Overconfidence in Cross-sectional Asset Returns

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Abstract

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Keywords: Overconfidence, Contrarian behavior, Response to Signal
JEL codes: G02, G12.

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I investigate the effects of overconfidence on cross-sectional asset returns by observing investors' responses to market-wide and firm-specific signals. My empirical results show that investors' overconfidence is more likely to occur for mature firms that are relatively easy to price: i.e. large firms, value firms, dividend-paying firms, firms with more tangible assets, firms with little external financing, and firms with low sales growth. I also find that the effects of investors' overconfidence on returns are reversed without delay. Therefore, large unexpected responses to signals by overconfident investors explain a significant proportion of short-term return reversals. The average return reversal due to overconfidence is over 1.2% per month for the past four decades and still significant despite the active arbitrage trading in the 2000s.

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1. Introduction

Theoretical and empirical studies have extensively documented that overconfidence affects asset prices.[1] However, less known are its empirical effects on cross-sectional asset returns: the characteristics of firms that are affected by overconfidence; how much asset returns are affected by overconfidence; how fast these biases are subsequently corrected; and if other existing cross-sectional return patterns can explain the effects of overconfidence on asset returns. I fill the gap in the literature by answering these questions when overconfidence is defined as over-precision in signals as in Odean (1999), Daniel, Hirshleifer, and Subrahmanyam (DHS) (1998, 2001), and Epstein and Schneider (2008).

For this purpose, I propose a simple measure for how investors respond to signals during their Bayesian updating process. It shows whether investors respond too much or too little to signals, and whether they respond to or against what the signals suggest. When investors over-respond (under-respond) to signals, overconfidence (underconfidence) arises whether the responses are positive or negative. On the other hand, momentum (contrarian) to signals can be observed when investors positively (negatively) respond to signals regardless of the magnitudes of the responses. Therefore, momentum-overconfidence behavior can be observed when investors positively over-respond to signals, whereas contrarian-overconfidence behavior arises when they respond too much against what the signal suggests.

The response to signal is estimated for non-penny and non-financial stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ from July 1967 to June 2011. Four types of signals are considered in order to investigate whether or not investors respond differently to these types of signals: i.e., macroeconomic variables, Fama-French three factors and momentum, five factors from principal component analysis, and seven firm-specific characteristics. The responses to these signals and their effects on cross-sectional returns are analyzed using monthly Fama-MacBeth regression with individual stocks as well as portfolios formed on the signals and the responses to the signals.

I find that overconfidence is prevalent in equity markets regardless of investors' momentum or contrarian behavior. Investors believe that their signals are less noisy

[1] For example, De Long et al. (1991), Griffin and Tversky (1992), Odean (1998), Daniel, Hirshleifer, and Subrahmanyam (1998, 2001), Gervais and Odean (2001), Chuang and Lee (2006), Moore and Healy (2008), Barone-Adesi, Mancini, and Shefrin (2013), and Hwang, Hwang and Noh (2015).

than they actually are. Their perceived confidence intervals for signals are on average half of the true confidence interval, which is similar to the survey results of Merkle (2013). I also find that the proportion of contrarian behavior is significant: approximately one-third of stocks move against what the signals suggest. In fact, the two extreme cases, i.e., momentum-overconfidence and contrarian-overconfidence, are widespread in equity markets, distorting cross-sectional stock returns and causing large subsequent return reversals.

Interestingly, investors tend to be overconfident for large stocks, value stocks, dividend-paying stocks, stocks with large tangible assets, stocks with little external financing, and stocks that show low sales growth. These stocks have the characteristics of mature firms that have long operating histories and are well known by investors and analysts (Benartzi, Michaely, and Thaler, 1997; Berger and Udell, 1998; Grullon, Michaely and Swaminathan, 2002; De Angelo, De Angelo and Stulz, 2006; Bulan, Subramanian and Tanlu, 2007; Bulan and Yan, 2010). For an explanation of why overconfidence is observed in mature firms, I propose the overconfidence of institutional investors. If market experts are more overconfident than novices (De Long et al., 1991; Griffin and Tversky, 1992; Odean, 1998), then the stocks they trade will be affected by their overconfidence. Gompers and Metrick (2001), Bennett et al. (2003), and Yan and Zhang (2009) show that institutional investors indeed prefer large stocks, value stocks, or stocks with a superior past performance and a long listing history. The valuation of mature firms may also appear to be relatively easy with fewer problems of information asymmetry between managers and investors (Easley and O'Hara, 2004), which make investors over-place themselves relative to others.

The empirical results also show that the dynamics of the responses to signals are consistent with the results in the behavioral finance literature, in that overconfidence arises as past performance increases (Gervais and Odean, 2001; Statman, Thorley, Vorkink, 2006). Investors' confidence increases when the economy is in a good condition and outcomes have improved, when term spread increases since it predicts the economic outlook (Wheelock and Wohar, 2009), or when dividends or momentum increases (Chui, Titman and Wei, 2010). On the other hand, confidence decreases when the credit spread increases (Philippon, 2009). It also decreases as Baker and Wurgler's (2006) sentiment increases, indicating that overconfidence is not likely to happen when sentiment is high. This finding is consistent with the cross-sectional result that overconfidence and sentiment affect different types of stocks, i.e., mature stocks vs. stocks that are difficult to price, respectively.

Most effects of overconfidence on stock prices, however, are reversed immediately after overconfidence arises. Therefore, the type of overconfidence I investigate in this study, i.e., over-precision, is less likely to be responsible for anomalies such as a size or value anomaly (Banz, 1981; Rosenberg, Reid, Lanstein, 1985; Lakonishok, Shleifer, Vishny, 1994; DHS, 1998, 2001), which last for considerable periods of time after the formation of portfolios. Instead, the immediate return reversals are closely related to the short-term return reversals of Jegadeesh (1990) and Lehmann (1990). When the short-run return reversals are decomposed into those from overconfidence and the others, I find that nearly half of the short-term return reversals can be explained by the return reversals following overconfidence.

Therefore, the return reversals due to overconfidence can be interpreted as a reward for rational investors who provide liquidity to overconfident institutional investors (Campbell, Grossman and Wang, 1993; Nagel, 2012; Cheng, Hameed, Subrahmanyam, and Titman, 2014). If institutional investors are overconfident (De Long et al., 1991; Griffin and Tversky, 1992; Odean, 1998; Hwang, Hwang, Noh, 2015), their over-responses to signals cause intense buying or selling. These results are consistent with the increase in short-term return reversals for stocks whose institutional holdings decrease (Cheng, Hameed, Subrahmanyam, and Titman, 2014). The short-term return reversals are profits that rational investors earn from their arbitrage trading, which are at the same time the cost of the irrationality that the overconfident experts should pay. Intense trading by institutional investors affects illiquid assets more than liquid assets, and thus a larger compensation is generated for assets that are less liquid (Campbell, Grossman, and Wang, 1993; Avramov, Chordia and Goyal, 2006).

The bias in cross-sectional stock returns created by overconfidence is large and statistically significant. The four-factor risk-adjusted return reversals (Fama-French three-factor and momentum) of hedge portfolios formed on two independent sorts on the responses to signals and the signals range from 1.2% to 1.5% per month, depending on the portfolio formation methods and signals. For the three sub-periods of the 1970s and 1980s, the 1990s, and the 2000s, the alphas are all statistically and economically significant, and these return reversals are not subsumed by the fifteen firm characteristic factors, e.g., size (Banz, 1980; Fama and French, 1992, 1993), momentum (Jegadeesh and Titman, 1993, 2001), book-to-market ratio (Rosenberg, Reid and Lanstein, 1985;

Fama and French, 1992, 1993), accruals (Sloan, 1996), asset growth (Cooper, Gulen, and Schill, 2008), investment to assets (Chen and Zhang, 2010), net stocks issues (Fama and French, 2008), liquidity (Amihud, 2002), and idiosyncratic volatility (Ang, Hodrick, Xing and Zhang, 2006; George and Hwang, 2011). These empirical results are robust under various conditions, including a bid-ask bounce, January effects, size and portfolio breakpoints, liquidity, market-wide factors, learning periods, and prediction horizons.

Signals in this study are firm specific or common to all firms and are available to investors who try to predict returns from their past experience. Therefore, the results are not specific to certain events, e.g., dividends or earnings announcements as in Kaniel, Liu, Saar, and Titman (2012). In addition, my results show a clear difference between the effects of overconfidence and sentiment on cross-sectional asset pricing, even though both sentiment and overconfidence affect stock prices. Baker and Wurgler (2006) show that stocks that are difficult to price are more likely to be affected by sentiment. Therefore, if excessive optimism is a driving force of sentiment (Barone-Adesi, Mancini, Shefrin, 2013), it affects stocks that are difficult to arbitrage (Stambaugh, Yu, and Yuan, 2012). Overconfidence is related to experts' expertise (Griffin and Tversky, 1992) and thus affects stocks that such experts actively trade. The characteristics of firms for which sentiment and overconfidence arise are mutually exclusive.

This paper is organized as follows. In the following section, I model investors' responses to signals, from which a measure is proposed for the magnitude and direction of their responses. In Section 3, the empirical tests show the properties of the responses to signals and how stock returns respond to overconfidence and contrarian behavior. Finally, Section 4 provides the conclusion.

