, the monthly returns of these hedge portfolios are calculated by high minus low decile portfolios for BEME, GP,

[15] We have considered other hedge portfolios, such as co-skewness and co-kurtosis (Kraus and Litzenberger, 1976; Hwang and Satchell, 1999; Harvey and Siddique, 2000), and downside beta (Bawa and Lindenberg, 1977; Ang, Chen and Xing, 2006); yet, we do not report the results of these hedge portfolios because they are not popular trading strategies in practice.

[16] We also used one- (no overlapping) and six-month holding periods. The results are similar to those with the three-month holding period.

Osc, ROA, FP, ESur, Liq, and Mom, whereas the others are calculated by low minus high decile portfolios.

The average hedge portfolio returns are similar to those reported in the literature. For the entire sample period from July 1970 to June 2011, Acc, AG, BEME, IA, NOA, NSI, ROA, ESur, and Mom show positive average returns significant at the 5% level, ranging from 0.66% (NSI) to 1.09% per month (ESur). Other hedge portfolios also convey similar results to those of the previous studies. The two distress factors, Osc and FP, are not significant, whereas Chen and Zhang (2010) report negative average returns for these two hedge portfolios at the 5% significance level. The main difference is that they calculate these hedge portfolio returns at the formation month, whereas we calculate the returns following the formation. Liq is affected significantly by our choice of universe. By removing small and illiquid stocks, the illiquidity premium disappears. According to the results of the four sub-periods, i.e., the 1970s, 1980s, 1990s, and 2000s, the performance of hedge portfolios changes over time. The details of the performance of the fifteen portfolios can be found in Appendix C.

4.3 Dynamics of time-varying parameters

The estimated alphas, betas, and idiosyncratic volatilities for the fifteen hedge portfolios are summarized in Table 1. The average values of alphas are close to the unconditional OLS estimates reported in Table A1 (CAPM alpha) in the Appendix. The average values of betas and idiosyncratic volatilities are also similar to those of the unconditional estimates of the CAPM (not reported). The standard errors of average alphas are all very small and thus the average alphas are significant except for Liq and ME. In the following, we briefly discuss the dynamics of alphas of the fifteen hedge portfolios.[17]

Alphas, betas, and idiosyncratic volatilities are highly persistent. For example, the AR coefficients on alphas and betas are on average 0.95. The persistence of alpha has an important implication for arbitrageurs: a trading strategy that performed well in

[17] As expected, beta changes over time. For example, as in Ang and Chen (2007), BEME beta decreases to -0.9 in the early 2000, and then increases to 0.4 in the early 2009. The substantial changes in beta indicate that the dynamics of alpha might be biased when the time-variation of beta is disregarded. In practice, for arbitrageurs who attempt to make their hedge portfolio market risk neutral, hedge portfolios whose betas are less persistent, e.g., Mom, might not be attractive, because risk hedging would be more difficult. Detailed results of betas can be obtained from the authors upon request.

the past is expected to work well in the near future. We estimate the half-lives of alphas ranging from 7 to 23 months from the AR coefficients of 0.91 to 0.97 (4 months for GP from its AR coefficient of 0.84). When large AR coefficients on alphas are considered together with relatively small variances of the error term ($\epsilon_{p\alpha t}$), these large unconditional variances of alphas suggest that the dynamics of alphas are smooth, but vary widely over time.

The performance of hedge portfolios can be better depicted by their cumulative realized profits and alphas. These cumulative realized profits and alphas are presented in log-scale under the assumption that the initial AUM is 100 with a gross leverage of two and that the realized profits are reinvested. Figure 1 indicates that one hedge portfolio, i.e., FP, shows a negative cumulative realized profit from July 1970 to June 2011, and three other portfolios, i.e., IVol, Liq, and Osc, report cumulative realized profits close to zero.

For many hedge portfolios, temporal profits (η_{pt}) significantly affect the performance of these arbitrage trading strategies. The alpha does not necessarily indicate a similar performance to its realized profit (r_{pt}=$\alpha_{pt} + \eta_{pt}$). Only four hedge portfolios (Acc, IA, NSI, and Liq) demonstrate that the cumulative realized profits and alphas have similar trends. The other eleven portfolios show deviations over the entire sample period or during sub-periods. IVol, ME, and GP show a significant difference between their cumulative realized profits and their corresponding cumulative alphas from the beginning of the sample period. The well-known ME does not show any sizable cumulative alpha over the entire sample period; however, its realized profits are significantly positive in the 1970s (Brown, Kleidon, and Marsh, 1983). On the other hand, the cumulative realized profits of AG, NOA, Esur, Mom, Osc, ROA, and FP show significant deviations from their cumulative alphas from some points in the middle of the sample period; for example, the bust of the high-tech bubble in the early 2000s or the credit crisis in 2008 appear to affect the cumulative realized profits in a negative way in the late 1990s and 2007-2009 for AG, NOA, Mom, and ROA.

5. Overconfidence and Ambiguity Aversion

In this section, we test the hypotheses proposed in section 2 by focusing on two sub-periods, i.e., the 1970s and 1980s, and the 2000s. We first explain various control variables that may affect the performance of the hedge portfolios. The results of least-squares dummy variable models (dummy variables for the fifteen hedge portfolios) are reported for equations (5) to (7).

5.1. Sentiment, fund flows, and other control variables

In order to investigate the effects of arbitrageurs' overconfidence on the performance of equity market neutral hedge portfolios, we use various control variables that could affect the performance of these portfolios. The control variables include sentiment, performance related fund flows, alphas, and other macroeconomic variables.

Baker and Wurgler (2006) and Stambaugh, Yu, Yuan (2012) show that sentiment affects the performance of equity neutral trading strategies due to the valuation difficulties or arbitrage restrictions in certain equities. Although both sentiment and overconfidence represent behavioral biases, there is no clear distinction between the two. Recently, Barone-Adesi, Mancini, Shefrin (2013) argue that overconfidence together with excessive optimism is a driving force of sentiment.

We regard sentiment as a market-wide bias in market participants' expectations relative to fundamentals, whereas overconfidence is trading strategy specific bias in experts' expertise (Griffin and Tversky, 1992). Market-wide sentiment can be measured by aggregating behavioral biases of experts as well as novice as in Barone-Adesi, Mancini, Shefrin (2013), but does not necessarily represent experts' behavioral biases. We use several sentiment indices, i.e., Baker and Wurgler's (2006) index, the Investors Intelligence sentiment index, the American Association of Individual Investors' sentiment, and a component of the Index of Consumer Sentiment, Michigan University. Our results are robust to these sentiments and thus we report the results with the Baker and Wurgler's index.

The behavioral biases of arbitrageurs need to be differentiated from the price effects of fund flows initiated by performance-chasing investors (Shleifer and Vishny, 1997; Shleifer and Vishny, 1997; Coval and Stafford, 2007; Jotikasthira, Lundblad, and Ramadorai, 2012). The literature on the effects of fund flows on asset prices suggests immediate effects of fund flows on the performance of arbitrage strategies, which are then reversed with a time lag: for example, the dumb money effects (Frazzini and Lamont, 2008; Akbas, Armstrong, Sorescu, and

Subrahmanyam, 2012) or liquidity driven reversals (Jotikasthira, Lundblad, and Ramadorai, 2012). These results suggest that the temporal profits of trading strategies may respond positively to the most recent performance by performance chasing investors, which is subsequently reversed.

The relationship between fund flows and the performance of hedge funds may not be as clear as that of mutual funds. Changes in the long and short positions are possible without fund flows because hedge fund managers can take advantage of leverage (Ang, Gorovyy, and Inwegen, 2011). In this study we use alphas and past returns of hedge portfolios to control the effects of performance related fund flows on temporal profits.

The first variable, alphas, is specific to trading strategies. As alphas represent profitability of trading strategies, arbitrageurs as well as investors would increase (decrease) their investments in trading strategies with high (low) alphas. Therefore, by including alphas as control variables, we can investigate the effects of overconfidence, i.e., the learning bias that changes dynamically with past success or failure (Gervais and Odean, 2001).

The second variable is past returns of equity market neutral hedge portfolios, which we use for the reversals following good performance. Our preliminary tests show that temporal profits appear to be negatively affected by several months lagged performance. Thus, in order to control these reversal effects, we use the lagged past average return (LPAR) of the three months (the (*t*-3, *t*-5) window), $\frac{1}{3}\sum_{\tau=3}^{5} r_{t-\tau}$, [18] where $r_{t-\tau}$ is the overall performance of the portfolio of equity market neutral hedge portfolios, i.e., $r_{t-\tau} = \frac{1}{15}\sum_{p=1}^{15} r_{pt-\tau}$.[19] This reversal period is shorter than those of

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[18] The lags are chosen on the following bases. First, if past performance of a trading strategy affects fund flows, which in turn affect the performance of the trading strategy, the return reversal would be observed with several month lags after the initial past performance of the strategy. For example, Akbas, Armstrong, Sorescu, and Subrahmanyam (2012) use the most recent two months for the effects of past performance on fund flows. In addition, the return reversals from the impact of fund flows appear a few months later in mutual funds (Frazzini and Lamont, 2008). Second, in the preliminary tests with pooled regressions, we find that hedge portfolio returns are negatively and significantly autocorrelated with the time lags of 3, 4, or 5 months.

[19] The overall performance of equity market neutral trading strategies is used to control the fund flow effects. Performance-chasing investors are not assumed to identify specific equity market neutral hedge portfolios that perform better than others. They are more likely to follow certain types of hedge strategies (emerging market, event driven, long/sort equity, managed futures, etc.) which have performed well recently.

Frazzini and Lamont (2008) or Lou (2012), and is close to the 12 weeks in the emerging markets (Jotikasthira, Lundblad, and Ramadorai, 2012).

The advantage of using alphas and the LPAR is that the price effects of performance related fund flows can be controlled when hedge fund flow data are not available, e.g., during the 1970s and 1980s, or when fund flows to each trading strategy are not known. For robustness we have used the LPAR* calculated with raw returns ($r^*_{pt-\tau}$) and found that the results are not different from those with the LPAR.

Other control variables include one-month Treasury bill rate, the term spread (the difference between the US ten year and one year Treasury bond rate), the credit spread (the difference between Moody's Aaa and Baa rated corporate bonds), and the dividend yield of S&P500. In most cases, these variables are not significant and thus are not reported to conserve space.

The correlation coefficients between the overconfidence measures, i.e., c^p_{pt}s and c^α_{pt}s, and the Baker and Wurgler's index are summarized in Table 2. As expected, the overconfidence levels are not always positively cross-correlated. For example, the correlation coefficients calculated with c^p_{pt}s in the lower triangular matrix in Table 2 show that the overconfidence levels of some trading strategies, such as IVol, Mom, and ROA, tend to be negatively correlated with those of other trading strategies. Moreover, the sentiment index is not always positively correlated with the overconfidence levels, except in a few cases.

These results show that overconfidence is specific for each of the equity market neutral trading strategies, and that market-wide sentiment does not necessarily indicate overconfidence in each of these trading strategies. Overconfidence is highly persistent as in the literature (Kyle and Wang, 1997; Hirshleifer and Luo, 2001): their autocorrelation coefficients range from 0.97 (Mom) to 0.99 (ESur).

5.2. Overconfidence, trading volume, and volatility of hedge portfolios

Previous studies show that overconfident investors trade more, which contributes to the volatility increase (Odean 1998; DHS, 1998; Gervais, Odean 2001; Chuang and Lee, 2006). However, these results for individual assets may not hold for equity market neutral portfolios. Trading volume of a hedge portfolio would increase with a heterogeneity interpretation of signals (Kandel and Pearson, 1995) between arbitrageurs and other traders but not necessarily with arbitrageurs' overconfidence, and volatility of a hedge portfolio may even decrease when overconfident arbitrageurs try to exploit its profit opportunity. In this subsection we investigate the relationship between our overconfidence measures, trading volume, and volatility of hedge portfolios.

Changes in trading volume by overconfidence are measured as follows. When overconfident arbitrageurs trade aggressively, they trade the top and bottom decile portfolios rather than the middle portfolios. Therefore, we calculate turnover difference between the top and bottom decile portfolios and the middle two decile portfolios, and then divide it by the total turnover of the universe to minimize the impact of the sharp increase in trading volume during the last four decades (Dichev, Huang, Zhou, 2011). [20]

The effects of overconfidence on the trading volume and log-volatility of hedge portfolios are investigated using least-squares dummy variable models. For control variables we use the four macro-variables, LPAR, α_{pt}, and sentiment index. Due to the contemporaneous relationship between trading volume and volatility (Karpoff, 1987; Ross, 1989, Chuang and Lee, 2006), contemporaneous log-volatility (h_{pt}) from the time varying CAPM and turnover difference are added as a control variable for the turnover difference and log-volatility, respectively.

The results of pooled regressions in Table 3 do not support the notion that overconfidence increases trading volume or volatility of the hedge portfolios even in the last subsample period. Our results also show the weak contemporaneous relationship between trading volume and volatility: log-volatility increases trading volume in the second and third sample periods only, but trading volume does not affect volatility. We should have a stronger relationship between trading volume and volatility of hedge portfolios if both of them increase with overconfidence.

Our results indicate that the relationships between overconfidence, trading volume and volatility in hedge portfolios are not the same as those in individual stocks (Chuang and Lee, 2006). Most previous studies focus on how asset prices are distorted by overconfidence in general (DHS, 1998, 2001; Gervais and Odean, 2001; Chuang and Lee, 2006), but not on how hedge portfolios are affected by arbitrageurs'

[20] Turnover (trading volume divided by total shares outstanding) is used to minimize the effects from firm size and thus is consistent with trading activity of equally weighted hedge portfolios. For Nasdaq stocks, the turnover is scaled by two because of the double-counting of trading volume (Anderson and Dyl 2005). We also use turnover difference not scaled by two, and find that the results are not different.

overconfidence. If arbitrage trading is designed to exploit the profit opportunities that have been created by other traders in the market, arbitrageurs' overconfidence may reduce rather than increase volatility. Our empirical results in the 2000s weakly support our interpretation.