2. Responses to signals and cross-sectional asset returns

Suppose that investors predict returns using signals available to them. I propose a measure that represents investors' responses to these signals in a Bayesian framework similar to the one used by DHS (1998) and Epstein and Schneider (2008). This measure can capture investors' rational response as well as behavioral biases such as overconfidence and contrarian behavior.

2.1 Bayesian prediction with signals

Following the CAPM, suppose that the excess return of asset *i* can be presented as follows

$$r_{it}=\beta_i r_{mt} + \epsilon_{it}, \tag{1}$$

where β_i is the systematic risk of asset i, r_{mt} is the excess market return, and ϵ_{it} represents an idiosyncratic shock (payoff) that affects only asset i, $\epsilon_{it} \sim N(0, \sigma_{\epsilon_i}^2)$. The excess market return consists of a market risk premium, μ_m, and a shock:

$$r_{mt} = \mu_m + \epsilon_{mt}, \tag{2}$$

where $\epsilon_{mt} \sim N\left(0, \sigma_{\epsilon_m}^2\right)$.

At time *t*, investors receive signals to predict ϵ_{mt+1} and ϵ_{it+1} in a similar way to those of DHS (1998), Epstein and Schneider (2008), and Hwang et al. (2015). The signal for the market portfolio consists of a shock on the future payoff at time *t*+1 and noise at time *t*:

$$s_{mt} = \epsilon_{mt+1} + \varepsilon_{mt},$$

where $\varepsilon_{mt} \sim N(0, \sigma_{\varepsilon_m}^2)$ represents the noise. The signal for the idiosyncratic payoff can be obtained from various factors that have been discussed in the literature to predict individual asset returns.[2] Suppose that f_{kt} is one of these factors, which can be decomposed into a shock (ϵ_{kt+1}) and noise (ε_{kt}): $f_{kt} = \epsilon_{kt+1} + \varepsilon_{kt}$, where $\epsilon_{kt+1} \sim N\left(0, \sigma_{\epsilon_k}^2\right)$ and $\varepsilon_{kt} \sim N(0, \sigma_{\varepsilon_k}^2)$. Here ϵ_{kt+1} represents the information that can be used to predict the idiosyncratic payoffs of individual assets, and thus $cov(f_{kt}, \epsilon_{it+1}) = cov(\epsilon_{kt+1}, \epsilon_{it+1}) = \rho_{ik}\sigma_{\epsilon_i}\sigma_{\epsilon_k}$, where ρ_{ik} is the correlation coefficient between ϵ_{kt+1} and ϵ_{it+1}. With K such factors, the signal appears as:

$$s_t = \sum_{k=1}^{K} f_{kt} = \sum_{k=1}^{K} \epsilon_{kt+1} + \sum_{k=1}^{K} \varepsilon_{kt}.$$

As in DHS (2001), neither the shocks nor the noises of s_t are assumed to be correlated to those of the market portfolio, i.e., $cov(\epsilon_{mt}, \epsilon_{ikt}) = 0$ and $cov(\varepsilon_{mt}, \varepsilon_{ikt}) = 0$ for all k. As in the typical factor model, the factors are assumed to be orthogonal to each other, i.e., $cov(f_{kt}, f_{lt}) = 0$ for $k \neq l$. For investors, the state of the world is presented by (r_{mt}, r_{it}, s_{mt}, s_t), and investors' belief about r_{it+1} is decided by their posteriors about ϵ_{mt} as well as ϵ_{it} given s_{mt} and s_t whose variances are unknown to investors.

[2] For example, see Harvey, Liu, and Zhu (2014) for a comprehensive summary of these factors in the literature.

Upon receiving these signals, investors apply Bayes' rule to update their prior beliefs. In order to investigate the effects of investors' psychological biases on cross-sectional asset returns, I focus on risk-adjusted returns.[3] With the posterior of the market return, $E[r_{mt+1}|s_{mt}] = \mu_m + \frac{\sigma^2_{\epsilon_m}}{\sigma^2_{\epsilon_m}+\sigma^2_{\varepsilon_m}} s_{mt}$, the posterior expectation of asset i's risk-adjusted return becomes

$$E[r^A_{it+1}|I_t] = \sum_{k=1}^{K} \frac{\rho_{ik}\sigma_{\epsilon_k}/\sigma_{\epsilon_i}}{1+\lambda^2_{ik}} f_{kt}, \tag{3}$$

where $r^A_{it+1} = r_{it+1} - \beta_i r_{mt+1}$ is the risk-adjusted return, $I_t = \{s_{it}, s_{mt}\}$, and $\lambda^2_{ik} = \frac{\sigma^2_{\varepsilon_{ik}}}{\sigma^2_{\epsilon_i}}$. The impact of f_{kt} on the expected risk-adjusted return, i.e., φ_{ik}, is in fact the regression coefficient of the risk-adjusted return on factor f_{kt}, i.e., $r^A_{it+1} = \alpha_i + \sum_{k=1}^{K} \varphi_{ik} f_{kt} + \eta_{it+1}$, where $\varphi_{ik} = \frac{\rho_{ik}\sigma_{\epsilon_k}/\sigma_{\epsilon_i}}{1+\lambda^2_{ik}}$ and $\eta_{it+1} \sim N(0, \sigma^2_{\eta_i})$.

The R-squared value of this regression is typically small, indicating that λ^2_{ik} is very large (or φ_i is small). For example, Goyal and Welch (2008) and Kelly and Pruitt (2013) report that most factors proposed in the literature have R-squared values less than 1% for the prediction of the market return. For individual stocks, the factors that are tested in this study contribute less than 2% of the R-squared value, regardless of the types of signals.[4] Then, with the approximation $\frac{1}{1+\lambda^2_{ik}} \approx \lambda^{-2}_{ik}$, the posterior expectation (3) becomes

$$E[r^A_{it+1}|I_t] \approx \sum_{k=1}^{K} \lambda^{-2}_{ik} \rho_{ik}\sigma_{\epsilon_k}/\sigma_{\epsilon_i} f_{kt}, \tag{4}$$

with a posterior variance approximated as

$$var[r^A_{it+1}|I_t] \approx \sum_{k=1}^{K} \lambda^{-4}_{ik} (\rho_{ik}\sigma_{\epsilon_k}/\sigma_{\epsilon_i})^2 var(f_{kt}). \tag{5}$$

Equation (4) shows how the Bayesian optimizers rationally form their expectations on the risk-adjusted return (idiosyncratic payoff) using a signal. Note that $\lambda^{-2}_{ik}\rho_{ik}\sigma_{\epsilon_k}/\sigma_{\epsilon_i}$ is an approximate factor loading on factor k for the forecast of asset

[3] Empirically, betas are correlated with other firm characteristics (e.g., Fama and French, 1992; Lin and Zhang, 2013). Therefore, by controlling betas, we can focus on the net contribution of signals to asset returns. The effects of behavioral biases on the systematic risk have been investigated by Hwang and Salmon (2015).

[4] For example, the R-squared values of the risk-adjusted returns of individual assets on the four macroeconomic variables that are widely used in the literature (i.e., risk-free rate, credit spread, term spread, and dividend yield) are on average 0.076. Those on the seven firm characteristics I test (book-to-market, asset growth, accruals, net stock issue, size, total volatility, and illiquidity) are on average 0.114. See Table 1 for details.

i's risk-adjusted return, and thus $\sum_{k=1}^{K} \lambda_{ik}^{-2} \rho_{ik} \sigma_{\epsilon_k} / \sigma_{\epsilon_i} f_{kt}$ can be interpreted as the expected return predicted by the signal (ERS).

2.2 Irrational response to signal and biases in asset returns

Suppose that overconfidence appears in the form of overprecision, as described in Odean (1998), DHS (1998, 2001), Gervais and Odean (2001), and Epstein and Schneider (2008). For example, when investors' prior beliefs are confirmed by a signal, they are likely to overestimate the precision of the signal by under-estimating the variance of the noise, $\sigma_{\varepsilon_{ik}}^2$. For simplicity, let us assume that overprecision occurs in the same way for all factors included in the signal, and δ_{it} be a variable that represents the bias in the precision of the signal such that the variance of the noise perceived by investors can be represented as $\sigma_{\varepsilon_{ik}}^2 / \delta_{it}$. When $\delta_{it} > 1$ ($1 > \delta_{it} > 0$), the variance of the noise is underestimated (overestimated) and overprecision (underprecision) occurs. On the other hand, when $\delta_{it} = 1$, investors update their expectations in a rational way.

With this response-to-signal (RS) variable, δ_{it}, the posterior expectation in Equation (4) appears as:

$$E^b[r_{it+1}^A | I_t] \approx \delta_{it} s_{it}^* \tag{6}$$

$$var^b[r_{it+1}^A | I_t] \approx \delta_{it}^2 var(s_{it}^*) \tag{7}$$

where b represents a bias in the expectation due to overprecision or underprecision, and $s_{it}^* = \sum_{k=1}^{K} k_{ik}^{-2} \rho_{ik} \sigma_{\epsilon_k} / \sigma_{\epsilon_i} f_{kt}$ is ERS. Equation (6) clearly shows that when $\delta_{it} > 1$, overprecision occurs and s_{it}^* is weighted more than it should be. On the other hand, when $1 > \delta_{it} > 0$, s_{it}^* is weighted less than it should be, which is dubbed 'under-confidence' in this study. If a self-attribution bias exists in the equity market, as in DHS (1998), δ_{it} is expected to be larger for positive s_{it}^*s than for negative s_{it}^*s because of the positive net supply of equity. The approximation in Equation (7) shows that overconfidence also increases the posterior variance.

Contrarian behavior can also be captured by allowing a negative δ_{it}. A negative δ_{it} indicates investors' contrarian behavior with respect to ERS: investors' posterior expectations become positive for negative s_{it}^*s and negative for positive s_{it}^*s. This 'signal-contrarian' behavior is not specific to certain events as in Kaniel, Liu, Saar, Titman (2012), and is also different from contrarian trading that simply sells overpriced assets or buys underpriced assets (Jegadeesh, 1990; Lehmann, 1990; Lakonishok, Shleifer, and Vishny, 1994). A negative δ_{it} represents investors' irrational response to

ERS. When this signal-contrarian behavior is combined with overconfidence, $\delta_{it} < -1$ is referred to as 'contrarian-overconfidence'. Likewise, $-1 < \delta_{it} < 0$ can be named as 'contrarian-underconfidence'.

In contrast to this signal-contrarian behavior, $\delta_{it} > 0$ can be called 'signal-momentum' since the posterior expectation has the same sign as that of s_{it}^*: investors expect a positive risk-adjusted return upon receiving a positive s_{it}^* and a negative risk-adjusted return from a negative s_{it}^*. Therefore, the two signal-momentum cases, i.e., $\delta_{it} > 1$ and $1 > \delta_{it} > 0$, can be referred to as 'momentum-overconfidence' and 'momentum-underconfidence', respectively.

The RS variable δ_{it} describes the way that investors respond to ERS: i.e., rational behavior when $\delta_{it} = 1$, or irrational biases depending on the value of δ_{it} (contrarian or momentum behavior as well as underconfidence or overconfidence). An absolute value of δ_{it} represents investors' perception of the precision of the signal regardless of momentum or contrarian behavior, and thus increases with confidence. On the other hand, the sign of δ_{it} represents momentum or contrarian behavior regardless of the perception of the precision. Summarizing, the effects of RS on the posterior expectation depend on the sign of ERS as follows:

	$s_{it}^* < 0$	$s_{it}^* > 0$
$\delta_{it} < -1$	positive bias (contrarian-overconfidence)	negative bias (contrarian-overconfidence)
$1 > \delta_{it} > -1$	Under-response to signal	
$\delta_{it} > 1$	negative bias (momentum-overconfidence)	positive bias (momentum-overconfidence)

Therefore, without considering ERS, RS alone may not show any difference in cross-sectional asset returns since positive and negative biases may be cancelled out. RS conditional on ERS would show differences in the cross-sectional asset returns.

The two extreme cases of overconfidence – momentum-overconfidence and contrarian-overconfidence – are more likely to affect the posterior expectation than those of underconfidence, because δ_{it} is either positively or negatively unbounded. Therefore, in empirical studies, under-reaction may appear less clear than that of overreaction (Fama and French, 1996).

2.3 Return reversals subsequent to irrational response to a signal

The effects of irrational responses to signals on asset returns are expected to be subsequently reversed (De Bondt and Thaler, 1985; Barberis, Shleifer and Vishny, 1998;

Daniel, Hirshleifer and Subrahmanyam, 1998, 2001; Baker and Wurgler, 2006; Hwang and Rubesam, 2013). This behavioral explanation for return reversals has been treated differently from the liquidity provision explanation for short-term return reversals. According to the liquidity provision explanation, short-term return reversals are compensation for providing liquidity to institutional (informed) investors who require intense buying or selling due to exogenous shocks or non-informational trading (Campbell, Grossman and Wang, 1993; Nagel, 2012; Hameed and Mian, 2014; Cheng, Hameed, Subrahmanyam and Titman, 2014).

However, return reversals following behavioral biases are not necessarily inconsistent with the liquidity provision theory, because overconfidence could trigger non-informational trading: the exogenous shocks or non-informational trading by institutional investors may reflect their irrational responses to signals. As is well-known in the literature, if experts are more overconfident than novices (De Long et al., 1991; Griffin and Tversky, 1992; Odean, 1998; Hwang, Hwang, Noh, 2015), then they may respond too much to signals, either positively or negatively, causing intense buying or selling. From this perspective, return reversals are excess profits that rational investors earn from their arbitrage trading by providing liquidity, and at the same time reflect the cost of irrationality that these experts pay (Cheng, Hameed, Subrahmanyam and Titman, 2014). Intense trading due to irrational responses to signals affects illiquid assets more than liquid assets, and thus generates larger compensation for more illiquid assets (Campbell, Grossman, and Wang, 1993; Avramov, Chordia and Goyal, 2006). Therefore, the RS variable may be closely related to illiquidity and to subsequent return reversals.

The speed of the return reversals is a critical issue related to the above behavioral explanation for return reversals. In many behavioral finance studies, price distortions created by behavioral biases last months or even years, mainly due to the risk or restrictions in arbitrage trading (Daniel, Hirshleifer and Subrahmanyam, 1998, 2001; Baker and Wurgler, 2006; Hwang and Rubesam, 2013). For example, Daniel, Hirshleifer and Subrahmanyam (1998) argue that the initial overreaction created by investors' overconfidence is gradually reversed. Baker and Wurgler (2006) show that the impacts of sentiment on certain equities that are difficult to value or lack liquidity are reversed for over a year. Hwang and Rubesam (2013) show that the speed of return reversals is dynamic and increases when investors asymmetrically respond to public signals or when public signals become noisy.

However, the speed of return reversals following overconfidence is yet to be investigated empirically: it may be faster than the theoretical studies in the area of behavioral finance suggest or may also differ depending on the signals. When biases in returns are reversed without delay, then they may explain the short-term return reversals reported by Jagedeesh (1990) and Lehmann (1990). I investigate this possibility in the empirical tests.

3. Empirical Tests

In the empirical tests, I calculate ERS and RS for each individual stock on a monthly basis and then investigate their properties. The main results for the effects of irrational responses to signals on cross-sectional stock returns are analyzed with individual stocks as well as portfolios formed on ERS and RS.

3.1 Estimation of the response to signal

Suppose that investors try to predict stock returns using a signal that consists of K factors. They first need to learn how stock returns have responded to signals in the past. A simple method to model their learning would be a linear regression whose coefficients indicate how returns are expected to respond to the signal. Therefore, the main issue rests on estimating investors' expectation, ERS, from what they have learned from their historical experience, and investigating how investors respond to the ERS, i.e., RS. The details of the timeline of the estimation procedure are given in Figure 1.

The first step is to obtain risk-adjusted returns at time $t-1$. Excess returns of stocks are regressed on excess market returns (with a constant) using the past τ monthly returns (minimum 24 monthly observations) in order to calculate risk-adjusted returns,

$$\hat{r}_{it-s}^{A} = r_{it-s} - \hat{\beta}_i r_{mt-s},\ \ s = 1, \dots, \tau. \tag{8}$$

The second step is to estimate at time $t-1$ how the risk-adjusted returns have responded to the lagged signal in the past. This reflects investors' learning process for the prediction of the risk-adjusted returns using the factors available to them. The learning process can be estimated by using the following regression equation, i.e.,

$$\hat{r}_{it-s}^{A} = \textstyle\sum_{k=0}^{K} \varphi_{ik} f_{kt-s-1} + \eta_{it-s}, \text{ where } f_{0t-s-1} = 1 \text{ and } s = 1, \dots, \tau. \tag{9}$$

The parameters (φ_{ik}s) show how much the lagged factors affect the risk-adjusted return. For investors who expect this relationship to hold in the future, $\hat{s}^*_{it-1} = \sum_{k=0}^{K} \hat{\varphi}_{ik} f_{kt-1}$ at time $t-1$ is an unbiased estimate of ERS for $\hat{r}^A_{it}$, i.e., $\mathrm{E}(r^A_{it}|I_{t-1})$ in equation (3), because the estimation errors in the first step are not correlated with the lagged factors.[5]

At the final stage, the response to signal for stock i, δ_i, can be estimated at time t using past $\tau+1$ monthly observations:

$$r_{it-s} = \alpha_i + \beta_i r_{mt-s} + \delta_i \hat{s}^*_{it-s-1} + \eta_{it-s}, \ s = 0, \dots, \tau.^6 \tag{10}$$

By using $\tau+1$ observations rather than τ observations, any adverse effect from omitting the most remote observation can be avoided. The least square estimate of δ_i is unbiased as long as the estimation errors of $\hat{\varphi}_{ik}$ are not correlated with the factors. However, the estimated RS value, $\hat{\delta}_i$, represents the 'average' response to the lagged signal over $\tau+1$ months, and thus the RS of stock i at month t can be calculated using $\hat{\delta}_{it} = (\hat{\delta}_i - 1)\tau + \hat{\delta}_i$. These three steps are repeated for each stock, and then the stocks that have extreme estimates of RS and ERS are omitted to minimize the impact of outliers.[7] The procedure is repeated every month.

The estimates following the three steps are noisy. In the empirical tests, the signals do not include all available information when investors predict returns, and new information arrives for the period from when the prediction is made to when trading occurs. Therefore, for robustness of the results, I test four different signals and use individual stocks as well as portfolios formed on ERS and RS. In addition, the effects of overconfidence on cross-sectional stock returns are investigated using subsequent return reversals of the portfolios formed on the estimates of $\hat{s}^*_{it-1}$ and $\hat{\delta}_{it}$, because reversals may arise only when previous returns are biased by overconfidence.