5.3. Overconfidence, self-attribution bias, and reversals

The evidence of overconfidence is strong in equity market neutral trading strategies. Table 4 presents the results of Equation (5) (Hypothesis 1), where coefficients of two overconfidence measures are positive and significant in the presence of the control variables.[21] More importantly, the last row in panel A shows that the coefficients on overconfidence measures increase significantly in the 2000s: in the 1970s and 1980s, when arbitrage trading was less popular, the effects of overconfidence are much weaker than those in the 2000s. The coefficients on the market-wide sentiment are not different from zero in all cases.

The results in panel A are supported by those of long only and short only portfolios in panels B and C, respectively. Temporal profits of long only portfolios increase with overconfidence, whereas those of short only portfolios decrease with overconfidence. Interestingly, in the 1970s and 1980s, the temporal profits of short only portfolios are not much affected by overconfidence due to the unpopularity of or the restrictions of short-sale during the early sample period. It is in the 2000s when overconfidence affects both long only and short only portfolios in a similar way.

However, we do not find conclusive evidence that arbitrageurs' overconfidence asymmetrically responds to positive or negative signals. Table 5 presents the results of Equation (6) (Hypothesis 2). The pooled regression results in panel A of Table 5 do not support $\gamma_{sc}^{+} > \gamma_{sc}^{-}$, in particular during the 2000s: the differences in the coefficients on positive and negative signals are not statistically different.

Contrary to our expectation, the effects of overconfidence on equity market neutral portfolios are not subsequently reversed. Figure 2 shows the cumulative autoregressive coefficients on the AR(36) model for the three sub-periods. The cumulative coefficients tend to be negative, but none of the cumulative coefficients for

[21] In most cases of Tables 3 to 6, the likelihood ratio test rejects the null hypothesis that the fixed effects are redundant. However, the results of the Hausman test do not support the random effects.

the 36 months, i.e., -0.17, -0.33, -0.45, -0.36 for the entire period, the 1970s and 1980s, the 1990s, and the 2000s, respectively, are significant at the 5% level. We have tested more than 36 months, e.g., 48 and 60 months, but found no evidence of the reversals: the cumulative autoregressive coefficients tend to increase slightly after 36 months though the tendency is not statistically significant.

Little evidence of subsequent reversals is not inconsistent with the theoretical model of DHS (1998), who demonstrate that the price impact of short-term overreaction is reversed in the long-run. As reasons for why the initial impact of overconfidence does not appear corrected, we suggest annual changes in the universe and periodic rebalancing of the hedge portfolios. When the universe is annually adjusted for delisted or new stocks, the hedge portfolios that are constructed with the equities in the new universe do not include the same equities over time. Moreover, the hedge portfolios are rebalanced on a monthly or annual basis. When the top and bottom decile portfolios are rebalanced, they do not necessarily include the same individual stocks in the portfolios. Therefore, to arbitrageurs, the initial impact does not appear to be subsequently reversed.

Finally, our evidence of overconfidence holds after controlling the effects of market-wide sentiment and fund flows. The result that the coefficients on sentiment are not different from zero does not seem to support the empirical evidence of Stambaugh, Yu, and Yuan (2012) that sentiment affects the performance of equity neutral trading strategies due to short-sale restrictions.[22] However, our equity neutral hedge portfolios are constructed with stocks that are less likely to suffer short-sale restrictions than those in Stambaugh, Yu, and Yuan (2012).

The two performance-related variables show signs consistent with our expectation. The positive coefficients on α_{pt}s support the notion that temporal profits of hedge portfolios increase with their alphas as arbitrageurs increase (decrease) their investments in trading strategies with high (low) alphas. The negative coefficients on LPAR support the notion that the effects of performance-chasing investors' fund flows driven by past performance do have reversals three to five months later in the equity market neutral hedge portfolios. Despite these effects of performance related variables, however, the positive effects of arbitrageurs' overconfidence on their trading strategies

[22] We also use raw returns rather than temporal profits in the pooled regression, but the coefficient on sentiment is not statistically significant (not reported).

subsist. In fact, we find that these positive effects hold regardless of these control variables (not reported).

5.4. Ambiguity aversion and asymmetric response to signals

The results of Equation (7) are presented in Table 6 (Hypothesis 3), which show evidence of ambiguity aversion in the fifteen hedge portfolios for the three sub-periods. The pooled regression results show some evidence that arbitrageurs respond to more to negative signals under a worst-case scenario: the estimates of $\gamma_\eta^{+-} - \gamma_\eta^{-+}$ are positive and significant during the 1990s and all of them are positive regardless of sample periods. When responses to ambiguous and unambiguous signals are compared, responses to ambiguous signals are always significantly higher than those to unambiguous signals, i.e., $\gamma_\eta^{-+} > \gamma_\eta^{++}$ for positive signals and $\gamma_\eta^{+-} > \gamma_\eta^{--}$for negative signals. One notable result in the tests of ambiguity aversion is that the estimates of $\gamma_\eta^{-+} - \gamma_\eta^{++}$ and $\gamma_\eta^{+-} - \gamma_\eta^{--}$ become smaller in the 2000s than in the 1970s and 1980s. As the effects of overconfidence increase in the 2000s, those of ambiguity aversion tend to decreases, indicating a negative association between overconfidence and ambiguity aversion (Brenner, Izhakian, and Sade, 2011).

However, we do not find conclusive evidence of asymmetric responses of temporal profits to positive and negative signals after controlling ambiguity aversion. The estimates of $\gamma_\eta^{++} - \gamma_\eta^{--}$ are neither positive nor significant. Together with the results in Table 5 where overconfidence does not asymmetrically depend on signals, the empirical evidence in Table 6 indicates that arbitrageurs do not asymmetrically respond to signals.

Summarizing the empirical results, we find clear evidence of overconfidence in the equity market neutral trading strategies; more importantly, the effects of overconfidence become stronger in the 2000s when arbitrage trading is active. Contrary to the previous studies in the literature (Odean, 1998; DHS, 1998, 2001; Gervais and Odean, 2001; Chuang and Lee, 2006), trading volume and volatility do not increase with overconfidence in the hedge portfolios. We also report empirical evidence that the effects of overconfidence on equity market neutral portfolios are not subsequently reversed, and that arbitrageurs treat signals that are inconsistent with their confidence as ambiguous. The results support that overconfidence and ambiguity aversion are not mutually exclusive (Epstein and Schneider, 2008).

6. Excessive Arbitrage Trading

What is the impact of behavioral biases on the performance of hedge fund managers? In this section, we first investigate how much arbitrage opportunities have been eroded away in the 2000s, and then explore the effects of overconfidence on the performance of hedge portfolios.[23]

6.1 Out-of-sample forecasting

We perform out-of-sample forecasting tests from the arbitrageurs' perspective by focusing on the changes in alphas and temporal profits. At the end of June every year, we decide which hedge portfolios to be traded for the next 12 months, and form equally weighted portfolios of the selected hedge portfolios (PHPs). The selection methods are kept simple, as our aim is not to compare the sophisticated forecasting methods, but to find changes in the common trends of alphas and temporal profits.

We use the entire hedge portfolios (ENT) as the benchmark, and form four other PHPs as follows: 1) hedge portfolios whose alphas are larger than 0.5 (A5), 2) hedge portfolios whose monthly Sharpe ratios of alphas (i.e., α_{pt}/σ_{pt}) are larger than 0.14 (SRA), 3) hedge portfolios whose monthly Sharpe ratio of realized profits (i.e., average realized profits divided by volatility of realized profits over the last 12 months) are larger than 0.14 (SRR), and 4) hedge portfolios whose monthly Sharpe ratio of raw returns (i.e., average raw return divided by volatility of raw returns over the last 12 months) are larger than 0.14 (SRRR).

As alphas are persistent and their half-lives are over 12 months, we use the most recent alpha at the formation month, i.e., at the end of June of every year. The

[23] We answer these questions by identifying the changes in the performance of multiple hedge portfolios. It is not easy to empirically establish the connection between the arbitrageurs' behavioral biases and the profitability of equity market neutral hedge portfolios. Both the performance of hedge portfolios and arbitrage trading change over time, and the sources of profitability in these trading strategies are not clearly known in many cases. See Barberis and Thaler (2003) for example. Our approach is comparable with those of Fama and French (2006), who investigate the value premium in the international as well as in the US equity markets, or those of Rouwenhorst (1998), Griffin, Ji, and Martin (2003), Asness, Liew, and Stevens (1997), Bhojraj and Swaminathan (2006), and Asness, Moskowitz, and Pedersen (2009), who investigate the momentum in different markets or asset classes.

three selection methods, i.e., SRA, SRR, and SRRR, reflect a popular performance measure in practice, which we use to identify the profitable trading strategies.[24] Raw returns are used in the SRRR because the systematic risk of SRRR is on average close to zero (i.e., -0.05 for the entire sample period) and is often disregarded in practice for equity market neutral portfolios.

The average numbers of the hedge portfolios that are included in the five PHPs are 15 (ENT), 8.9 (A5), 9 (SRA), 9.8 (SRR) and 8.6 (SRRR). They do not show an upward or downward trend for the four decades since the early 1970s. Panel A of Table 7 shows that the PHPs formed on alphas (i.e., A5 and SRA) perform better than the ENT portfolio: the Sharpe ratios of these two PHPs are higher than that of ENT. However, SRR and SRRR, which are calculated using the Sharpe ratios of realized profits and raw returns, respectively, do not outperform the PHPs formed on alphas. In almost all cases, the alphas and realized profits of the PHPs forecasted by A5 and SRA outperform those of SRR and SRRR.

6.2 Has alpha been eroded away?

Our first question asks whether the profitability of equity market neutral portfolios has disappeared in the 2000s or not. A decline in the alphas of the hedge portfolios in the 2000s could be interpreted as the erosion of profitable opportunities due to the market-wide increase in arbitrage trading. Panel B of Table 7 reports that in all cases, the average alphas in the 2000s are significantly lower than those in the previous sub-periods. For example, the alpha of the fifteen hedge portfolios (ENT) has decreased from 0.61% per month during the three decades from the 1970s to the 1990s to 0.5% per month during the 2000s. This is consistent with the results of the unconditional models in the Appendix.

However, the average alphas in the 2000s are still significant despite the statistically significant decrease in the 2000s (Panel B): the alphas are still economically sizeable, i.e., 0.5% per month with the Sharpe ratio of 8.7 (ENT). Alphas are much higher than the benchmark in a few cases: for example, A5 shows that its average alpha is 0.86% per month with an annual Sharpe ratio of 21.6 during the 2000s. Therefore,

[24] The cutoff point, the monthly Sharpe ratio of 0.14, is equivalent to 0.5 in terms of annual Sharpe ratios. Our results remain robust to other various cutoff points.

although arbitrageurs suffer difficult times in the 2000s as in Chan, Getmansky, Haas, and Lo (2007) and Lo (2008), the equity market neutral trading strategies still have sizable alphas.

Compared with an approximately 20% decrease in the profitability of equity market neutral portfolios, temporal profits appear far worse in the 2000s. The realized profits, which are the sum of temporal profits and alphas, decrease more than the alphas during the last decade. The main reason for the relatively low realized profits is the large negative returns of the three trading strategies, IVol, Mom, and ROA during the three months from March to May 2009, which are -41.7%, -61.6%, and -29.8% respectively. When these three months is removed from the analysis, average realized profits increase significantly: for example, the average realized profits of SRR and SRRR increase by 0.3% per month. The cumulative realized profits of the five PHPs in Figure 3 clearly indicate that temporal profits suffer significant negative returns in the early 2009, whereas alphas are still positive.

6.3 Excessive arbitrage trading and anomalous profits

Arbitrage trading has not eroded away the profit opportunities of the hedge portfolios, but arbitrageurs' overconfidence has positively affected the temporal profits of the portfolios, which is not subsequently reversed. Therefore, it is likely that the excessive arbitrage trading instigated by overconfidence creates anomalous profits.

To investigate the anomalous profits by overconfidence, we form three equally weighted PHPs depending on the overconfidence levels at the end of June every year, and then hold the PHPs for the next 12 months. The procedure is repeated from June 1971 to June 2010. Each PHP includes five equity market neutral portfolios. The three PHPs, i.e., low confidence, middle confidence, and high confidence PHPs, are named as Low-PHP, Mid-PHP, and High-PHP, respectively. Table 8 reports the performance of raw returns, alphas, and temporal profits of the three PHPs and the differences between the High-PHP and the Low-PHP.

The performance difference between the High-PHP and the Low-PHP is both economically and statistically significant. Over the entire sample period, the raw return difference is 1.4% per month (16.8% per year), but tends to decrease over time and is 0.77% and 1.08% per month in the 2000s for c_{pt}^{p} and c_{pt}^{α}, respectively. However, when the raw returns are decomposed into alphas and temporal profits, the decrease in the raw return difference comes from the sharp drop in the alpha difference in the 2000s.

Overconfidence creates anomalous profits that have not been weakened recently. The differences in the average temporal profits between the High-PHP and the Low-PHP are 0.80% and 0.94% per month (9.6% and 1.13% per year respectively) for c_{pt}^{p} and c_{pt}^{α}, respectively in the 2000s, whereas they are 0.38% and 0.67% per month for c_{pt}^{p} and c_{pt}^{α}, respectively in the 1970s and 1980s. The differences in temporal profits between the High-PHP and the Low-PHP increase when arbitrage trading is highest in the 2000s.[25] Note that the differences in alphas between the High and Low PHPs continue to decrease and become small in the 2000s, i.e., 0.07% and 0.21% per month for c_{pt}^{p} and c_{pt}^{α}, respectively, being less than one fifth of the average temporal profits.

The effects of overconfidence on the temporal profits are not confined to a small number of extreme hedge portfolios. The absolute average temporal profits of the Low-PHP are similar to those of the High-PHP, and thus both High- and Low-PHPs are responsible for the anomalous profits. Moreover, our results do not come from a few hedge portfolios that consistently belong to the High- or Low-PHP over time: for example, the probability that a hedge portfolio belongs to the High-PHP is between 28% and 38% over the 40 years since 1971.