To minimize the effects of new information that arrives between prediction and trading on the return reversals, I use contemporaneous signals instead of the lagged signals. If overconfidence is more likely to affect mature firms that are well known by investors and analysts (empirical results are reported later), it may be mature firms' new information, not investors' overconfidence, that is responsible for subsequent return reversals. We can avoid this problem using contemporaneous signals. Investors may

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[5] See Brennan, Chordia, and Subrahmanyam (1998) for further discussion.

[6] I also use the risk-adjusted return in the third stage, i.e., $\hat{r}^A_{it-s}$, and the results are not different from those reported in the paper.

[7] The stocks that have extreme estimates of RS and ERS are those whose $\hat{\delta}_{it}$s and $\hat{s}^*_{it-1}$s lie outside three standard deviations from their own means.

also predict returns over longer horizons, and thus I test the effects of overconfidence on stock returns when the forecasting horizon increases from one month to several months. Therefore, I estimate RS and ERS in the second and third stages as follows:

$$\hat{r}^{A}_{it-s} = \sum_{k=0}^{K} \hat{\varphi}_{ik} f_{kt-s-h} + \eta_{it-s}, \; s = 1, \dots, \tau. \tag{11}$$

and

$$r_{it-s} = \alpha_i + \beta_i r_{mt-s} + \delta_i \hat{s}^{*}_{it-s-h} + \eta_{it-s}, \; s = 0, \dots, \tau \tag{12}$$

where $\hat{s}^{*}_{it-s-h} = \sum_{k=0}^{K} \hat{\varphi}_{ik} f_{kt-s-h}$, and the forecasting horizon parameter h is set to 0, 2, 3, … in addition to the default case of one month ahead forecast ($h = 1$). When $h = 0$ stock returns are predicted with contemporaneous signals without delay, whereas when $h > 0$ investors use lagged signals to forecast h period ahead returns.

3.2 Data and signals

I use the Center for Research in Security Prices (CRSP) as well as the Compustat database for common stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and NASDAQ to calculate ERS and RS. Financial stocks (Standard Industrial Classification code from 6000 to 6999) are excluded because the accounting practices and variables of the financial sector are not compatible with those of the other sectors. Stocks whose prices are less than \$1 at the time of the estimation are excluded and investors' learning period τ is set as 60 months. The results for other learning periods, i.e., 12, 24, 36, 48, and 84 months, are discussed later.

Four signals are tested for the robustness of the empirical results: three sets of market-wide common factors and a set of firm characteristics specific to individual firms. The three sets of market-wide common factors are macroeconomic variables (MA), Fama-French three factors and momentum (FFM), and factors from principal component analysis (PCA). The macroeconomic variables are those that are typically found in the literature, e.g., Ferson and Harvey (1999): 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 (the dividend yield of the S&P500 index). The PCA factors are calculated as suggested by Connor and Korajczyk (1988). Following Lehmann and Modest (1988) and Connor and Korajczyk (1988), five factors are calculated every month using the past sixty monthly returns of non-penny stocks larger than the NYSE 20^{th} percentile to minimize the effects of a number of microcaps (Fama and French, 2008).[8] Finally, the seven firm-specific characteristics (FC) include four accounting variables (book-to-market ratio, asset growth, accruals, and net stock issue) and three market variables (size, idiosyncratic volatility, and illiquidity).[9] The accounting variables are calculated at the end of June using accounting data for the fiscal year ending in the previous year, as in Fama and French (1992), and are then assumed to remain the same from July to June of the following year. The other three firm characteristics are calculated every month.[10]

Table 1 provides summary statistics of $\hat{s}^*_{it-1}$ and $\hat{\delta}_{it}$ for the four signals. As expected, the statistics show differences in RS and ERS, depending on the signals. When the levels of $\hat{\delta}_{it}$ are compared, investors tend to show a slight overconfidence for MA, i.e., 1.33, but are underconfident for FFM and PCA, i.e., 0.71 and 0.64, respectively. The average RS value of FC is the lowest because of the large and negative RS values from July to September after annual accounting variables are updated in June.[11]

Investors appear to respond less to ERSs estimated with the signals available within the stock market, i.e., FFM, PCA, and FC. This could be due to the endogeneity problem of these signals. When some factors in a signal are affected by overconfidence, increasing $\hat{s}^*_{it-1}$, then investors' response to the upwardly biased $\hat{s}^*_{it-1}$ would appear lower because of the return reversals following overconfidence. Examples of such factors are the value anomaly or momentum that may represent mispricing due to investors' over- or under-confidence in signals (Lakonishok, Shleifer, and Vishny, 1994; DHS, 1998; Jegadeesh and Titman, 2001). The macroeconomic variables, on the other hand, do not have this endogeneity problem, and thus I report the main results with the

[8] Three and seven PCA factors have been tested but the main empirical results do not change.

[9] The four accounting variables are selected as they explain large cross-sectional equity returns among other accounting variables, e.g., dividends, sales growth, profitability, investment, net operating assets. These other accounting variables when used instead of the four accounting variables, do not change the empirical results.

[10] The firm characteristics are obtained as follows: size (price times shares outstanding), book-to-market (shareholders equity plus balance sheet deferred taxes, divided by size), asset growth (the change in total assets divided by previous year total assets), accruals (the change in operating working capital divided by total assets), net stock issue (the split-adjusted shares outstanding divided by previous year's split-adjusted shares outstanding), Ang et al.'s (2006) idiosyncratic volatility (the standard deviation of idiosyncratic errors of daily returns in a month using the Fama-French three factors), and Amihud's (2002) illiquidity. The number of annual accounting variables is kept to four (book-to-market, asset growth, accruals, and net stock issue) because it should not exceed the number of years (i.e., 5 years) in the time series regressions that are used to calculate ERS and RS.

[11] When this seasonal effect is controlled, the average RS of FC becomes 1.43. See panel A of Table 3.

macroeconomic variables. The results with the other three signals can be viewed as illustrative even though they are not much different.

The result – that the average RS of MA is larger than one in Table 1 – supports the view that investors are in general overconfident in the stock market (Chuang and Lee, 2006; Hwang, Hwang, and Noh, 2015). Stocks with positive RS values are more common than those with negative RS values: approximately two thirds of stocks show positive RS values. Their average RS values are approximately 4.9, indicating momentum-overconfidence. However, contrarian behavior is also widespread: approximately a third of stocks show negative RS values. Moreover, the average absolute values of negative RS are larger than those of positive RS. These results indicate that regardless of either momentum or contrarian behavior, investors are in general overconfident concerning signals. Contrarian behavior in particular, however, is affected by severe overconfidence.

3.3 Properties of the response-to-signal with respect to firm characteristics

The properties of $\hat{\delta}_{it}$s are investigated with and without taking the absolute value of RS. Confidence increases with the absolute values of RS, regardless of their signs: a large positive or negative RS value represents momentum-overconfidence or contrarian-overconfidence. On the other hand, the results with the raw RS show a difference between momentum and contrarian behavior with respect to ERS.

Table 2 shows that the numbers of stocks that are used to investigate the properties of RS are fewer than those reported in Table 1 as a result of the requirement of the firm characteristics (explained below) in the monthly Fama-MacBeth regression. On average, 1,818 stocks are used, except for FC where only 1,333 stocks are available. The average values of $|\hat{\delta}_{it}|$ range from 3.42 (PCA) to 5.21 (MA), suggesting that investors' confidence intervals are only half of the true confidence interval despite the difference in the signals. Since δ_{it} measures investors' perceived variance of noise, their biased confidence intervals for signals can be calculated by taking the square root of $|\hat{\delta}_{it}|$. For example, in the MA case, when the square root is taken of 5.21, the outcome, 2.28, suggests that investors believe that the standard deviation of noise is only $\frac{1}{2.28}$ of the true value and thus overprecision arises. The estimate is in fact similar to the results of Merkle (2013), whose survey reports the levels of overprecision as 2 to 2.5.

RS is investigated using various firm characteristics as well as other variables that may affect investors' behavior. De Bondt and Thaler (1985), Lakonishok, Shleifer, and Vishny (1994), and DHS (2001) demonstrate that price-to-fundamental ratios or size comprises mispricing created by investors' overconfidence. Other studies, such as Baker and Wurgler (2006) and Stambaugh, Yu, and Yuan (2012), indicate that investors' sentiment is more likely to appear in firms that are difficult to price or that have short-sale restrictions. I include seven firm characteristics to investigate what types of stocks are likely to be affected by overconfidence: size, book-to-market ratio, sales growth, external finance, asset tangibility, profitability, and dividends, as defined in Baker and Wurgler (2006).

Other variables include contemporaneous volatility, turnover, and illiquidity, as well as contemporaneous and one month lagged returns and momentum return. Excessive trading volume and volatility are attributable to overconfident investors who trade more aggressively (De Long et al., 1991; Kyle and Wang, 1997; Odean, 1998; Gervais and Odean, 2001; DHS, 1998, 2001; Scheinkman and Xiong, 2003; Statman, Thorley, and Vorkink, 2006; Darrat, Zhong, and Cheng, 2007; Chuang and Lee, 2006). If the demand curves for illiquid stocks are less elastic than for liquid stocks (Campbell, Grossman, and Wang, 1993; Avramov, Chordia and Goyal, 2006), then overconfidence would show a positive relationship with illiquidity. On the other hand, contemporaneous returns should show a positive relationship with overconfidence if a self-attribution bias exists. One month lagged returns are included to test whether short-term reversals influence overconfidence or contrarian behavior. Finally, past performance (returns from $t-11$ to $t-2$) is included to test if overconfidence increases for stocks that have performed well in the past (Gervais and Odean, 2001; Statman, Thorley and Vorkink, 2006; Chuang and Lee, 2006). Volatility is calculated using daily returns in the month, and illiquidity is calculated as in Amihud (2002). The logarithmic values of volatility, Amihud illiquidity, turnover, and size are used because of their right tails. All variables are standardized to have zero mean and unit variance, and then are winsorized at the three standard deviations to minimize the impact of outliers.

Panel A presents the estimates of the monthly Fama-MacBeth regression for absolute values of RS with their corresponding Newey-West standard errors. An interesting pattern emerges: large stocks, value stocks, dividend-paying stocks, stocks with tangible assets, stocks with little external financing, and stocks with low sales growth are likely to be overconfident. These characteristics − large, value, dividend-paying, tangible assets, little external financing, and low sales growth − are frequently observed in mature firms that have long operating histories and are well known by investors and analysts (Bulan, Subramanian and Tanlu, 2007; Bulan and Yan, 2010). Mature firms do not rely on external financing because they have large cash flows and few investment opportunities, and thus are largely self-financing (Berger and Udell, 1998; De Angelo, De Angelo and Stulz, 2006; Baker, 2009). According to Benartzi, Michaely, and Thaler (1997) and Grullon, Michaely and Swaminathan (2002), mature firms pay more dividends, which delivers information about their diminishing investment opportunities and thus declining earnings growth and profitability (Grullon et al., 2002; De Angelo, De Angelo and Stulz, 2006).

The characteristics of firms that are affected by overconfidence stand in sharp contrast with those of firms that are likely to be affected by sentiment. According to Baker and Wurgler (2006), sentiment affects stocks that are difficult to value and arbitrage: i.e., small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, growth stocks, and distressed stocks. The results in panel A, however, show that these stocks do not respond to ERS as much as they should and thus are subject to under-confidence. Threfore, the characteristics of firms where sentiment and overconfidence arise are mutually exclusive. If excessive optimism is a driving force of sentiment (Barone-Adesi, Mancini, and Shefrin, 2013), it affects stocks that are difficult to arbitrage. For mature stocks that are relatively easy to price, investors' overconfidence in signals matters.

Why then is overconfidence likely to be found in mature stocks rather than in stocks that are difficult to price? I propose explanations based on the characteristics of mature firms and of the investors who trade these stocks. First, the valuation of mature firms is relatively easy with fewer problems of information asymmetry between managers and investors (Easley and O'Hara, 2004). Their investment and financing patterns have settled down, and thus their risk and returns are stable over time, resulting in overconfidence in signals for the valuation of these firms (Damodaran, 2009). Second, institutional investors are more overconfident than novices (De Long et al., 1991; Griffin and Tversky, 1992; Odean, 1998), and thus are likely to be overconfident for the stocks they trade. Blume (1976), Gompers and Metrick (2001), Bennett et al. (2003), and Yan and Zhang (2009) report that these investors prefer large, value stocks, or stocks that have superior past performance and a long listing history with characteristics that are largely consistent with those of mature stocks. In addition, institutional investors may believe that their pricing ability is better than that of others for relatively easy tasks (Moore and Healy, 2008; Merkle, 2013). For example, valuation of stocks that pay regular dividends may appear to be straightforward to these investors and thus they could overweight their signals.

As expected, volatility, illiquidity, and turnover all increase with confidence. Confidence increases with contemporaneous returns: the absolute values of the RS are positively related to contemporaneous returns. However, the effects of the lagged return and the lagged past return on confidence are negative, suggesting that confidence decreases when past performance was good. Thus, contrary to what Gervais and Odean (2001) suggest, in the cross-section investors lose confidence in signals for stocks whose past performance was better than the others. Finally, confidence is positively autocorrelated.

Among the firm characteristics, firm size shows the strongest relationship with confidence, and then illiquidity and volatility follow: for example, one standard deviation increase in log size increases the absolute value of RS by 0.79 for MA. Although statistically significant, other firm characteristics such as book-to-market ratio, sales growth, asset tangibility, and profitability, do not affect RS as much as size, illiquidity, or volatility does.

Finally, the difference in RS between momentum and contrarian behavior is not clear in many cases because the estimates with the raw RS in panel B either show different signs for different signals or only a few of them are significant. However, turnover, illiquidity, and volatility appear to increase momentum behavior whereas the lagged ERS increases contrarian behavior. Finally, RS is positively autocorrelated, and thus investors' response to signals persists.

3.4 Dynamics of the market-wide response-to-signal

For the analysis of time series properties of RS in the stock market, individual $\hat{\delta}_{it}$s are cross-sectionally aggregated to calculate market-wide indices of RS for the four signals. The difference between value-weighted and equally-weighted RS indices is negligible: they are highly correlated with the minimum Spearman correlation of 0.86 and their average levels are close to each other (panels A and B of Table 3).

Figure 2 shows that the RS indices change substantially over time. In all cases, the indices are negatively skewed: investors' response to ERS plummets during crises, e.g., after the first Oil Shock in 1974, the early 1980s, from the Russian Crisis in 1998 to the early 2000s, and the recent financial crisis. During other periods, investors respond positively to ERS, e.g., from 1975 to the end of the 1970s, from the middle of the 1980s to the early 1990s, and from 2009 to the end of the sample period.

The results in Table 3 show that investors' confidence in signals increases as economic outlook or performance in the stock market increases. For example, investors' RS increases with dividends and momentum, supporting the empirical results of Chui, Titman and Wei (2010). Investors' confidence also increases when the term spread increases because the term spread predicts economic outlook (Wheelock and Wohar, 2009). On the other hand, poor performance lowers investors' confidence in signals. The one month ahead NBERS recession dummy is significant at the 5% level in most cases, indicating that investors' confidence decreases at the anticipation of recession. Similarly, the RS indices tend to decrease as the credit spread increases (Philippon, 2009).

Interestingly the RS index of MA decreases as Baker and Wurgler's (2006) sentiment increases, indicating that overconfidence is likely to occur when sentiment is low. This is consistent with the above cross-sectional result that overconfidence and sentiment affect different types of stocks, i.e., mature stocks and stocks that are difficult to price, respectively. Mature stocks are affected by overconfidence when sentiment fades. The negative relationship between sentiment and overconfidence is consistent with the results of Glaser, Langer, and Weber (2009) and Moore and Healy (2008), who find that the relationship between overconfidence and sentiment is often low or even negative despite their similarities (Larrick, Burson, and Soll, 2007).

In summary, the dynamics of RS are largely consistent with the results found in the literature. Overall confidence in signals increases when the economy is predicted to be in a good condition and economic performance has improved. On the other hand, confidence decreases when sentiment increases or when a recession is expected.

3.5 The effects of behavioral biases on cross-sectional returns

Although overconfidence is more likely to be observed in mature firms, it does not necessarily indicate that stock prices of mature firms are affected by overconfidence more than those of small and illiquid firms are. Mature stocks are less restricted for arbitrage trading, and thus the price impact of overconfidence on mature stocks would not appear as much as that on small and illiquid stocks (Stambaugh, Yu, and Yuan, 2012). In this section, I investigate the effects of RS on the contemporaneous and one month ahead risk-adjusted returns, using monthly Fama-MacBeth regressions from July 1967 to June 2011. All explanatory variables are cross-sectionally standardized to have zero mean and unit variance and then winsorized at the three standard deviations.[12]

The contemporaneous risk-adjusted returns are significantly affected by RS and ERS. Panel A of Table 4 shows that without $\hat{\delta}_{it}$, $\hat{s}^*_{it-1}$ or $\hat{\delta}_{it}\hat{s}^*_{it-1}$, the average R-squared value is only 0.09. When these three terms are included, the average R-squared value jumps to 0.36, and most improvements in the R-squared value come from $\hat{\delta}_{it}\hat{s}^*_{it-1}$: one standard deviation difference in $\hat{\delta}_{it}\hat{s}^*_{it-1}$ affects the risk-adjusted return by more than 6%, which is larger than any other variables. The variable $\hat{s}^*_{it-1}$ is negative and significant, indicating that risk-adjusted returns are not just cross-sectionally linear to $\hat{\delta}_{it}\hat{s}^*_{it-1}$ but also are negatively affected by the past ERS.