We also find that the difference in temporal profits between the High-PHP and the Low-PHP is not well explained by the fund flow variable (LPAR), sentiment, Fama-French three factors and momentum, or the four macroeconomic variables which we have considered in this study. For example, when differences of raw returns, alphas, and temporal profits between High and Low-PHPs (sorted by c_{pt}^{p}) are regressed on these variables, we find that the estimates of the constant become 0.94% (with t-statistic of 1.03), -0.25% (with t-statistic of -0.94), and 1.49% (with t-statistic of 1.86), respectively. When these are compared with the estimates with those in the "Entire Sample Period"

[25] Average temporal profits appear to be highest in the 1990s; yet, these high average temporal profits are due to the abnormal temporal profits during the burst of the High-tech bubble in the late 1990s. As indicated by the study of Hwang and Rubesam (2014), the High-tech bubble during the late 1990s is likely to have substantial effects on these hedge portfolios. For example, after excluding these abnormal temporal profits from November 1999 to June 2000, both of the average temporal profits are less than 1% per month in the second sub-period.

of panel A, Table 8, we find that the difference in temporal profits is still not explained by these control variables. Moreover, considering that all these variables are not significant, we conclude that overconfidence create anomalous profits in PHPs.[26]

Proponents of the behavioral approach often argue that profitable opportunities from mispricing may not be exploited because arbitrage trading can be both risky and costly and thus, are unattractive to investors (Barberis and Thaler, 2005). What we find in this study is that despite noise-traders' risk (Shleifer and Vishny, 1997), arbitrage opportunities are indeed excessively exploited by overconfident investors who do not know how much of these profitable opportunities can be exploitable. Excessive arbitrage trading by overconfidence creates an anomalous profit opportunity.

Theories do not tell us if overconfident traders can make more profits than rational investors. The models of DHS (1998, 2001) and Gervais and Odean (2001) suggest that overconfident traders have lower gains on average, whereas Kyle and Wang (1997) argue that a higher profit is possible. Although we demonstrate that overconfident arbitrageurs can make extra profits, the reason for the extra profits is different from those suggested in the literature: arbitrageurs' overconfidence creates profitable opportunities that are not reversed subsequently. Arbitrage trading expected to exploit mispricing opportunities and thus improve market efficiency creates another anomaly due to arbitrageurs' own overconfidence.

7 Conclusions

Over the last two decades, the size of investment funds managed by sophisticated investors such as hedge funds has grown dramatically. In 1990, the total assets under management of hedge funds are less than $50 billion, but become almost $2 trillion in the middle of the 2000s. This spectacular rise in the size of those funds, along with their aggressive investment strategies, has significant effects on asset returns. The conventional view is that arbitrage opportunities erode quickly as the arbitrage activity increases and thus, asset prices move closer to its true fundamental value.

[26] In addition, the average temporal profits of the High-Minus-Low-PHPs change little by the abnormal temporal profits of IVol, Mom, and ROA during the three months from March to May 2009: excluding these months, the difference in the average temporal profits of the High-Minus-Low-PHPs is 0.72% per month for c_{pt}^{p} and 0.79% per month for c_{pt}^{α} in the 2000s.

However, market efficiency may not have been necessarily improved despite increasing the number of arbitrageurs, because these experts are more likely overconfident than inexperienced investors (De Long et al., 1991; Griffin and Tversky, 1992; and Odean, 1998). The effects of their overconfidence on asset prices may have increased as the trading volume by institutional investors increase dramatically in the 2000s. It is an empirical question as to whether or not assets are priced efficiently due to increased arbitrage trading.

In this study, we investigate whether the effects of arbitrage trading on cross-sectional asset returns can be attributed to arbitrageurs who are overconfident or ambiguity averse, or have self-attribution bias. Using the conditional CAPM, we decompose the alpha and idiosyncratic payoffs, which represent the unbiased estimate of profit opportunity as well as the temporal profit that arbitrageurs experience in practice, respectively.

Using fifteen equity market neutral portfolios, our results demonstrate that overconfidence plays an important role in the performance of arbitrageurs. During the 2000s when arbitrage trading is active, overconfidence has led to excessive arbitrage. Despite the erosion of alphas in the 2000s, we find strong evidence that profit opportunities in the equity market neutral strategies still exist: the average alpha of fifteen hedge portfolios are 0.5% and its Sharp ratio is 8.7. Interestingly, we find that the performance of arbitrage trading strategies can be further improved by exploiting overconfidence of arbitragers, because their excessive arbitrage positively affects temporal profits which are not subsequently reversed. We show that the average return is 9.6% per month in the 2000s if the arbitrageurs' overconfidence were exploited.

This could be evidence explaining that arbitrage trading actually damages rather than improves market efficiency. The sharp increase in the trading volume by institutional investors, reported by Hendershott, Jones, and Menkveld (2011) and Dichev, Huang, and Zhou (2011), indicate that the market may become more inefficient due to experts' behavioral biases.

Appendix A Bayesian Computation (Monte Carlo Markov Chain Sampling)

The conditional CAPM that we estimate can be represented as follows using state space form:

$$r_{pt} = H_{pt}\bar{B}_p + H_{pt}(B_{pt} - \bar{B}_p) + e^{0.5h_{pt}}\varepsilon_{pt},$$

where $H_{pt} = (1 \quad r_{mt}), B_{pt} = (\alpha_{pt} \quad \beta_{pt})'$, $\bar{B}_p = (\mu_\alpha \quad \mu_\beta)'$, and $\varepsilon_{pt} \sim i.i.d.\ N(0,1)$. For the dynamics of market beta (β_{pt}) and market risk-adjusted return (α_{pt}), we use the autoregressive process of order one, AR(1).

$$B_{pt} - \bar{B}_p = \Phi(B_{pt-1} - \bar{B}_p) + \epsilon_{pt},$$

where $\Phi = \begin{pmatrix} \phi_\alpha & 0 \\ 0 & \phi_\beta \end{pmatrix}, \epsilon_{pt} = \begin{pmatrix} \epsilon_{\alpha t} \\ \epsilon_{\beta t} \end{pmatrix}$, and $\begin{pmatrix} \epsilon_{\alpha t} \\ \epsilon_{\beta t} \end{pmatrix} \sim i.i.d.\ N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\alpha^2 & \sigma_{\alpha\beta} \\ \sigma_{\alpha\beta} & \sigma_\beta^2 \end{pmatrix}\right)$. Note that $c_\alpha = \mu_\alpha(1 - \phi_\alpha)$ and $c_\beta = \mu_\beta(1 - \phi_\beta)$. To model the heteroskedasticity of idiosyncratic volatility, we use a stochastic volatility model as follows:

$$h_{pt} - \mu_h = \gamma_1(h_{pt-1} - \mu_h) + \upsilon_{p\sigma t},$$

where $\upsilon_{p\sigma t} \sim i.i.d.\ N(0, \sigma_{p\sigma}^2)$ and $\gamma_0 = \mu_h(1 - \gamma_1)$. Therefore, the set of parameters we need to estimate is $\{B_{pt}\}, \{h_{pt}\}, \gamma_0, \gamma_1,\ \sigma_{p\sigma}^2, F = (c_\alpha, \phi_\alpha, c_\beta, \phi_\beta)'$, and $Q = \begin{pmatrix} \sigma_\alpha^2 & \sigma_{\alpha\beta} \\ \sigma_{\alpha\beta} & \sigma_\beta^2 \end{pmatrix}$.

We first estimate the time-varying market beta, market risk-adjusted return, and idiosyncratic volatility for each portfolio; then, conditional on the simulated series of these time-varying parameters, the other parameters are updated using standard conjugate draws. The Gibbs sampler takes the following steps:

a. Initialize $\{B_{pt}\}, \{h_{pt}\}, \gamma_0, \gamma_1, F$ and $\sigma_{p\sigma}^2, Q$.
b. Generate $\{B_{pt}\}$ from $p(\{B_{pt}\}|\{r_{pt}\}, \{h_{pt}\}, \gamma_0, \gamma_1, F, \sigma_{p\sigma}^2, Q)$.
c. Generate $\{h_{pt}\}$ from $p(\{h_{pt}\}|\{r_{pt}\}, \{B_{pt}\}, \gamma_0, \gamma_1, F, \sigma_{p\sigma}^2, Q)$.
d. Generate γ_0, γ_1 from $p(\gamma_0, \gamma_1|\{r_{pt}\}, \{B_{pt}\}, \{h_{pt}\}, F, \sigma_{p\sigma}^2, Q)$.
e. Generate F from $p(F|\{r_{pt}\}, \{B_{pt}\}, \{h_{pt}\}, \gamma_0, \gamma_1, \sigma_{p\sigma}^2, Q)$.
f. Generate $\sigma_{p\sigma}^2, Q$ from $p(\sigma_{p\sigma}^2, Q|\{r_{pt}\}, \{B_{pt}\}, \{h_{pt}\}, \gamma_0, \gamma_1, F)$.

Repeat the procedure from b to f until convergence.

A.1. Generating $\{\boldsymbol{B_{pt}}\}|\{\boldsymbol{r_{pt}}\}, \{\boldsymbol{h_{pt}}\}, \boldsymbol{\gamma_0}, \boldsymbol{\gamma_1}, \boldsymbol{F}, \boldsymbol{\sigma_{p\sigma}^2}, \boldsymbol{Q}$

To generate the $\{B_{pt}\}$, we use the algorithm of forward filtering and backward sampling, described in Carter and Kohn (1994).

A.2. Generating $\{\boldsymbol{h_{pt}}\}|\{\boldsymbol{r_{pt}}\}, \{\boldsymbol{B_{pt}}\}, \boldsymbol{\gamma_0}, \boldsymbol{\gamma_1}, \boldsymbol{F}, \boldsymbol{\sigma_{p\sigma}^2}, \boldsymbol{Q}$

Given the generated parameters, the observation equation and the state equation are represented as follows:

$$r_{pt} - H_{pt}B_{pt} = \sigma_{pt}\varepsilon_{pt} = \exp(h_{pt}/2)\varepsilon_{pt},$$
$$h_{pt} - \mu_h = \gamma_1(h_{pt-1} - \mu_h) + \upsilon_{p\sigma t}.$$

To generate the series of unobserved volatilities, we use the algorithm of the multi-move sampler following Shephard and Pitt (1997) and Watanabe and Omori (2004).

A.3. Generating $\boldsymbol{\gamma_0}, \boldsymbol{\gamma_1}|\{\boldsymbol{r_{pt}}\}, \{\boldsymbol{B_{pt}}\}, \{\boldsymbol{h_{pt}}\}, \boldsymbol{F}, \boldsymbol{\sigma_{p\sigma}^2}, \boldsymbol{Q}$

We use the normal distribution as a prior for γ_0; however, by allowing a large variance on the normal distribution, we set γ_0 to have a nearly diffuse prior.

To draw γ_1, we assume that $(\gamma_1 + 1)/2$ ~ Beta(α_h, β_h) in order to guarantee the stationary condition, $|\gamma_1| < 1$, where α_h and β_h are matched to the first two moments of γ_1 (mean and variance), which are estimated by using the series of h_{pt} obtained from the 12-month rolling OLS regressions. The conditional posterior distribution of γ_1 is given by

$$\pi(\gamma_1|\{r_{pt}\}, \{h_{pt}\}, \gamma_0, \sigma_{p\sigma}^2) \propto$$

$$\pi(\gamma_1)\sqrt{1-\gamma_1{}^2}\exp\left\{-\frac{\sum_{t=2}^{T}(h_{pt}-\bar{h}_p)}{2\sigma_{p\sigma}^2}\left(\gamma_1-\frac{\sum_{t=1}^{T-1}(h_{pt}-\bar{h}_p)(h_{pt+1}-\bar{h}_p)}{\sum_{t=2}^{T}(h_{pt}-\bar{h}_p)}\right)^2\right\}.$$

Because the posterior is not standard, we use the Metropolis-Hasting algorithm (e.g., Chib and Greenberg (1995)). We use $TN_{(-1,1)}(\widehat{\gamma_1}, s_{\gamma_1}^2)$ as a proposal density, where TN refers to the truncated normal distribution on the $-1 < \gamma_1 < 1$ and

$$\widehat{\gamma_1} = \frac{\sum_{t=1}^{T-1}(h_{pt}-\bar{h}_p)(h_{pt+1}-\bar{h}_p)}{\sum_{t=2}^{T}(h_{pt}-\bar{h}_p)}, \qquad s_{\gamma_1}^2 = \frac{\sigma_{p\sigma}^2}{\sum_{t=2}^{T}(h_{pt}-\bar{h}_p)}.$$

A.4. Generating $\boldsymbol{\sigma_{p\sigma}^2|\{r_{pt}\},\{B_{pt}\},\{h_{pt}\},\gamma_0,\gamma_1,F,Q}$

We update the $\sigma_{p\sigma}^2$ using the inverse Wishart standard conjugate distribution with less informative prior elicitation.

$$\sigma_{p\sigma}^2 \sim IW(v_\varepsilon \hat{\sigma}_{p\sigma OLS}^2, v_\varepsilon),$$

where $\hat{\sigma}_{p\sigma OLS}^2$ is obtained using the series of logarithm scaled variance from the 12-month rolling OLS regressions. We give less informative prior belief by setting $v_\varepsilon = 4$ (Gelman, 2007).

The conditional posterior distribution is of the same form as the prior distribution:

$$\sigma_{p\sigma}^2|\{r_{pt}\},\{h_{pt}\},\gamma_0,\gamma_1 \;\sim\; IW(\bar{\sigma}_{p\sigma}^2, \bar{v}_\varepsilon),$$

where

$$\bar{\sigma}_{p\sigma}^2 = v_\varepsilon \hat{\sigma}_{p\sigma OLS}^2 + (1-\gamma_1^2)(h_{p1}^2-\bar{h}_p)^2 + \sum_{t=1}^{T-1}\left(h_{pt+1}-\bar{h}_p-\gamma_1(h_{pt}-\bar{h}_p)\right)^2,$$

$$\bar{v}_\varepsilon = v_\varepsilon + T.$$

A.5. Generating $\boldsymbol{F,Q|\{r_{pt}\},\{B_{pt}\},\{h_{pt}\},\gamma_0,\gamma_1,\sigma_{p\sigma}^2,Q}$

Given the simulated parameters, the state equation for the process of $\boldsymbol{B_{pt}}$ becomes a simple variant of the Seemingly Unrelated Regression (SUR) model:

$$y_t = X_t F + \epsilon_t$$

where $X_t = \begin{pmatrix} 1 & \alpha_{pt-1} & 0 & 0 \\ 0 & 0 & 1 & \beta_{pt-1} \end{pmatrix}$, $y_t = (\alpha_{pt}, \beta_{pt})'$, $\varepsilon_t = (\epsilon_{\alpha t}, \epsilon_{\beta t})'$, $F = (c_\alpha, \phi_\alpha, c_\beta, \phi_\beta)'$. We use the normal distribution as a prior for F and inverse Wishart prior distribution for Q:

$$F \sim N(\underline{F},\ \underline{V}),\ Q \sim IW(\underline{v},\ \underline{Q}),$$

where $\underline{F}$ is prior mean for F, $\underline{V}$ is prior variance-covariance matrix for F, $\underline{Q}$ is set to have $\underline{v}\begin{pmatrix} \mathrm{var}(\alpha_{pt})(1-\phi_\alpha^2) & 0 \\ 0 & \mathrm{var}(\beta_{pt})(1-\phi_\beta^2) \end{pmatrix}$ under the stationary condition, where $\mathrm{var}(\alpha_{pt})$ and $\mathrm{var}(\beta_{pt})$ are from the results of equating the unconditional variances of α_{pt}, and β_{pt} $(\text{e.g.}, \mathrm{var}(\alpha_{pt}) = \sigma_\alpha^2/(1-\phi_\alpha^2))$ to the variances of unconditional series of estimated α_{pt}, and β_{pt} from a 12-month rolling OLS, and $\underline{v} = 4$ implying less informative prior on Q.