Investors' overconfidence (the large absolute values of $\hat{\delta}_{it}$ in panel A of Table 2) and the large impact of $\hat{\delta}_{it}\hat{s}^*_{it-1}$ on the contemporaneous returns suggest that the contemporaneous returns would be biased by overconfidence and that the subsequent return reversals may not be trivial. In order to investigate to what extent investors' overconfidence affects asset returns and subsequent reversals, I decompose the contemporaneous returns into two components using the following cross-sectional regression:

$$
\begin{aligned}
r_{it} &= \gamma_{0i} + \gamma_{1i} s^*_{it-1} + \gamma_{2i}\delta_{it} + \gamma_{3i}\delta_{it}s^*_{it-1} + \sum_{k=1}^{K}\gamma_{ik}c_{kt} + \xi_{it} \\
&= \left[\gamma_{0i} + \sum_{k=1}^{K}\gamma_{ik}c_{kt} + \xi_{it}\right] + \left[\gamma_{1i}s^*_{it-1} + \gamma_{2i}\delta_{it} + \gamma_{3i}\delta_{it}s^*_{it-1}\right] \\
&= \text{Returns\_Others}_{it} + \text{Returns\_BS}_{it},
\end{aligned}
$$

where c_{kt} denotes the control variables in panel A of Table 4. The term, $Returns\_BS_{it}$, represents returns attributable to investors' response to ERS while $Return\_Others_{it}$ is the component of the return unrelated to their response to ERS. If contemporaneous returns are affected by investors' overconfidence and the bias is to be reversed subsequently, then Returns_BS_{it} predicts returns in a negative way.

The results in panel B show that the effects of $\hat{\delta}_{it}\hat{s}^*_{it-1}$ or Returns_BS_{it} on the contemporaneous returns are reversed in the following month. The magnitudes of

[12] For the explanation of cross-sectional risk-adjusted returns, the firm characteristics in Table 2 are used except for the idiosyncratic volatility (IVol) which is calculated as in Ang et al (2006) with the Fama-French three factors. The signs on the coefficients of the control variables in Table 4 are consistent with the predictions in the literature. However, the coefficients on momentum and size (log-ME) become insignificant or positive in the presence of lagged returns.

the reversals are similar, i.e., one standard deviation of these variables changes over 0.4% risk-adjusted returns in the following month. As expected, the unconditional effects of $\hat{\delta}_{it}$ or $\hat{s}^*_{it-1}$ on the subsequent returns are rather limited.

The coefficient on the lagged return in the fourth column indicates that one standard deviation difference in the lagged return would lead to subsequent return difference by 0.78%, similar to the short-term return reversals reported by Jagedeesh (1990) and Lehmann (1990). When the lagged return is decomposed into $\text{Returns\_Others}_{it}$ and Returns_BS_{it}, the last column shows that the significant proportion of the short-term return reversals can be explained by investors' overconfidence: one standard deviation difference in the lagged Returns_BS_{it} and $\text{Returns\_Others}_{it}$ would cause subsequent return differences of 0.42% and 0.64%, respectively.

These results indicate that investors' overconfidence in their signals is one of the major reasons for the short-term return reversals: institutional investors are major players of mature stocks, and thus mature firms are more likely to be affected by their overconfidence. Overconfident institutional investors overreact to signals, ending up in them pursuing intense buying or selling, the effects of which are subsequently reversed. These results explain why short-term return reversals increase for stocks whose institutional holdings decrease (Cheng, Hameed, Subrahmanyam, and Titman, 2014). Therefore, a significant proportion of the short-term return reversals is the profits that rational investors earn from their arbitrage trading, and at the same time the cost of irrationality that institutional investors pay. Illiquid assets are affected more than liquid assets by the intense trading, and thus their return reversals are larger than those of liquid assets (Campbell, Grossman, and Wang, 1993; Avramov, Chordia and Goyal, 2006).

Summarizing the results, after controlling for various firm-specific characteristics we find that contemporaneous returns are significantly affected by overconfidence, the effects of which are then subsequently reversed. Overconfidence is one major reason for the short-term return reversals but is not the only reason.

3.6 Portfolios formed on signal and response-to-signal

In order to investigate whether RS and ERS show distinct patterns in returns and in other firm characteristics, I form 25 portfolios by two independent sorts on ERS ($\hat{s}^{*}_{it-1}$) and RS ($\hat{\delta}_{it}$) of individual equities.

First, the RS values of the 25 portfolios vary widely from -8.29 to 10.14. Panel A of Table 5 shows that the RS differences between the high and low RS portfolios are over 17 and are statistically significant regardless of the ERS values. Under-confidence is not clearly visible in the 25 RS-ERS sorted portfolios whereas overconfidence, i.e., either momentum-overconfidence or contrarian-overconfidence, is far more common. Ten portfolios among the 25 portfolios have negative values of $\hat{\delta}_{pt}$, which is consistent with the above results that a third of stocks show contrarian behavior. Overconfidence in contrarian beliefs is not trivial because the magnitude of negative $\hat{\delta}_{pt}$s is as large as that of positive $\hat{\delta}_{pt}$s.

The difference in ERS between high and low RS portfolios decreases as ERS increases (panel B), indicating that extreme positive or negative signals are more likely to be associated with contrarian behavior. On the other hand, the differences in profits and past returns between the high and low RS portfolios increase as ERS increases (panels G and H). Therefore, for stocks whose profits or past returns are large, investors become contrarian for negative signals and become momentum traders for positive signals. Other firm characteristics show clear a difference between high and low RS portfolios regardless of ERS: large stocks, stocks with large tangible assets, dividend paying stocks, and stocks with small idiosyncratic volatility, are more likely to be contrarian (panels C, E, F, and J).[13]

The contrasting return patterns due to momentum- and contrarian-overconfidence create large cross-sectional contemporaneous return differences between high and low RS portfolios, and these differences range from -23.3% a month to 23.9% for the low and high ERS portfolios, respectively (panel A1 of Table 6). These return differences are robust to the well-known four factors, i.e., the Fama-French three factors and momentum: alphas of these High-Low RS portfolios in panel A2 are not different from the raw returns in panel A1.

[13] The results of the 25 portfolios by two independent sorts on ERS ($\hat{s}^{*}_{it-1}$) and RS ($\hat{\delta}_{it}$) are not necessarily the same as those of the Fama-MacBeth regression with individual stocks in panel B of Table 2.

The large return difference between the high minus low RS portfolios is reversed in the following months. The return reversals between the high and low RS portfolios are 1.85% and -0.88% for the low and high ERS portfolios (panel B1), respectively, and their alphas from the four factor model are 1.93% and -0.95% (panel B2), respectively. For the two months subsequent to the formation month, the aggregated return difference between high and low confidence portfolios is 2.42% (2.66% for alpha) for the low ERS portfolios, whereas it is -0.8% (-0.98% for alpha) for the high ERS portfolios. The cumulative alphas of the four portfolios (high-RS high-ERS (HH), high-RS low-ERS (HL), low-RS high-ERS (LH), and low-RS low-ERS (LL)) and the two hedge portfolios (high-minus-low RS portfolios in the lowest and highest ERS portfolios, HL-LL and HH-LH) in Figure 3 summarize the cumulative returns at the formation month and for the five subsequent months. The reversals are prominent during the first month. The return dynamics of these portfolios are indeed very similar to the theoretical model proposed by DHS (1998), except that the return reversals arise quickly.

The return reversals of these four portfolios are relatively much smaller than what the contemporaneous return differences in panels A1 and A2 of Table 6 suggest. The large estimates of RS in Table 5 and contemporaneous returns in Table 6 may reflect information that is not included in the empirical tests, i.e., new information or information omitted from the signal. For example, share prices would increase (decrease) at the arrival of unexpected good (bad) news at time *t* when δ_{it} is estimated, and thus large positive or negative values of $\hat{\delta}_{it}$ may reflect the new information at time *t*. Despite this problem, portfolios formed on RS and ERS should not show the subsequent return reversals unless RS contains investors' irrational response to signals. Subsequent return reversals represent the initial biases included in the contemporaneous returns due to overconfidence (DHS, 1998, 2001). Later in the robustness tests, I use contemporaneous signals instead of lagged signals (i.e., $\delta_{it}s^*_{it}$ instead of $\delta_{it}s^*_{it-1}$) to minimize the effects of new information at time *t*. The results do not change.

3.7 Overconfidence Factors

In this section I create an overconfidence factor that measures return reversals following investors' overconfidence in their signals. Using the four extreme portfolios from the two independent sorts on ERS ($\hat{s}^*_{it-1}$) and RS ($\hat{\delta}_{it}$) in Table 6, i.e., high-RS high-ERS (HH), high-RS low-ERS (HL), low-RS high-ERS (LH), and low-RS low-

ERS (LL), I form a hedge portfolio (RS_ERS) as follows: (HL+LH-LL-HH)/2. The performance of RS_ERS increases when return reversals increase following overconfidence. For comparison purposes, I also report the return reversals of the low-minus-high decile portfolios formed on r_{it} (Return_D), $\mathrm{Returns\_Others}_{it}$ (Returns_Others_D), and $\mathrm{Returns\_BS}_{it}$ (Returns_BS_D).

The overconfidence factor return is large and significant. Panel A of Table 7 shows that the average return of RS_ERS is 1.23% per month. It is still significant in the 2000s despite active arbitrage trading by institutional investors (Chan, Getmansky, Haas, and Lo, 2007; Lo, 2008; Hendershott, Jones, and Menkveld, 2011; Dichev, Huang, and Zhou, 2011). The performance of Returns_BS_D is not different from that of RS_ERS: in fact, Returns_BS_D shows slightly larger average return and alpha than RS_ERS.