Using this prior, we can derive the conditional posterior $p(F|y,Q)$ in a straightforward fashion,

$$F|y,Q \sim N(\bar{F},\bar{V}),$$

where $\bar{V} = (\underline{V}^{-1} + \sum_{t=1}^{T} X_t' Q^{-1} X_t)^{-1}$ and $\bar{F} = \bar{V}(\underline{V}^{-1}\underline{F} + \sum_{t=1}^{T} X_t' Q^{-1} y_t)$. The posterior for Q conditional on F is inverse-Wishart:

$$Q|y,F \sim IW(\bar{v},\bar{Q}),$$

where $\bar{v} = T + \underline{v}$ and $\bar{Q} = \underline{Q} + \sum_{t=1}^{T}(y_t - X_t F)(y_t - X_t F)'$.

Appendix B Equity Market Neutral Hedge Portfolios

The data for the construction of hedge portfolios are from the CRSP data file, the Compustat and CRSP merged data file, and Kenneth French's data library from 1963 through 2011. We use all NYSE, Amex, and NASDAQ, except for illiquid stocks which are not tradable for arbitrageurs and financial firms whose fundamentals are not directly comparable with those of other firms. For each hedge portfolio, firms are assigned to one of 10 decile portfolios based on firm characteristics in order to form equally weighted decile portfolios; then, we take long minus short positions with the long leg being higher-performing extreme decile and the short leg being the lower-performing extreme decile.

We also calculate the turnover for the hedge portfolios in order to compare the trading costs for the hedge portfolios. Turnover is calculated by changes in both long and short positions, assuming the gross leverage of two; thus, the theoretical maximum turnover is 400% when all existing long and short positions are cleared and new positions are taken on different stocks.

Detailed explanations for the construction of these portfolios are as follows.

Monthly rebalanced portfolios

When information is updated every month, arbitragers attempt to use the new information in order to maximize the performance of their trading strategies. Typically, for the hedge portfolios formed on market data (for example, price, volume, returns), portfolios are rebalanced every month. For these portfolios, we construct overlapping portfolios, as in Jegadeesh and Titman (2001), in order to reduce the volatility of portfolio returns as well as transaction costs. At month t, portfolios are formed and held for the following h months (holding period), and in the following month (month t+1), we follow the same procedure again. When this procedure is repeated every month, then at any month (except for the first h-1 and last h-1 months), we have h portfolios formed at t-h, t-h+1, …,t-1. These portfolios are then equally weighted to calculate hedge portfolio returns. The holding period depends on the trading strategies. In our study, we try h=1, 3, and 6 for each of the trading strategies, and use the holding period that provides the best Sharpe ratio for the trading strategy.

Momentum (Mom):In order to minimize the effects of the bid-ask bounce, at the end of each month t, we sort stocks into decile portfolios based on their past eleven month returns from t-11 to t-1, skipping month t (formation period: twelve months), as in Cooper, Gutierrez and Hameed (2004).

Liquidity (Liq): We calculate the measure of illiquidity at the end of every month using daily return and daily trading volume in US dollar. We follow Amihud (2002) for illiquidity measure, $\gamma_{i,m}$:

$$\gamma_{i,m} = \frac{1}{D_{i,m}} \sum_{d=1}^{D_{i,m}} \frac{|r_{i,d.m}|}{v_{i,d.m}},$$

where $D_{i,m}$ is the number of days for which data are available for stock i over the past one year from month m, $r_{i,d.m}$ is the daily stock return of firm i on day d over the past one year from month m, and $v_{i,d.m}$ is the daily trading volume in US dollar for stock i on day d over the past one year from month m. As in Amihud (2002), a stock must have return and volume data for at least 200 days.

Idiosyncratic Volatility (IVol): Following Ang, Hodrick, Xing and Zhang (2006) and George and Hwang (2011), we measure the idiosyncratic volatility of a security i at the end of every month using one prior month of daily returns and Fama-French three factors. It is measured by the standard deviation of the residuals, which is the result of regression for security i's excess return on Fama-French (1992, 1993) three factors.

Market Equity (ME): Market equity is the price times shares outstanding, both of which come from the monthly CRSP data file.

Return on assets (ROA): Return on assets (ROA), defined as in Chen and Zhang (2010), is income before extraordinary (Compustat quarterly IBQ) divided by last quarter's total assets (Compustat quarterly ATQ).

Earnings Surprises (ESur): Following Chan et al. (1996), Standardized Unexpected Earnings (Esur) is defined as the change in quarterly earnings per share (Compustat quarterly EPSPIQ) from its value four quarters ago divided by the standard deviation of the change in quarterly earnings over the prior eight quarters.

Ohlson's O (Osc): We calculate the O-score distress measure, following Ohlson (1980, Model One in Table 4).

Failure Probability (FP): We construct the failure probability, following Campbell et al. (2008, the third column in Table 4).

Annually rebalanced portfolios

For the hedge portfolios which use annual accounting information, we follow Fama and French (1992) by allowing at least a six-month gap between the fiscal year end and portfolio formation. We form portfolios at the end of June of year *t* using previous years' accounting information and hold equally weighted portfolios from July of year t to June of year t+1.

Book to Market Equity (BEME): Book to Market equity is calculated as in Fama and French (1993).

Accruals (Acc): Following Sloan (1996), accrual component is measured as the change in operating working capital divided by total assets.

Asset Growth (AG): Following Cooperr, Gulen, and Schill (2008), the firm asset growth rate for year *t* is calculated as the percentage change in total assets (Compustat AT) from fiscal year ending in calendar year *t*-2 to fiscal year ending in calendar year *t*-1 as below:

$$\mathrm{AG(t)} = \frac{\mathrm{Total\ assets(t-1) - Total\ assets(t-2)}}{\mathrm{Total\ assets(t-2)}}.$$

To compute this measure, a firm must have nonzero total assets in both years, *t*-1 and *t*-2.

Gross profitability premium (GP): Gross profits is defined as total revenue (Compustat REVT) minus cost of goods sold (Compustat COGS), following Novy-Marx (2010).

Net operating assets (NOA): Net operating assets (NOA) are calculated as in Hirshleifer, Hou, Teoh, and Zhang (2004).

$$\mathrm{NOA = (Operating\ Assets - Operating\ Liabilities)/Lagged\ Total\ Assets.}$$

Net stock issues (NSI): Following Fama and French (2008), we measure net stock issues as the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year-end t-1 divided by the split-adjusted shares outstanding at the fiscal year-end in t-2.

Investment to assets (IA): We define investment-to-assets (IA), as in Chen and Zhang (2010). Investment-to-assets is the annual change in gross property, plant and equipment (Compustat PPEGT) plus the annual change in inventories (Compustat INVT) divided by the lagged book value of assets (Compustat AT).

Appendix C Performance of Equity Market Neutral Hedge Portfolios

Table A1 shows that the average hedge portfolio returns are similar to those reported in the literature. For the entire sample period from July 1970 to June 2011, Acc, AG, BEME, IA, NOA, NSI, ROA, ESur and Mom show positive average returns significant at the 5% level, ranging from 0.66% per month (NSI) to 1.09% per month (ESur). As claimed by the authors who investigate these factors, the alphas from the CAPM and the Fama-French three factor model with momentum are not much different from the average returns of these factors.

Other hedge portfolios also show similar results to those of the previous studies. IVol shows a slightly lower average returns than those reported in Harvey and Siddique (2000) and George and Hwang (2011) respectively. As in George and Hwang (2011), the average return of IVol is not significant when the portfolios are equally-weighted; yet, it tends to increase after controlling for risk. The two distress factors, Osc and FP, are not significant, whereas Chen and Zhang (2010) report negative average returns for these two hedge portfolios at the 5% significance level. The main difference is that they calculate these hedge portfolio returns at the formation month, whereas we calculate the returns following the formation. Liq is affected significantly by our choice of universe. By removing the small and illiquid stocks, illiquidity premium disappears.

Annual rebalancing requires far less turnover than monthly rebalancing. At the bottom of Table A1, it is reported that all seven annually rebalanced hedge portfolios need 10% to 26% of turnover, whereas the monthly rebalanced portfolios require a minimum of 53.5% (Osc) to 240.7% (IVol) turnover a month. The hedge portfolios which require more than 100% of turnover are IVol, Mom, and ESur. Although the direct fee to the prime broker is quite small, other trading costs, such as slippage, are not negligible for these hedge portfolios.

Many hedge portfolio returns are highly correlated with others. For example, the correlation coefficient between Liq and ME is 0.84, which is not surprising because small firms are illiquid. We find that ME is closely related to IVol, although IVol is not entirely driven by size (George and Hwang, 2011). The negative correlations between the ROA factor and two distress factors (Osc and FP) and the positive correlation between ME and the two distress factors are consistent with the results reported by Chen, Novy-Marx, and Zhang (2011). Less distressed firms are more profitable with higher expected ROA; therefore, they should earn higher average returns. The positive correlation between ME and the two distress factors indicates that small firms are more distressed. Finally, as expected, the two investment measure, AG and IA, have a high correlation (Chen and Zhang, 2010).

The results of the four sub-periods, i.e., the 1970s, 1980s, 1990s, and 2000s in Tables A2 to A5, respectively, show that the performance of hedge portfolios changes over time. For example, AG shows the highest average monthly return of 1.6% per month in the 1990s, whereas it shows the lowest average monthly return of 0.56% per month in the 1980s. The two distress factors demonstrate dramatic changes: in the 1980s, both show significant negative average returns; however, in the 2000s, they show large positive average returns. Their alphas also show similar patterns.

In order to obtain the overall trend in the performance of our hedge portfolios, we count the numbers of hedge portfolios that show significant average returns. These are 8, 12, 6, and 4 in the 1970s, 1980s, 1990s, and 2000s, respectively. The numbers of significant alphas also show similar patterns. Roughly speaking, the performance of hedge portfolios has been decreasing for the last four decades. Interestingly, for the four sub-periods, the numbers of high correlation coefficients, i.e., larger than 0.5, remain similar, i.e., 31, 29, 35, and 26, respectively. Although different classes of arbitrage trading (Event Driven, Global Macro, Emerging Market, Equity Market Neutral, Fixed Income, etc.) are more correlated in the 2000s than in the 1990s (Lo, 2008), the equity market neutral trading strategies do not show a tendency for stronger correlation in the 2000s within this class.

Descriptive Statistics and OLS Alphas from CAPM, 4-Factor Model for Various Hedge Portfolios.

The basic statistical properties of fifteen hedge portfolios formed on various firm characteristics are reported for the whole periods from July 1970 to June 2011 as well as for the four sub-periods. The data for the construction of hedge portfolios are from the Compustat and CRSP merged data file. For the construction of hedge portfolios, we use all stocks listed in the NYSE, Amex, and NASDAQ, except for the illiquid stocks which are not tradable for arbitrageurs and financial firms whose fundamentals are not directly comparable with those of other firms. For each of the 15 hedge portfolios, we calculate 10 deciles of equal-weighted portfolio returns and then take long-short positions with the long leg being the higher-performing decile and short leg being the lower performing decile. The four factor alpha is calculated with the Fama-French three factors and momentum, which are obtained from Kenneth French's data library. When we estimate alphas with the Fama-French three factors with momentum, we exclude size, book-to-market, and momentum factors for ME, BEME, and Mom, respectively. Monthly turnover for the portfolios that require annual rebalancing at the beginning of July every year is calculated by dividing the annual turnover by 12.

A1. July 1970 - June 2011

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Acc	AG	BEME	GP	IA	NOA	NSI	Osc	ROA	FP	Esur	Liq	ME	Mom	IVol
Means	0.628	1.067	1.077	0.277	0.790	0.747	0.656	0.086	0.818	-0.131	1.093	0.207	0.485	0.956	0.078
t-statistics	6.345	7.307	5.259	1.706	6.515	4.224	4.577	0.445	3.723	-0.408	9.111	0.997	1.877	3.324	0.237
Alpha (CAPM)	0.645	1.092	1.187	0.261	0.832	0.706	0.787	0.044	0.927	-0.608	1.123	0.133	0.419	1.014	0.469
t-statistics	6.055	6.181	5.047	1.410	6.387	3.397	5.583	0.225	4.052	-2.647	11.046	0.665	1.652	3.697	1.670
Alpha (4 factors)	0.547	0.795	1.298	0.269	0.662	0.794	0.473	-0.246	0.729	-0.058	0.968	-0.073	0.552	1.323	0.274
t-statistics	4.559	4.851	5.871	1.600	4.932	4.091	3.901	-1.418	3.384	-0.238	8.453	-0.546	1.973	5.006	1.130
Monthly Turnover	0.259	0.259	0.161	0.100	0.254	0.186	0.249	0.535	0.782	0.789	1.134	0.558	0.702	1.985	2.407
Spearman Rank Correlation															
(2)	0.478														
(3)	0.256	**0.500**													
(4)	-0.192	-0.172	-0.046												
(5)	0.401	**0.750**	0.352	-0.057											
(6)	0.324	0.435	-0.100	-0.126	**0.512**										
(7)	0.096	0.238	0.453	0.358	0.269	-0.109									
(8)	0.139	0.440	0.439	-0.212	0.239	0.063	-0.031								
(9)	-0.159	-0.375	-0.127	0.429	-0.230	-0.324	0.324	**-0.509**							
(10)	0.170	0.397	0.170	-0.240	0.241	0.329	-0.305	**0.679**	**-0.764**						
(11)	-0.018	-0.114	-0.102	0.181	-0.048	-0.041	0.080	-0.319	**0.540**	-0.428					
(12)	-0.018	0.245	0.150	0.040	0.204	0.159	-0.169	**0.606**	-0.303	**0.512**	-0.073				
(13)	0.094	0.449	0.318	-0.013	0.340	0.264	-0.121	**0.723**	-0.457	**0.672**	-0.164	**0.839**			
(14)	0.066	-0.044	-0.173	0.142	0.015	-0.031	0.129	-0.288	0.474	-0.487	0.489	-0.080	-0.273		
(15)	-0.137	-0.263	0.028	0.069	-0.163	-0.344	0.424	**-0.523**	**0.559**	**-0.773**	0.204	**-0.662**	**-0.744**	0.264	

A2. July 1970 - June 1980

	(1) Acc	(2) AG	(3) BEME	(4) GP	(5) IA	(6) NOA	(7) NSI	(8) Osc	(9) ROA	(10) FP	(11) Esur	(12) Liq	(13) ME	(14) Mom	(15) IVol
Means	0.870	0.963	1.038	-0.172	0.837	0.399	0.844	0.108	1.387	-0.629	1.397	0.720	0.989	1.100	-0.401
t-statistics	4.403	3.483	2.308	-0.626	3.136	1.871	3.715	0.218	3.808	-1.114	5.188	1.418	1.503	2.078	-0.637
Alpha (CAPM)	0.909	0.974	0.995	-0.271	0.852	0.394	0.857	0.076	1.394	-0.650	1.430	0.610	0.823	1.158	-0.138
t-statistics	5.594	3.710	2.308	-0.932	3.295	1.657	3.561	0.181	5.187	-1.391	8.675	1.425	1.509	2.612	-0.287
Alpha (4 factors)	0.561	0.412	0.671	-0.130	0.403	0.252	0.343	-0.836	1.562	-1.242	1.537	-0.298	0.607	1.516	0.675
t-statistics	4.031	1.917	1.854	-0.572	1.765	0.996	1.800	-3.320	6.670	-3.566	9.287	-1.265	1.070	3.313	2.503
Turnover	0.261	0.253	0.149	0.088	0.261	0.185	0.246	0.484	0.842	0.779	1.039	0.539	0.608	1.950	2.421
Spearman Rank Correlation															
(2)	0.469														
(3)	0.197	**0.634**													
(4)	-0.035	-0.214	-0.071												
(5)	0.474	**0.856**	**0.592**	-0.108											
(6)	0.464	0.446	0.250	0.282	**0.518**										
(7)	0.372	**0.543**	**0.522**	0.176	**0.520**	0.347									
(8)	0.048	0.366	**0.653**	0.016	0.338	0.041	0.342								
(9)	0.064	-0.382	**-0.555**	0.330	-0.268	0.060	-0.094	-0.410							
(10)	0.022	0.327	**0.622**	0.296	0.323	0.178	0.327	**0.768**	-0.449						
(11)	0.145	-0.192	-0.370	0.132	-0.091	0.048	-0.014	-0.465	**0.657**	-0.477					
(12)	-0.013	0.307	**0.565**	0.264	0.329	0.161	0.315	**0.726**	-0.236	**0.680**	-0.257				
(13)	-0.003	0.317	**0.632**	0.301	0.323	0.158	0.296	**0.768**	-0.354	**0.761**	-0.337	**0.922**			
(14)	0.279	0.007	-0.189	-0.037	0.014	-0.029	0.210	-0.198	**0.543**	-0.419	0.483	-0.172	-0.313		
(15)	-0.057	-0.227	**-0.523**	-0.375	-0.238	-0.210	-0.188	**-0.700**	0.264	**-0.778**	0.281	**-0.793**	**-0.883**	0.256	

A3. July 1980 - June 1990

	(1) Acc	(2) AG	(3) BEME	(4) GP	(5) IA	(6) NOA	(7) NSI	(8) Osc	(9) ROA	(10) FP	(11) Esur	(12) Liq	(13) ME	(14) Mom	(15) IVol
Means	0.295	0.559	0.931	0.879	0.832	0.517	0.896	-0.738	2.055	-1.463	1.660	0.017	-0.124	1.861	1.233
t-statistics	1.582	2.576	2.970	3.708	4.242	3.465	4.737	-2.629	7.612	-4.074	9.271	0.049	-0.310	5.189	3.135
Alpha (CAPM)	0.366	-0.669	1.176	0.791	0.927	0.600	0.994	-0.722	1.987	-1.497	1.602	-0.021	-0.043	1.750	1.493
t-statistics	2.032	2.749	3.877	3.230	4.126	3.643	5.586	-2.199	6.584	-4.087	10.825	-0.052	-0.092	5.419	3.979
Alpha (4 factors)	0.148	0.363	1.259	0.998	0.660	0.469	0.656	-0.990	2.022	-1.353	1.454	0.031	0.147	2.111	1.122
t-statistics	0.744	1.840	4.178	3.713	3.241	3.020	3.466	-3.907	6.556	-4.088	9.950	0.145	0.273	7.304	4.111
Turnover	0.255	0.252	0.157	0.101	0.258	0.190	0.250	0.493	0.814	0.716	1.145	0.527	0.618	1.957	2.401
Spearman Rank Correlation															
(2)	0.496														
(3)	0.423	**0.666**													
(4)	-0.445	-0.349	-0.455												
(5)	0.424	**0.825**	**0.542**	-0.213											
(6)	0.302	**0.535**	0.375	-0.127	**0.557**										
(7)	0.264	**0.502**	**0.529**	0.164	0.428	0.315									
(8)	0.164	0.456	0.368	-0.255	0.325	0.081	0.107								
(9)	-0.236	-0.478	-0.427	0.478	-0.328	-0.177	-0.067	**-0.564**							
(10)	0.153	0.438	0.235	-0.283	0.278	0.070	-0.005	**0.776**	**-0.715**						
(11)	-0.108	-0.078	-0.153	0.267	0.000	0.055	0.006	-0.204	0.457	-0.369					
(12)	-0.206	0.153	-0.041	0.198	0.200	0.120	-0.004	**0.539**	-0.128	0.413	0.068				
(13)	-0.037	0.448	0.244	-0.042	0.398	0.190	0.101	**0.702**	-0.386	**0.610**	-0.013	**0.819**			
(14)	-0.080	-0.223	-0.223	0.406	-0.101	0.038	0.128	-0.318	**0.559**	**-0.562**	**0.529**	-0.019	-0.244		
(15)	0.125	-0.092	0.242	-0.106	-0.033	0.118	0.229	**-0.529**	0.267	**-0.625**	0.003	**-0.650**	**-0.657**	0.209	

A4. July 1990 - June 2000

	(1) Acc	(2) AG	(3) BEME	(4) GP	(5) IA	(6) NOA	(7) NSI	(8) Osc	(9) ROA	(10) FP	(11) Esur	(12) Liq	(13) ME	(14) Mom	(15) IVol
Means	0.788	1.623	0.609	-0.213	1.049	1.769	0.369	0.050	-0.131	0.568	0.860	-0.040	0.372	1.773	-0.530
t-statistics	3.865	4.841	1.506	-0.519	4.568	3.347	1.126	0.124	-0.232	0.993	4.344	-0.083	0.699	3.274	-0.675
Alpha (CAPM)	0.962	1.761	1.161	-0.258	1.194	1.579	0.701	0.177	0.195	0.405	0.876	-0.181	0.481	1.405	0.190
t-statistics	4.325	4.709	2.607	-0.572	5.028	2.707	2.182	0.387	0.325	0.702	5.062	-0.348	0.781	3.250	0.256
Alpha (4 factors)	0.764	1.470	1.502	0.033	0.972	1.351	0.503	0.119	0.011	0.753	0.652	-0.027	0.703	1.712	-0.201
t-statistics	3.189	4.572	3.694	0.081	4.329	3.755	2.012	0.322	0.023	1.552	2.980	-0.089	1.096	4.450	-0.373
Turnover	0.257	0.260	0.166	0.106	0.253	0.190	0.249	0.549	0.757	0.819	1.154	0.581	0.787	1.945	2.254
Spearman Rank Correlation															
(2)	0.474														
(3)	0.212	0.235													
(4)	-0.222	-0.291	-0.139												
(5)	0.484	**0.778**	0.170	-0.145											
(6)	0.300	**0.581**	-0.316	-0.149	**0.530**										
(7)	0.069	-0.094	0.423	0.329	-0.019	-0.354									
(8)	0.183	0.464	0.319	-0.438	0.229	0.109	-0.337								
(9)	-0.127	-0.427	0.199	0.423	-0.227	-0.434	**0.626**	**-0.627**							
(10)	0.169	**0.521**	0.034	-0.412	0.269	0.357	**-0.590**	**0.803**	**-0.837**						
(11)	-0.113	-0.220	0.029	0.270	-0.112	-0.055	0.157	-0.379	**0.563**	-0.442					
(12)	0.086	0.376	-0.091	-0.199	0.272	0.381	**-0.680**	**0.619**	**-0.618**	**0.765**	-0.168				
(13)	0.119	**0.505**	0.093	-0.197	0.367	0.411	**-0.526**	**0.717**	**-0.621**	**0.807**	-0.205	**0.910**			
(14)	0.062	-0.010	-0.391	0.061	0.050	0.178	-0.065	-0.324	0.235	-0.323	0.317	-0.119	-0.278		
(15)	-0.045	-0.371	0.231	0.192	-0.228	-0.451	**0.747**	**-0.576**	**0.787**	**-0.833**	0.331	**-0.847**	**-0.833**	0.191	

A5. July 2000 - June 2011

	(1) Acc	(2) AG	(3) BEME	(4) GP	(5) IA	(6) NOA	(7) NSI	(8) Osc	(9) ROA	(10) FP	(11) Esur	(12) Liq	(13) ME	(14) Mom	(15) IVol
Means	0.567	1.119	1.668	0.585	0.471	0.345	0.528	0.850	0.040	0.801	0.514	0.136	0.685	-0.740	0.017
t-statistics	2.796	3.482	3.686	1.683	1.758	0.888	1.466	2.406	0.086	1.025	1.857	0.441	1.506	-0.990	0.023
Alpha (CAPM)	0.544	1.108	1.686	0.618	0.475	0.316	0.586	0.829	0.111	0.693	0.537	0.127	0.659	-0.661	0.152
t-statistics	2.771	2.725	3.081	1.858	1.638	0.788	1.950	2.336	0.279	1.172	2.122	0.398	1.344	-0.863	0.270
Alpha (4 factors)	0.461	0.706	1.601	0.362	0.322	0.592	0.326	0.344	0.107	0.539	0.599	-0.074	0.686	-0.464	0.221
t-statistics	2.272	2.208	2.914	1.211	1.190	1.645	1.371	1.282	0.436	1.557	3.611	-0.254	1.473	-0.694	0.644
Turnover	0.264	0.269	0.171	0.103	0.247	0.180	0.250	0.600	0.756	0.821	1.153	0.584	0.789	2.078	2.541
Spearman Rank Correlation															
(2)	0.463														
(3)	0.217	0.479													
(4)	-0.066	0.078	0.298												
(5)	0.275	**0.597**	0.180	0.159											
(6)	0.308	0.262	-0.452	-0.383	0.456										
(7)	-0.181	0.131	0.432	**0.632**	0.218	-0.443									
(8)	0.168	0.467	0.411	-0.175	0.173	0.064	-0.085								
(9)	-0.317	-0.262	0.125	**0.531**	-0.171	**-0.592**	**0.587**	-0.409							
(10)	0.314	0.323	-0.004	-0.400	0.181	**0.520**	**-0.541**	0.468	**-0.869**						
(11)	0.020	0.047	0.072	0.095	-0.010	-0.146	0.106	-0.156	0.414	-0.377					
(12)	0.056	0.136	0.136	-0.051	0.029	0.003	-0.224	**0.519**	-0.212	0.253	0.094				
(13)	0.284	**0.521**	0.300	-0.101	0.308	0.284	-0.240	**0.702**	-0.445	**0.556**	-0.065	**0.651**			
(14)	-0.023	-0.001	0.067	0.186	0.032	-0.228	0.213	-0.251	**0.544**	**-0.587**	**0.610**	0.062	-0.226		
(15)	-0.464	-0.308	0.122	0.387	-0.132	**-0.595**	**0.662**	-0.333	**0.762**	**-0.814**	0.169	-0.367	**-0.606**	0.369	

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Table 1 Estimates of time-varying CAPM

This table reports the estimates of the time-varying model in equations (8) and (9), which we estimate using the Bayesian Markov Chain Monte Carlo Gibbs sampler. The estimated time series of alphas, betas, and idiosyncratic volatilities represent the posterior means of 10,000 draws, which we take after 10,000 burn-in iterations. The average represents the average values of the time-series of alphas, betas, and idiosyncratic volatilities, and their standard errors are reported in Standard Error. Constant, AR Coefficient, and Variance of Error Term represent the average values of the 10,000 draws of constants, AR parameters, and idiosyncratic volatility of AR(1) processes for alpha, beta, and idiosyncratic volatility, respectively.