As reported by Cheng, Hameed, Subrahmanyamm, and Titman (2014), the average return reversal (Return_D) has recently decreased. When the performance of Returns_BS_D and Returns_Others_D is compared, it becomes clear that the return reversals of Returns_Others_D did indeed decrease in the 2000s when compared with those in the 1970s and 1980s.[14] On the other hand, return reversals driven by overconfidence are still significant both statistically and economically. The changes in the performance of these hedge portfolios are notable when they are value weighted. As in Hameed and Mian (2014) and Cheng, Hameed, Subrahmanyamm, and Titman (2014), the average return reversals decrease significantly when value weighted (panel B). However, the alphas of RS_ERS are still large and significant, i.e., 0.71%. In contrast, the alpha of Returns_Others_D in the 2000s becomes negative though it is not different from zero.

Since arbitrage trading was active in the 2000s rather than in the 1970s or 1980s, the return reversals due to behavioral biases should have decreased in the 2000s. My results in Table 7 show that, in general, the short-term return reversals have decreased over the past 40 years, but the decrease in the short-term return reversals becomes apparent when the effects of overconfidence are excluded. Despite this general trend in the reversals, the equally weighted RS_ERS still shows monthly alpha of 0.88% in the 2000s, and thus arbitrage trading does not erode away the behavioral bias. This result is

[14] The performance of various hedge portfolios was significantly affected by the dot com bubble in the 1990s (Chan, Getmansky, Haas, and Lo, 2007) and thus is excluded from the analysis.

consistent with those presented by Hwang, Hwang, and Noh (2015), who demonstrate that the effects of arbitrageurs' overconfidence on cross-sectional asset returns have increased in the 2000s.

Finally, the overconfidence factor may be explained by other firm characteristics factors. For example, DHS (1998, 2001) argue that factors formed on the book-to-market ratio, size, and momentum can be explained by overconfidence. Moreover, the cross-sectional analysis using individual stocks in Table 2 shows that large stocks, value stocks, dividend-paying stocks, stocks with tangible assets, stocks with little external financing, and stocks with low sales growth are more subject to overconfidence. Therefore, I test whether the overconfidence factor (RS_ERS) can be explained by fifteen firm characteristic factors.[15] Although these fifteen factors do not cover all cross-sectional return patterns in the literature (Harvey et al, 2014), they do include frequently used factors such as size (ME), accruals (Acc), asset growth (AG), book-to-market ratio (BEME), idiosyncratic volatility (IVol), illiquidity (Liq), and momentum (Mom).

The results in Table 8 show that the alphas of RS_ERS are still large and significant, i.e., from 1.26% to 1.55%, for the four signals that are tested in this study, and their t-statistics are all well over 3 suggested by Harvey et al (2014). Therefore, these fifteen factors do not subsume the overconfidence factor.[16] Among the fifteen factors, momentum is negatively related to the overconfidence factor. Momentum reflects delayed overreactions (Jegadeesh and Titman, 2001), and thus the overconfidence factor that measures return reversals subsequent to overreaction should be negatively associated with momentum. The negative coefficients on the net stock issue (NSI) can also be explained in a similar way: investors under-respond to changes in stock issues (Daniel and Titman, 2006; Hwang et al., 2008). The positive coefficients on the investment to asset (IA) are consistent with the view that investors' over-

[15] The hedge portfolios are formed on 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), net stocks issues (NSI) (Fama and French, 2008), 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). The detailed explanation of the calculation of these factors is explained in Hwang, Hwang, and Noh (2015).

[16] I find that these factors are not explained by the overconfidence factor. The details can be obtained from the author upon request.

response to firms' investment is subsequently reversed (Cooper, Gulen, and Schill, 2008). These results are therefore consistent with those reported in Table 4 in that the return reversals subsequent to overconfidence are not subsumed by various firm characteristics, such as Fama and French's (2014) five factors nor by others such as momentum, volatility, illiquidity and turnover.

3.7 Robustness tests

In this section, I investigate whether the return reversals due to overconfidence and contrarian behavior are robust to different types of signals, bid-ask bounce, January effects, size and portfolio breakpoints, liquidity, learning periods, and prediction horizons. These robustness tests are performed using the RS_ERS and the results are reported in Table 9.[17]

Other signals

The main empirical results are specific to the macroeconomic variables that are used to predict future stock returns. Investors may use firm characteristics or other factors derived from stock returns. The results with the four factor model (Fama-French three factors and momentum), five PCA factors, and seven firm characteristics in panel A of Table 9 show that the return reversals are similar to those with the macroeconomic variables. Alphas are over 1% per month and are significant for the entire sample period, and more importantly, are still significant during the 2000s. The overconfidence factors are highly correlated with each other despite their difference: the Spearman rank correlations range from 0.54 (between PCA and FC) to 0.62 (between FFM and PCA).

Return reversals and bid-ask bounce

The return reversals created by overconfidence may be sensitive to the bid-ask bounce. For example, for a positive ERS, the end-of-month prices are likely to be at ask prices for momentum-overconfidence or at bid prices for contrarian-overconfidence, which are reversed in the following month when these behavioral biases disappear. In general, a significant proportion of the short-term return reversals is attributable to the bid-ask bounce (Jegadeesh and Titman, 1995; Conrad, Gultekin and Kaul, 1997; Hameed and Mian, 2014). To evaluate the effects of bid-ask bounce on the return

[17] The results of Returns_BS_D are similar to those reported in Table 9 and thus are not reported

reversals due to overconfidence, I exclude the return of the first day in the month following the formation month, as in Jegadeesh (1990) and Hameed and Mian (2014). Panel B of Table 9 shows that although the return reversals due to overconfidence decrease, alphas are still significant during the sub-periods. The bid or ask prices at the end of the formation month are not critical for the return reversals due to overconfidence.

Return reversals excluding January

The return reversals are known to be strong in January (Jegadeesh, 1990; Hameed and Mian, 2014), mainly due to tax-loss selling (George and Hwang, 2004). Panel C in Table 9 shows that the average return reversals due to overconfidence are higher in January, but are still large and significant in non-January months at 1.13% per month for the entire sample period and 0.98% per month in the 2000s. Moreover, RS does not exhibit any particular pattern around January for all four signals, except for FC where its RS shows seasonal patterns from July to September following annual accounting variable updates (Table 3). Therefore, the overconfidence factor is not attributable to tax-loss selling.

Robustness to breakpoints, size, and universe

The difference in the performance of the overconfidence factor between value- and equal weights in Table 7 suggests that a significant proportion of the overconfidence factor is driven by small stocks. Despite the fact that mature firms are more likely to be affected by overconfidence, their returns are less affected by overconfidence.

A few tests are performed to investigate how much of the return reversals come from a large number of microcaps. First, when portfolios are formed with small and large stocks (larger than bottom 20% of NYSE), the average return reversals are lower than those using microcaps. However, they are still significant at the 5% level. For example, the average return reversal in the 2000s of portfolios formed with small and large stocks is 0.83% (its alpha is 0.79%). When the NYSE breakpoints are used to form the decile portfolios, the return reversals are not significantly different from those using the breakpoints of all non-financial firms in the NYSE, AMEX, and Nasdaq. Finally, the two other cases – (1) all stocks instead of non-financial stocks, and (2) non-penny stocks larger than \$5 instead of \$1 – also show that the average return reversals are significant for the entire sample period as well as for various subsample periods. Therefore, although the effects of overconfidence on returns decrease for large firms, they are still significant.

Robustness to Liquidity

Previous studies suggest that a large portion of short-term return reversals come from stocks that are illiquid (Avramov, Chordia and Goyal, 2006). Using the median of Amihud illiquidity measure as the breakpoint, I calculate the return reversals from liquid and illiquid stocks and then investigate their performance. The results in panel E show that although return reversals become smaller when only liquid stocks are used to form portfolios, the alphas of the return reversals from liquid stocks are all larger than 1% per month and are significant. Therefore, the return reversals subsequent to overconfidence are also significant in liquid stocks, while overconfidence is stronger in illiquid stocks (Table 2).

Learning Periods

So far, investors have been assumed to predict future returns from their experiences over the prior 60 months. Investors may consider a longer or shorter period to learn the predictive power of the signals. Various learning periods are tested by setting τ=12, 24, 36, 48, 72, and 84 to investigate differences in the performance of the overconfidence factor. The results in panel F show that the return reversals are similar. When the learning period is too short, i.e., only 12 months, the estimates of ERS and RS become noisier, and thus the return reversals subsequent to overconfidence slightly decrease.

Prediction horizon

Finally, I test whether the forecasting horizon has any relation to the return reversals subsequent to overconfidence. The first case I investigate is where investors trade stocks using contemporaneous signals rather than the lagged signals. Contemporaneous ERS can minimize the possibility that unexpected large RSs may come from the arrival of new information. The results in panel G show that when $h = 0$ in equations (11) and (12), the return reversals increase slightly and are significant in all sub-periods. Therefore, the return reversals following overconfidence are not affected by new information during the formation month.

When investors predict returns over longer horizons, rather than just over one month, the return reversals by overconfidence may be observed over longer periods. To investigate this possibility, I assume that investors try to predict returns two, three, and four months ahead in the second and third step of the RS and ERS estimation: $h = 2, 3,$ and 4 in equations (11) and (12). All three cases reported in panel G show that the return reversals arise during the first month after formation. Almost all alphas are not significant after the first month during the entire sample period or other subperiods. Therefore, the cross-sectional bias in the stock prices is corrected immediately after the overconfidence regardless of the forecasting horizons.