	Acc	AG	BEME	GP	IA	NOA	NSI	Osc	ROA	FP	Esur	Liq	ME	Mom	IVol
Alpha															
Average	0.640	0.890	1.024	0.384	0.752	0.457	0.823	-0.126	1.202	-0.952	1.273	0.002	0.030	1.422	0.957
Standard Error	0.010	0.025	0.021	0.005	0.017	0.018	0.006	0.031	0.023	0.026	0.012	0.022	0.031	0.022	0.029
Constant	0.022	0.030	0.046	0.064	0.030	0.024	0.055	-0.005	0.033	-0.049	0.036	0.000	0.001	0.125	0.034
AR Coefficient	0.965	0.964	0.954	0.835	0.959	0.944	0.933	0.971	0.972	0.949	0.971	0.968	0.965	0.913	0.965
Variance of Error Term	0.014	0.056	0.071	0.047	0.035	0.055	0.017	0.063	0.039	0.098	0.011	0.046	0.113	0.170	0.092
Unconditional Variance	0.195	0.791	0.788	0.154	0.440	0.506	0.131	1.112	0.700	0.993	0.193	0.734	1.638	1.018	1.346
Beta															
Average	-0.045	-0.090	-0.294	0.037	-0.111	0.082	-0.280	0.026	-0.110	0.237	0.015	0.071	0.030	0.045	-0.612
Standard Error	0.007	0.005	0.012	0.008	0.002	0.008	0.010	0.005	0.012	0.010	0.002	0.004	0.004	0.016	0.011
Constant	-0.002	-0.002	-0.007	0.000	-0.013	0.002	-0.003	0.001	-0.002	0.004	0.001	0.005	0.002	0.006	-0.013
AR Coefficient	0.949	0.972	0.974	0.986	0.881	0.982	0.988	0.975	0.986	0.980	0.938	0.923	0.931	0.864	0.978
Variance of Error Term	0.004	0.001	0.006	0.001	0.002	0.002	0.002	0.002	0.003	0.003	0.001	0.004	0.004	0.066	0.004
Unconditional Variance	0.039	0.025	0.124	0.043	0.010	0.050	0.062	0.031	0.093	0.076	0.006	0.027	0.033	0.262	0.101
Idiosyncratic Volatility															
Standard Error	0.019	0.046	0.071	0.054	0.036	0.097	0.044	0.062	0.095	0.105	0.042	0.069	0.090	0.122	0.128
Constant	0.186	0.242	0.241	0.223	0.185	0.120	0.169	0.382	0.269	0.510	0.285	0.360	0.534	0.271	0.457
AR Coefficient	0.820	0.864	0.886	0.890	0.874	0.923	0.890	0.835	0.881	0.804	0.800	0.857	0.817	0.898	0.843
Variance of Error Term	0.216	0.241	0.292	0.183	0.218	0.270	0.207	0.319	0.341	0.580	0.382	0.277	0.393	0.350	0.452
Unconditional Variance	0.660	0.952	1.357	0.882	0.923	1.830	0.996	1.054	1.524	1.641	1.064	1.040	1.181	1.806	1.566
Noise-Signal Ratio	48.730	17.005	19.076	18.931	26.000	33.445	58.461	16.742	39.426	16.686	97.566	22.494	10.476	10.613	17.064

Table 2 Correlation coefficients between confidence measures

The table reports Spearman rank correlation coefficients between confidence of hedge portfolios (c_{pt}^{p} in the lower triangular matrix and c_{pt}^{α} in the upper triangular matrix) and Baker and Wurgler's (2006) market-wide sentiment for the period from July 1970 to June 2011. All of these confidence measures are standardized to have mean zero with unit variance. The first order autocorrelation coefficients are reported in the last row of the table.

	Acc	AG	BEME	GP	IA	NOA	NSI	IVol	Liq	ME	Mom	Osc	ROA	FP	Esur	Sent_BW
Acc	1.000	0.642	0.130	-0.065	0.679	0.400	0.024	-0.503	0.073	0.324	-0.250	0.186	-0.468	0.420	0.120	0.520
AG	0.674	1.000	0.396	0.101	0.806	0.564	0.204	-0.568	0.257	0.606	-0.294	0.335	-0.627	0.683	0.012	0.756
BEME	0.161	0.364	1.000	0.191	0.381	-0.063	0.470	-0.173	0.338	0.501	-0.366	0.516	-0.263	0.331	-0.333	0.563
GP	-0.033	0.039	0.125	1.000	0.139	0.208	0.584	-0.006	0.179	0.151	0.036	-0.015	0.242	-0.083	0.107	0.441
IA	0.743	0.720	0.266	0.142	1.000	0.525	0.191	-0.364	0.078	0.447	-0.283	0.155	-0.518	0.519	-0.051	0.682
NOA	0.451	0.582	-0.024	0.102	0.441	1.000	0.120	-0.213	0.111	0.197	0.173	-0.186	-0.198	0.210	0.297	0.551
NSI	0.005	0.054	0.312	0.501	0.181	0.105	1.000	0.060	0.157	0.135	-0.118	0.013	0.100	-0.025	-0.178	0.482
Osc	-0.493	-0.541	-0.034	0.377	-0.257	-0.213	0.241	1.000	-0.585	-0.803	0.240	-0.684	0.479	-0.657	-0.104	-0.501
ROA	0.203	0.301	0.187	-0.310	0.062	0.151	-0.201	-0.664	1.000	0.791	-0.050	0.691	-0.183	0.340	0.033	0.563
FP	0.354	0.484	0.331	-0.233	0.325	0.108	-0.149	-0.700	0.831	1.000	-0.287	0.797	-0.473	0.671	-0.014	0.711
Esur	-0.289	-0.344	-0.250	0.023	-0.172	0.083	-0.003	0.405	-0.329	-0.423	1.000	-0.385	0.430	-0.405	0.397	-0.052
Liq	0.244	0.340	0.369	-0.428	0.020	-0.059	-0.180	-0.740	0.695	0.715	-0.459	1.000	-0.376	0.599	-0.180	0.437
ME	-0.320	-0.487	-0.197	0.242	-0.274	-0.075	0.375	0.414	-0.241	-0.314	0.418	-0.508	1.000	-0.706	0.343	-0.256
Mom	0.357	0.564	0.197	-0.142	0.219	0.073	-0.270	-0.538	0.315	0.461	-0.442	0.593	-0.739	1.000	-0.167	0.488
IVol	0.147	-0.025	-0.088	0.028	0.089	0.272	0.130	0.012	0.123	0.137	0.298	-0.186	0.604	-0.450	1.000	0.171
Sent_BW	0.084	0.071	0.151	0.459	0.119	0.090	0.250	0.449	-0.452	-0.353	0.136	-0.447	0.113	-0.095	0.020	1.000
Autocorrelation	0.986	0.985	0.983	0.977	0.985	0.986	0.987	0.988	0.989	0.989	0.973	0.985	0.988	0.988	0.993	0.983

Table 3 Overconfidence, trading volume and volatility

This table represents the results of the least-squares dummy variable model for the effect of overconfidence on the trading volume and the log of idiosyncratic volatilities of the fifteen equity market neutral hedge portfolios. Turnover represents turnover difference between the top and bottom decile portfolios and the middle two decile portfolios, which is divided by the total turnover of the universe. Log-volatility (h_{pt}) is obtained from the time varying CAPM in equation (9). Two overconfidence measures (c^{α}_{pt}, c^{p}_{pt}) for individual equity market neutral trading strategies are used: c^{α}_{pt} is the change in alpha over the past 12 months, whereas c^{p}_{pt} is the number of successful forecasts during the past 12 months. Sentiment represents the Baker and Wurgler (2006) index. The sentiment index and the overconfidence measures are standardized to have mean zero and unit variance. LPAR, which we use to control the effects of fund flows on hedge fund returns, represents the average return over the third to fifth months prior to the current month (the (t-3, t-5) window), i.e., $\frac{1}{3}\sum_{\tau=3}^{5}(\alpha_{pt-\tau}+\eta_{pt-\tau})$. In all cases, the least-squares dummy variable model is estimated in the presence of the four control variables, which include one-month Treasury bill rate, term spread (difference between the US ten year and one year Treasury bond rate), credit spread (difference between Moody's Aaa and Baa rated corporate bonds), and dividend yield (dividend yield of S&P500 Index). To conserve space, the estimates on the four control variables and the dummy variables for the fifteen portfolios are not reported. The numbers in parentheses are t-statistics using White cross-section standard errors. The bold numbers represent significance at the 5% level.

		Turnover				Log-volatility			
		c^{p}_{pt}		c^{α}_{pt}		c^{p}_{pt}		c^{α}_{pt}	
1970-1990	Constant	0.163	(1.547)	0.161	(1.536)	**0.059**	(2.029)	0.055	(1.895)
	Turnover					**0.005**	(1.982)	**0.005**	(1.971)
	Turnover (-1)	**0.722**	(38.871)	**0.721**	(38.866)				
	Log-volatility	0.071	(1.588)	0.069	(1.537)				
	Log-volatility (-1)					**0.947**	(51.249)	**0.947**	(50.959)
	Overconfidence	0.000	-(0.022)	-0.009	-(0.738)	**0.005**	(2.138)	0.001	(0.614)
	Sentiment	**0.065**	(3.132)	**0.064**	(3.117)	0.001	(0.092)	0.001	(0.143)
	Alpha	-0.014	-(0.476)	-0.008	-(0.312)	-0.004	-(0.801)	0.002	(0.559)
	LPAR	-0.008	-(0.418)	-0.008	-(0.412)	-0.010	-(1.524)	-0.009	-(1.473)
1990-2000	Constant	0.310	(1.731)	**0.366**	(2.093)	**0.114**	(1.970)	**0.115**	(2.016)
	Turnover					0.000	-(0.005)	0.000	(0.005)
	Turnover (-1)	**0.651**	(25.090)	**0.652**	(25.117)				
	Log-volatility	**0.231**	(2.993)	**0.223**	(2.919)				
	Log-volatility (-1)					**0.971**	(42.833)	**0.970**	(43.306)
	Overconfidence	**-0.049**	-(2.329)	-0.020	-(1.405)	0.002	(0.760)	0.003	(1.374)
	Sentiment	**-0.171**	-(2.233)	**-0.170**	-(2.207)	**-0.050**	-(2.496)	**-0.050**	-(2.476)
	Alpha	0.087	(1.431)	0.010	(0.188)	0.003	(0.351)	0.004	(0.558)
	LPAR	-0.055	-(1.860)	-0.056	-(1.873)	**-0.022**	-(2.217)	**-0.022**	-(2.218)
2000-2011	Constant	0.132	(0.419)	0.117	(0.366)	0.056	(0.583)	0.053	(0.556)
	Turnover					0.001	(0.364)	0.001	(0.364)
	Turnover (-1)	**0.720**	(33.913)	**0.720**	(33.931)				
	Log-volatility	**0.163**	(2.985)	**0.161**	(2.925)				
	Log-volatility (-1)					**0.930**	(37.118)	**0.930**	(37.250)
	Overconfidence	0.017	(0.734)	0.010	(0.503)	-0.005	-(1.227)	-0.005	-(1.860)
	Sentiment	-0.043	-(1.263)	-0.042	-(1.214)	-0.003	-(0.222)	-0.002	-(0.191)
	Alpha	**0.150**	(2.817)	**0.167**	(4.018)	0.004	(0.451)	0.002	(0.273)
	LPAR	-0.033	-(1.302)	-0.032	-(1.290)	0.000	(0.021)	0.000	(0.001)

Table 4 Empirical results for overconfidence

This table reports the results of the least-squares dummy variable model for the temporal profits of the fifteen equity market neutral hedge portfolios, long only portfolios, and short only portfolios. Two overconfidence measures (c_{pt}^{α}, c_{pt}^{p}) for individual equity market neutral trading strategies are used: c_{pt}^{α} is the change in alpha over the past 12 months, whereas c_{pt}^{p} is the number of successful forecasts during the past 12 months. Sentiment represents the Baker and Wurgler (2006) index. The sentiment index and the overconfidence measures are standardized to have mean zero and unit variance. LPAR, which we use to control the effects of fund flows on hedge fund returns, represents the average return over the third to fifth months prior to the current month (the (t-3, t-5) window), i.e., $\frac{1}{3}\sum_{\tau=3}^{5}(\alpha_{pt-\tau}+\eta_{pt-\tau})$. In all cases, the least-squares dummy variable model is estimated in the presence of the four control variables, which include one-month Treasury bill rate, term spread (difference between the US ten year and one year Treasury bond rate), credit spread (difference between Moody's Aaa and Baa rated corporate bonds), and dividend yield (dividend yield of S&P500 Index). To conserve space, the estimates on the four control variables and the dummy variables for the fifteen portfolios are not reported. The numbers in parentheses are t-statistics using White cross-section standard errors. The bold numbers represent significance at the 5% level.

A. Hedge portfolios		c_{pt}^{p}		c_{pt}^{α}	
1970-1990	Confidence (A)	**0.448**	(3.245)	**0.380**	(3.624)
	Sentiment	-0.016	-(0.108)	0.020	(0.138)
	Alpha	0.510	(1.844)	**0.821**	(3.241)
	LPAR	-0.248	-(1.786)	-0.223	-(1.626)
1990-2000	Confidence	**0.824**	(2.492)	**0.585**	(3.068)
	Sentiment	0.040	(0.118)	0.083	(0.257)
	Alpha	1.534	(1.832)	**2.571**	(2.348)
	LPAR	**-0.635**	-(4.943)	**-0.628**	-(5.028)
2000-2011	Confidence (B)	**1.128**	(3.709)	**0.987**	(5.031)
	Sentiment	-0.255	-(1.163)	-0.276	-(1.314)
	Alpha	0.251	(0.554)	**1.080**	(2.650)
	LPAR	**-0.351**	-(2.415)	**-0.322**	-(2.289)
	B-A (p-value)	**0.680**	(0.025)	**0.608**	(0.002)
B. Long only portfolios					
1970-1990	Confidence	**0.309**	(2.752)	**0.237**	(2.626)
	Sentiment	-0.181	-(0.606)	-0.156	-(0.528)
	Alpha	0.265	(1.435)	**0.498**	(3.090)
	LPAR	**-0.545**	-(2.127)	**-0.528**	-(2.069)
2000-2011	Confidence	**0.370**	(2.463)	**0.455**	(3.881)
	Sentiment	0.010	(0.020)	-0.033	-(0.066)
	Alpha	0.395	(1.118)	0.575	(1.894)
	LPAR	**-0.633**	-(2.159)	**-0.622**	-(2.142)
C. Short only portfolios					
1970-1990	Confidence	-0.040	-(0.439)	-0.083	-(1.201)
	Sentiment	-0.159	-(0.785)	-0.164	-(0.798)
	Alpha	-0.272	-(1.866)	**-0.262**	-(2.101)
	LPAR	-0.324	-(1.824)	-0.325	-(1.827)
2000-2011	Confidence	**-0.553**	-(2.470)	**-0.388**	-(2.646)
	Sentiment	0.194	(0.339)	0.177	(0.316)
	Alpha	0.085	(0.249)	-0.425	-(1.767)
	LPAR	-0.388	-(1.273)	-0.399	-(1.301)

Table 5 Self-attribution bias with respect to signs of signals

The results of the least-squares dummy variable model for the temporal profits of the fifteen equity market neutral hedge portfolios are reported. 'Pos Signal' and 'Neg Signal' represent positive and negative signals respectively. Two overconfidence measures (c^{α}_{pt}, c^{p}_{pt}) for individual equity market neutral trading strategies are used: c^{α}_{pt} is the change in alpha over the past 12 months, whereas c^{p}_{pt} is the number of successful forecasts during the past 12 months. Sentiment represents the Baker and Wurgler (2006) index. The sentiment index and the overconfidence measures are standardized to have mean zero and unit variance. LPAR, which we use to control the effects of fund flows on hedge fund returns, represents the average return over the third to fifth months prior to the current month (the (*t*-3, *t*-5) window), i.e., $\frac{1}{3}\sum_{\tau=3}^{5}(\alpha_{pt-\tau}+\eta_{pt-\tau})$. In all cases, the least-squares dummy variable model is estimated in the presence of the four control variables, which include one-month Treasury bill rate, term spread (difference between the US ten year and one year Treasury bond rate), credit spread (difference between Moody's Aaa and Baa rated corporate bonds), and dividend yield (dividend yield of S&P500 Index). To conserve space, the estimates on the four control variables and the dummy variables for the fifteen portfolios are not reported. The numbers in parentheses are t-statistics using White cross-section standard errors. For the difference between two estimates, the numbers in parentheses represent p-values. The bold numbers represent significance at the 5% level.

		c^{p}_{pt}		c^{α}_{pt}	
1970-1990	Pos Signal	**0.032**	(5.582)	**0.036**	(3.983)
	Neg Signal	0.003	(0.309)	**0.028**	(2.183)
	Sentiment	**0.053**	(2.980)	-0.039	-(1.411)
	Alpha	**1.306**	(46.072)	**0.701**	(12.393)
	LPAR	**0.079**	(3.337)	0.036	(0.996)
	Pos-Neg signal (p-value)	**0.029**	(0.003)	0.008	(0.597)
1990-2000	Pos Signal	**0.021**	(3.962)	**0.033**	(3.209)
	Neg Signal	0.008	(1.113)	0.008	(1.031)
	Sentiment	**-0.111**	-(2.887)	**-0.233**	-(4.103)
	Alpha	**1.963**	(20.980)	**0.994**	(7.040)
	LPAR	0.034	(2.972)	0.026	(1.500)
	Pos-Neg signal (p-value)	0.013	(0.094)	**0.025**	(0.005)
2000-2011	Pos Signal	**0.021**	(2.892)	**0.039**	(3.592)
	Neg Signal	**0.024**	(3.995)	**0.035**	(3.470)
	Sentiment	**0.225**	(10.672)	**0.282**	(9.417)
	Alpha	**1.449**	(37.977)	**0.783**	(9.773)
	LPAR	0.029	(1.790)	0.005	(0.213)
	Pos-Neg signal (p-value)	-0.003	(0.752)	0.004	(0.717)

Table 6 Signals, Ambiguity Aversion and Overprecision

Equation (7) is used to estimate the least-squares dummy variable model for the temporal profits of the fifteen equity market neutral hedge portfolios. 'Pos_Con Pos_Sig' represents positive confidence - positive signal, 'Neg_Con Neg_Sig' negative confidence - negative signal, 'Neg_Con Pos_Sig' negative confidence - positive signal, and 'Pos_Con Neg_Sig' positive confidence - negative signal. Two overconfidence measures (c_{pt}^{α}, c_{pt}^{p}) for individual equity market neutral trading strategies are used: c_{pt}^{α} is the change in alpha over the past 12 months, whereas c_{pt}^{p} is the number of successful forecasts during the past 12 months. Sentiment represents the Baker and Wurgler (2006) index. The sentiment index and the overconfidence measures are standardized to have mean zero and unit variance. LPAR, which we use to control the effects of fund flows on hedge fund returns, represents the average return over the third to fifth months prior to the current month (the (*t*-3, *t*-5) window), i.e., $\frac{1}{3}\sum_{\tau=3}^{5}(\alpha_{pt-\tau}+\eta_{pt-\tau})$. In all cases, the least-squares dummy variable model is estimated in the presence of the four control variables, which include one-month Treasury bill rate, term spread (difference between the US ten year and one year Treasury bond rate), credit spread (difference between Moody's Aaa and Baa rated corporate bonds), and dividend yield (dividend yield of S&P500 Index). To conserve space, the estimates on the four control variables and the dummy variables for the fifteen portfolios are not reported. The numbers in parentheses are t-statistics using White cross-section standard errors. For the difference between two estimates, the numbers in parentheses represent p-values. The bold numbers represent significance at the 5% level.

		c_t^p		c_{pt}^{α}	
1970-1990	Pos_Con Pos_Sig	**0.938**	(96.044)	**0.951**	(91.654)
	Neg_Con Neg_Sig	**0.909**	(94.052)	**0.937**	(73.045)
	Neg_Con Pos_Sig	**1.031**	(160.598)	**0.994**	(147.703)
	Pos_Con Neg_Sig	**1.039**	(96.737)	**1.000**	(110.986)
	Sentiment	0.002	(0.347)	0.022	(2.479)
	LPAR	**-0.019**	-(3.008)	**-0.046**	-(4.234)
	Pos_Neg - Neg_Pos (p-value)	0.008	(0.373)	0.006	(0.519)
	Neg_Pos - Pos_Pos (p-value)	**0.093**	(0.000)	**0.043**	(0.000)
	Pos_Neg - Neg_Neg (p-value)	**0.131**	(0.000)	**0.063**	(0.000)
	Pos_Pos - Neg_Neg (p-value)	**0.030**	(0.000)	0.014	(0.198)
1990-2000	Pos_Con Pos_Sig	**0.970**	(184.404)	**0.972**	(238.924)
	Neg_Con Neg_Sig	**0.977**	(180.980)	**0.982**	(231.465)
	Neg_Con Pos_Sig	**1.015**	(267.275)	**1.002**	(213.196)
	Pos_Con Neg_Sig	**1.031**	(255.846)	**1.013**	(152.127)
	Sentiment	**0.067**	(2.329)	0.055	(1.796)
	LPAR	-0.014	-(1.822)	**-0.026**	-(2.899)
	Pos_Neg - Neg_Pos (p-value)	**0.015**	(0.001)	**0.012**	(0.039)
	Neg_Pos - Pos_Pos (p-value)	**0.045**	(0.000)	**0.030**	(0.000)
	Pos_Neg - Neg_Neg (p-value)	**0.054**	(0.000)	**0.031**	(0.000)
	Pos_Pos - Neg_Neg (p-value)	**-0.007**	(0.024)	**-0.010**	(0.001)
2000-2011	Pos_Con Pos_Sig	**0.962**	(115.565)	**0.974**	(155.978)
	Neg_Con Neg_Sig	**0.975**	(127.155)	**0.981**	(161.033)
	Neg_Con Pos_Sig	**1.018**	(205.171)	**0.992**	(171.478)
	Pos_Con Neg_Sig	**1.033**	(127.566)	**1.002**	(170.361)
	Sentiment	0.026	(1.293)	0.021	(1.024)
	LPAR	-0.007	-(0.566)	-0.013	-(0.936)
	Pos_Neg - Neg_Pos (p-value)	0.015	(0.149)	0.009	(0.259)
	Neg_Pos - Pos_Pos (p-value)	**0.055**	(0.000)	**0.019**	(0.017)
	Pos_Neg - Neg_Neg (p-value)	**0.058**	(0.000)	**0.021**	(0.027)
	Pos_Pos - Neg_Neg (p-value)	**-0.012**	(0.002)	-0.007	(0.104)

Table 7 Out-of-sample forecasting performance comparison of portfolios of hedge portfolios

At the end of June every year, we form five equally weighted portfolios from the fifteen hedge portfolios. These portfolios of hedge portfolios are constructed using the entire fifteen hedge portfolios (ENT), hedge portfolios whose alphas are positive at the end of June (A0), hedge portfolios whose alphas are larger than 0.5 at the end of June (A5), hedge portfolios whose annual Sharpe ratios of alphas at June are larger than 0.5 (SRA), and hedge portfolios whose annual Sharpe ratio of realized profits (i.e., average realized profits divided by volatility of realized profits over the last 12 months) are larger than 0.5 at the end of June (SRR). The bold numbers represent significance at the 5% level.

				Alphas						Realized Profits			Raw Returns		
	All (ENT)			Alpha>0.5 (A5)			Annual Sharpe Ratio>0.5 (SRA)			Annual Sharpe Ratio>0.5 (SRR)			Annual Sharpe Ratio>0.5 (SRRR)		
	Raw Return	Alpha	Realized Profits	Raw Return	Alpha	Realized Profits	Raw Return	Alpha	Realized Profits	Raw Return	Alpha	Realized Profits	Raw Return	Alpha	Realized Profits
A. Performance of portfolios of hedge portfolios (PHPs)															
Entire Sample Period (July 1971 - June 2011)															
Mean	**0.596**	**0.588**	**0.631**	**0.999**	**1.053**	**1.044**	**0.992**	**0.986**	**1.029**	**0.775**	**0.888**	**0.789**	**0.819**	**0.868**	**0.823**
Standard Error	0.059	0.007	0.053	0.100	0.008	0.085	0.088	0.008	0.076	0.116	0.014	0.103	0.129	0.016	0.115
Annual Sharpe Ratio	1.588	13.236	1.891	1.580	20.531	1.941	1.779	19.380	2.136	1.055	10.199	1.215	1.004	8.821	1.134
July 1971 - June 1981															
Mean	**0.721**	**0.613**	**0.702**	**1.260**	**1.055**	**1.199**	**1.131**	**1.006**	**1.076**	**1.141**	**1.015**	**1.066**	**1.101**	**0.976**	**1.030**
Standard Error	0.139	0.010	0.131	0.171	0.011	0.140	0.169	0.010	0.140	0.184	0.015	0.156	0.179	0.016	0.154
Annual Sharpe Ratio	1.636	18.715	1.689	2.331	29.352	2.715	2.120	31.658	2.428	1.960	21.741	2.167	1.942	18.827	2.116
July 1981 - June 1990															
Mean	**0.545**	**0.579**	**0.612**	**1.222**	**1.226**	**1.283**	**1.066**	**1.101**	**1.139**	**0.899**	**1.087**	**1.009**	**0.909**	**1.106**	**1.019**
Standard Error	0.094	0.014	0.083	0.141	0.011	0.123	0.129	0.010	0.110	0.143	0.020	0.127	0.148	0.023	0.130
Annual Sharpe Ratio	1.841	13.270	2.335	2.738	34.230	3.294	2.623	34.306	3.274	1.987	17.156	2.512	1.948	15.200	2.481
July 1991 - June 2001															
Mean	**0.646**	**0.658**	**0.728**	**0.954**	**1.070**	**1.116**	**1.093**	**1.030**	**1.214**	**0.741**	**0.854**	**0.890**	**1.032**	**0.888**	**1.155**
Standard Error	0.104	0.008	0.089	0.151	0.009	0.136	0.169	0.013	0.148	0.181	0.021	0.172	0.274	0.025	0.260
Annual Sharpe Ratio	1.967	27.673	2.594	2.001	38.030	2.587	2.045	25.461	2.603	1.296	12.579	1.634	1.191	11.093	1.403
July 2001 - June 2011															
Mean	**0.473**	**0.504**	**0.483**	0.562	**0.861**	**0.580**	**0.675**	**0.807**	**0.686**	0.319	**0.594**	0.190	0.234	**0.504**	0.087
Standard Error	0.132	0.018	0.112	0.294	0.013	0.246	0.224	0.017	0.196	0.357	0.028	0.309	0.367	0.028	0.312
Annual Sharpe Ratio	1.131	8.708	1.364	0.603	21.557	0.745	0.952	15.427	1.105	0.283	6.805	0.194	0.202	5.736	0.088

	All (ENT)			Alphas						Realized Profits			Raw Returns		
				Alpha>0.5 (A5)			Annual Sharpe Ratio>0.5 (SRA)			Annual Sharpe Ratio>0.5 (SRR)			Annual Sharpe Ratio>0.5 (SRRR)		
	Raw Return	Alpha	Realized Profits	Raw Return	Alpha	Realized Profits	Raw Return	Alpha	Realized Profits	Raw Return	Alpha	Realized Profits	Raw Return	Alpha	Realized Profits
B. Tests of PHP performance difference between sub-periods															
Between the 1970s and 2000s															
Mean Difference	**-0.248**	**-0.109**	**-0.219**	**-0.698**	**-0.194**	**-0.618**	**-0.822**	**-0.422**	**-0.876**	**-0.456**	**-0.199**	**-0.391**	**-0.867**	**-0.472**	**-0.942**
t-stat	-14.120	-56.721	-13.879	-22.473	-124.779	-23.923	-22.423	-147.617	-27.730	-17.801	-112.374	-17.755	-23.234	-160.407	-29.666
Between the 1980s and 2000s															
Mean Difference	**-0.072**	**-0.075**	**-0.129**	**-0.660**	**-0.365**	**-0.703**	**-0.580**	**-0.493**	**-0.819**	**-0.391**	**-0.294**	**-0.453**	**-0.675**	**-0.602**	**-0.932**
t-stat	-4.868	-35.830	-10.122	-22.146	-235.415	-27.956	-16.541	-158.498	-26.845	-16.565	-166.159	-22.062	-18.672	-182.777	-30.191
Between the 1990s and 2000s															
Mean Difference	**-0.172**	**-0.154**	**-0.245**	**-0.392**	**-0.209**	**-0.536**	**-0.423**	**-0.261**	**-0.700**	**-0.418**	**-0.223**	**-0.529**	**-0.797**	**-0.384**	**-1.068**
t-stat	-11.219	-85.401	-18.787	-12.991	-148.090	-20.841	-11.572	-81.648	-21.664	-16.288	-116.863	-23.597	-19.058	-111.896	-28.778

Table 8 Effects of Overconfidence on the Performance of Hedge Portfolios

At the end of June every year, we form three equally weighted portfolios using the fifteen equity market neutral hedge portfolios, each of which includes five hedge portfolios depending on the levels of the confidence measures, c_{pt}^{α} and c_{pt}^{p}. These portfolios of hedge portfolios (PHPs) are held for the following one year. The procedure is repeated from June 1971 to June 2010. The bold numbers represent significance at the 5% level.

A. Probability of Successful Forecasts during the Past 12 Months (c_{pt}^{p})

	Low Overconfidence			Middle Overconfidence			High Overconfidence			High - Low Overconfidence		
	Raw Return	Alpha	Temporal Profits	Raw Return	Alpha	Temporal Profits	Raw Return	Alpha	Temporal Profits	Raw Return	Alpha	Temporal Profits
Entire Sample Period (July 1971 - June 2011)												
Mean	-0.177	**0.245**	**-0.404**	**0.765**	**0.610**	0.158	**1.237**	**0.929**	**0.385**	**1.414**	**0.684**	**0.788**
Standard Error	0.153	0.022	0.134	0.102	0.014	0.095	0.134	0.020	0.120	0.245	0.038	0.220
Annual Sharpe Ratio	-3.997	39.304	-10.427	25.943	146.784	27.890	32.061	164.674	11.124	19.997	62.638	12.432
Proportions to Raw Returns											48%	56%
July 1971 - June 1981												
Mean	-0.244	-0.051	-0.141	**0.817**	**0.696**	0.116	**1.412**	**1.184**	0.235	**1.656**	**1.236**	0.376
Standard Error	0.154	0.030	0.140	0.122	0.021	0.113	0.171	0.024	0.150	0.250	0.049	0.220
Annual Sharpe Ratio	-5.503	-5.857	-3.471	23.263	113.400	24.991	28.685	172.901	5.445	22.991	87.068	5.919
Proportions to Raw Returns											75%	23%
July 1981 - June 1991												
Mean	-0.234	**0.565**	**-0.812**	**0.800**	**0.589**	0.262	**1.359**	**0.817**	**0.752**	**1.593**	**0.251**	**1.564**
Standard Error	0.429	0.025	0.394	0.258	0.021	0.249	0.351	0.029	0.325	0.746	0.051	0.689
Annual Sharpe Ratio	-1.889	77.644	-7.142	10.733	97.378	11.849	13.424	96.484	8.019	7.398	17.194	7.866
Proportions to Raw Returns											16%	98%
July 2001 - June 2011												
Mean	0.009	**0.488**	**-0.496**	**0.629**	**0.468**	0.132	**0.782**	**0.556**	0.301	**0.773**	**0.069**	**0.797**
Standard Error	0.298	0.021	0.216	0.198	0.028	0.177	0.208	0.025	0.178	0.363	0.032	0.286
Annual Sharpe Ratio	0.101	81.000	-7.952	11.013	56.932	11.765	13.050	76.124	5.862	7.373	7.510	9.639
Proportions to Raw Returns											9%	103%

B. Change in Alpha over the Past 12 Months (c^{α}_{pt})

	Low Overconfidence			Middle Overconfidence			High Overconfidence			High - Low Overconfidence		
	Raw Return	Alpha	Temporal Profits	Raw Return	Alpha	Temporal Profits	Raw Return	Alpha	Temporal Profits	Raw Return	Alpha	Temporal Profits
Entire Sample Period (July 1971 - June 2011)												
Mean	-0.103	**0.413**	**-0.482**	**0.622**	**0.531**	0.123	**1.301**	**0.844**	**0.487**	**1.404**	**0.430**	**0.969**
Standard Error	0.144	0.022	0.126	0.114	0.014	0.095	0.133	0.020	0.121	0.235	0.038	0.213
Annual Sharpe Ratio	-2.472	65.330	-13.222	18.976	127.151	4.491	33.883	145.220	13.940	20.734	38.752	15.759
Proportions to Raw Returns											31%	69%
July 1971 - June 1981												
Mean	0.047	**0.384**	**-0.282**	**0.518**	**0.467**	0.083	**1.405**	**0.985**	**0.387**	**1.358**	**0.602**	**0.669**
Standard Error	0.141	0.037	0.123	0.131	0.020	0.114	0.173	0.035	0.157	0.252	0.069	0.223
Annual Sharpe Ratio	1.162	35.943	-7.967	13.759	81.417	2.508	28.132	97.295	8.541	18.701	30.290	10.386
Proportions to Raw Returns											44%	49%
July 1981 - June 1991												
Mean	-0.475	**0.448**	**-0.828**	**1.067**	**0.747**	0.301	**1.345**	**0.779**	**0.737**	**1.819**	**0.331**	**1.565**
Standard Error	0.391	0.035	0.360	0.282	0.022	0.235	0.318	0.026	0.307	0.665	0.054	0.634
Annual Sharpe Ratio	-4.209	44.886	-7.957	13.115	119.426	4.438	14.646	105.840	8.310	9.474	21.303	8.554
Proportions to Raw Returns											18%	86%
July 2001 - June 2011												
Mean	-0.016	**0.434**	**-0.515**	0.375	**0.439**	0.023	**1.060**	**0.639**	**0.429**	**1.076**	**0.205**	**0.944**
Standard Error	0.303	0.034	0.241	0.233	0.028	0.190	0.247	0.020	0.202	0.411	0.041	0.330
Annual Sharpe Ratio	-0.181	43.659	-7.407	5.578	54.187	0.422	14.871	110.677	7.373	9.069	17.161	9.904
Proportions to Raw Returns											19%	88%

Figure 1 Cumulative alphas and realized profits of hedge portfolios

Cumulative realized profits and alphas are presented in log-scale under the assumptions that the initial AUM is 100 with a gross leverage of two, and that the returns are reinvested.

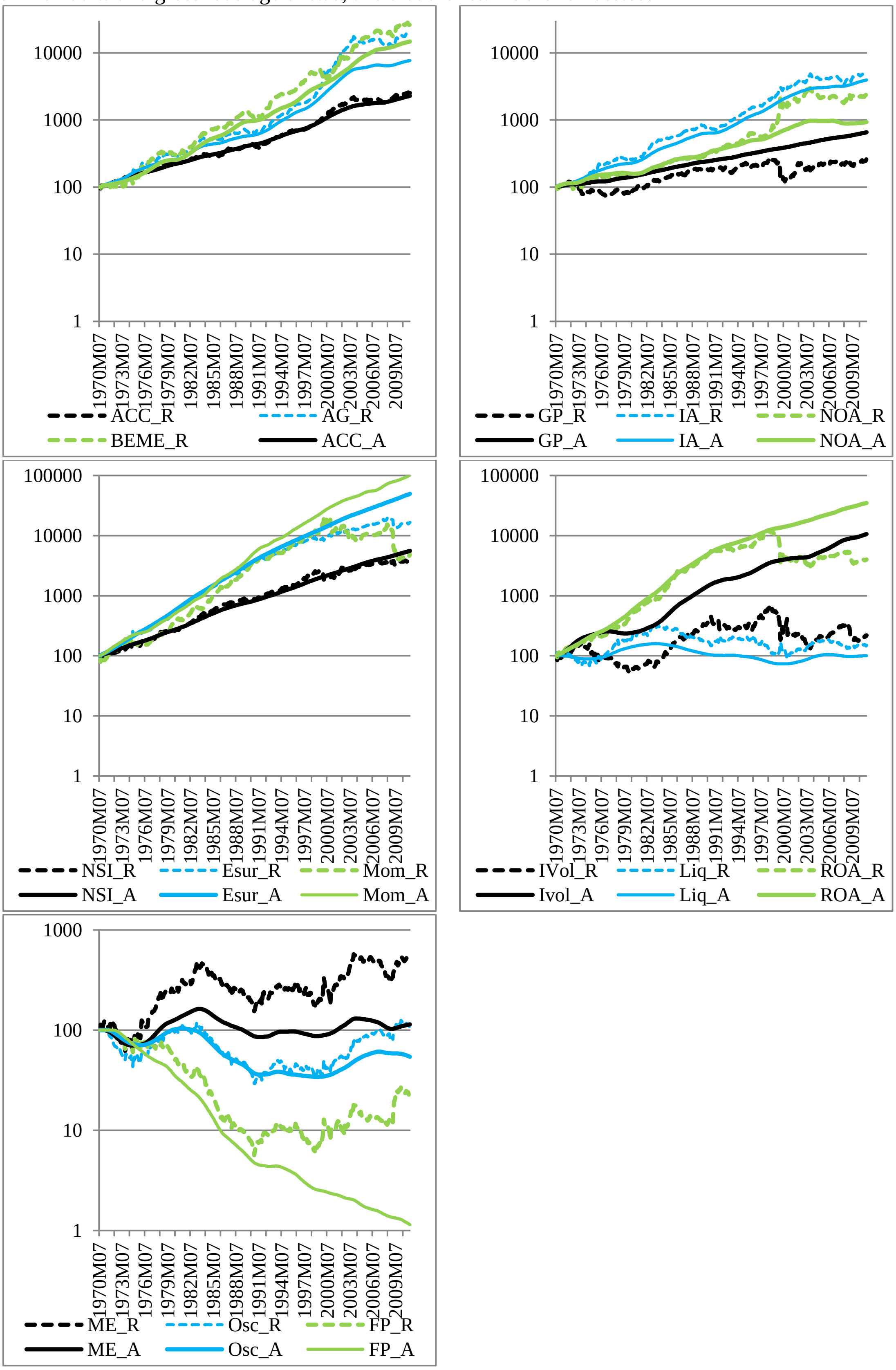

Figure 2 Cumulative Autoregressive Coefficients of Temporal Profits

The temporal profits of the fifteen equity market neutral hedge portfolios are regressed on their own lagged variables in the least-squares dummy variable model. As control variables, we use LPAR and four macroeconomic variables. LPAR represents the average return over the third to fifth months prior to the current month (the (t-3, t-5) window), i.e., $\frac{1}{3}\sum_{\tau=3}^{5}(\alpha_{pt-\tau}+\eta_{pt-\tau})$, which we use to control the effects of fund flows. The four macroeconomic variables include the one-month Treasury bill rate, term spread (difference between the US ten year and one year Treasury bond rate), credit spread (difference between Moody's Aaa and Baa rated corporate bonds), and dividend yield (dividend yield of S&P500 Index). The coefficients on the lags are then cumulated. TP represents 'temporal profit' and the numbers in the round brackets represent lags.

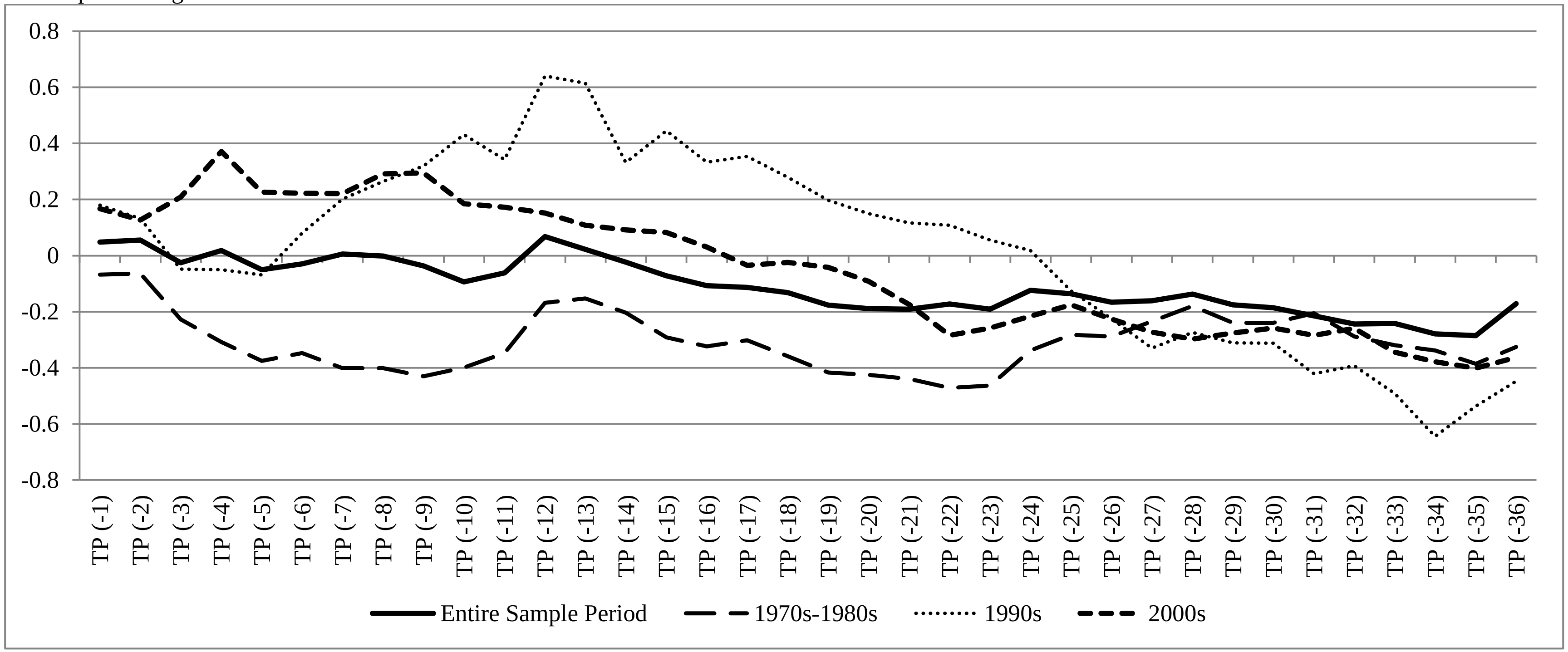

Figure 3 Cumulative alphas and realized profits of the five out-of-sample portfolios of hedge portfolios

At the end of June every year, we form equally weighted portfolios from the fifteen hedge portfolios. These portfolios of hedge portfolios are constructed using the entire fifteen hedge portfolios (ENT), hedge portfolios whose alphas are larger than 0.5 at the end of June (A5), hedge portfolios whose annual Sharpe ratio of realized profits (i.e., average realized profits divided by volatility of realized profits over the last 12 months) are larger than 0.5 at the end of June (SRR), and hedge portfolios whose annual Sharpe ratio of raw returns (i.e., average raw return divided by volatility of raw returns over the last 12 months) are larger than 0.5 at the end of June (SRRR).