4 Conclusions

Cross-sectional stock returns are affected by investors' overconfidence in signals, and these affects are then reversed quickly. The results do not support claims that overconfidence is responsible for various anomalies in the stock market, most of which assume that the effects of overconfidence last over longer horizons. If overconfidence explains these anomalies that last for longer periods, it might other forms of overconfidence (i.e., overplacement or overestimation) rather than overprecision. The effects of overestimation and overprecision on the posterior expectations may not be the same due to their weak correlation (Moore and Healy, 2008; Deaves, Lüders, and Luo, 2009; Merkle, 2013).

The immediate return reversals following overconfidence explain approximately half of the short-term return reversals reported by Jagedeesh (1990) and Lehmann (1990). The return reversals subsequent to overconfidence are a reward to rational investors who provide liquidity to overconfident investors (Campbell, Grossman and Wang, 1993; Nagel, 2012). These results also explain why short-term return reversals increase for stocks whose institutional holdings decrease (Cheng, Hameed, Subrahmanyam, and Titman, 2014). Short-term return reversals after intense trading by overconfident institutional investors (De Long et al., 1991; Griffin and Tversky, 1992; Odean, 1998; Hwang, Hwang, Noh, 2015) provide profit opportunities that other rational investors can exploit through their arbitrage trading. The intense trading by institutional investors affects illiquid assets more than liquid assets and thus generates a larger compensation for more illiquid assets (Campbell, Grossman, and Wang, 1993; Avramov, Chordia and Goyal, 2006).

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Table 1 Summary statistics of response to signal (RS) and expected return predicted by signal (ERS)

The macroeconomic variables (MA) include the 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 (the dividend yield of S&P500 index). Fama-French three factors and momentum (FFM) are from Kenneth French's data library. Five factors from the principal component analysis (PCA) are calculated as in Connor and Korajczyk (1988) with the non-penny stocks larger than the NYSE 20th percentile. These factors are calculated every month using the past 60 monthly returns. Firm-specific characteristics (FC) include three variables, i.e., size, idiosyncratic volatility, and illiquidity, which are calculated every month, and four annual variables, i.e., book-to-market ratio, asset growth, accruals, and net stock issue. The four annual firm characteristics are calculated at the end of June using accounting data for fiscal year-end in the previous year as in Fama and French (1992) and are assumed to remain the same from July to June of the following year. The R-squared values are calculated from the regression of risk-adjusted returns on lagged factors in the second stage of the estimation of the response to signal.

	MV	FFM	Five PCA	Seven FC
Number of stocks	2,220	2,216	2,218	1,564
Number of Positive ERS	1,206	1,305	1,299	684
Number of Negative ERS	1,013	911	919	880
Number of Positive RS	1,495	1,576	1,685	1,087
Number of Negative RS	725	640	533	477
Average value of ERS	0.598	0.599	0.614	-0.650
(Standard error)	(0.049)	(0.046)	(0.065)	(0.073)
Average value of positive ERS	3.922	2.899	3.841	4.988
(Standard error)	(0.077)	(0.082)	(0.175)	(0.193)
Average value of negative ERS	-3.391	-2.419	-3.337	-5.262
(Standard error)	(0.065)	(0.071)	(0.166)	(0.211)
Average value of RS	1.327	0.709	0.644	0.272
(Standard error)	(0.097)	(0.082)	(0.137)	(0.108)
Average value of positive RS	4.890	3.534	2.842	3.074
(Standard error)	(0.063)	(0.067)	(0.048)	(0.024)
Average value of negative RS	-5.259	-4.134	-3.269	-5.015
(Standard error)	(0.109)	(0.136)	(0.172)	(0.164)
R square value	0.076	0.066	0.122	0.171

Table 2 Properties of the response-to-signal with respect to firm characteristics

The raw and absolute values of the response-to-signal (RS) estimated with the three steps in Section 3.1 are regressed on the lagged ERS and other variables that are known to affect overconfidence. Firm characteristic variables are size (ME, price times shares outstanding), book-to-market ratio (BE/ME, shareholders equity plus balance sheet deferred taxes, divided by ME), sales growth (the change in net sales divided by prior-year net sales), external finance (the change in total assets minus the change in retained earnings, divided by total assets), asset tangibility (property, plant and equipment, divided by total assets), dividend (dividends per share at the ex-date times shares outstanding divided by BE), and profitability (income before extraordinary items plus income statement deferred taxes minus preferred dividends, divided by BE). These six firm characteristics (BE/ME, Sales Growth, External Financing, Asset Tangibility, Dividends, and Profitability) are calculated at the end of June using accounting data for fiscal year-end in the previous year as in Fama and French (1992) and are then assumed to remain the same from July to June of the following year. Illiquidity is calculated as in Amihud (2002). Logarithmic values of volatility, Amihud illiquidity, turnover, and size are used because of their right tails. All variables are standardized to have zero mean and unit variance and then are winsorized at three standard deviations to minimize the impact of outliers. The numbers in the round brackets represent the Newey-West standard errors and the bold numbers represent significance at the 5% level.

	Macroeconomic variables (MA)		Fama-French three factors and momentum (FFM)		Five PCA factors (PCA)		Seven firm characteristics (FC)	
Average Number of Equities	1818		1811		1812		1333	
A. Absolute values of RS								
RS	**5.212**	(0.079)	**3.941**	(0.103)	**3.420**	(0.130)	**3.876**	(0.090)
constant	**5.230**	(0.136)	**3.951**	(0.154)	**3.428**	(0.202)	**3.909**	(0.093)
RS(-1)	**1.355**	(0.068)	**0.615**	(0.035)	**0.673**	(0.048)	**1.122**	(0.018)
ERS(-1)	0.006	(0.021)	-0.001	(0.017)	-0.005	(0.023)	**-0.213**	(0.033)
Ret	**0.135**	(0.033)	**0.151**	(0.035)	**0.103**	(0.025)	**0.122**	(0.019)
Ret(-1)	**-0.061**	(0.018)	**-0.068**	(0.015)	**-0.038**	(0.012)	0.015	(0.015)
Ret(-2~-11)	**-0.110**	(0.020)	**-0.111**	(0.016)	**-0.054**	(0.011)	**-0.033**	(0.019)
log_Volatility	**0.465**	(0.016)	**0.440**	(0.019)	**0.215**	(0.014)	**0.281**	(0.012)
Log_Illiquidity	**0.579**	(0.037)	**0.364**	(0.029)	**0.174**	(0.025)	**0.430**	(0.030)
Log_Turnover	**0.217**	(0.018)	**0.228**	(0.016)	**0.137**	(0.013)	**0.141**	(0.012)
Log-ME	**0.790**	(0.042)	**0.572**	(0.036)	**0.316**	(0.032)	**0.597**	(0.034)
BE/ME	**0.138**	(0.014)	**0.084**	(0.012)	**0.064**	(0.010)	**0.188**	(0.021)
Sales Growth	**-0.148**	(0.025)	**-0.168**	(0.026)	**-0.075**	(0.020)	-0.047	(0.026)
External Financing	**-0.045**	(0.008)	**-0.040**	(0.008)	**-0.014**	(0.007)	**0.062**	(0.014)
Asset Tangibility	**0.072**	(0.012)	**0.042**	(0.012)	**0.026**	(0.009)	**0.025**	(0.010)
Dividends	**0.303**	(0.018)	**0.227**	(0.015)	**0.126**	(0.012)	**0.228**	(0.019)
Profitability	0.021	(0.027)	**0.031**	(0.020)	0.012	(0.033)	-0.038	(0.025)
R-square	0.148		0.094		0.180		0.171	

B. RS

	Macroeconomic variables (MA)		Fama-French three factors and momentum (FFM)		Five PCA factors (PCA)		Seven firm characteristics (FC)	
Average Number of Equities	1818		1811		1812		1333	
RS	**1.380**	(0.096)	**0.716**	(0.081)	**0.668**	(0.137)	**0.342**	(0.105)
constant	**1.371**	(0.166)	**0.718**	(0.106)	**0.668**	(0.207)	**0.313**	(0.109)
RS(-1)	**0.753**	(0.099)	**0.129**	(0.039)	**0.579**	(0.052)	**1.238**	(0.032)
ERS(-1)	**-0.129**	(0.047)	**-0.105**	(0.037)	-0.054	(0.037)	**0.381**	(0.051)
Ret	-0.074	(0.074)	0.006	(0.050)	0.044	(0.032)	**-0.543**	(0.075)
Ret(-1)	**-0.061**	(0.021)	0.000	(0.012)	0.004	(0.010)	**0.038**	(0.019)
Ret(-2~-11)	-0.025	(0.020)	-0.004	(0.011)	0.003	(0.009)	-0.028	(0.018)
log_Volatility	-0.007	(0.017)	**0.033**	(0.012)	**0.063**	(0.015)	**0.031**	(0.015)
Log_Illiquidity	**0.224**	(0.041)	**0.107**	(0.036)	0.021	(0.026)	**-0.078**	(0.036)
Log_Turnover	**0.146**	(0.019)	**0.061**	(0.016)	0.023	(0.013)	**-0.051**	(0.015)
Log-ME	**0.150**	(0.045)	0.054	(0.031)	0.013	(0.025)	**-0.203**	(0.037)
BE/ME	0.010	(0.017)	-0.010	(0.012)	-0.003	(0.009)	**-0.113**	(0.029)
Sales Growth	0.014	(0.035)	0.056	(0.029)	-0.009	(0.025)	**-0.057**	(0.029)
External Financing	-0.002	(0.013)	**0.023**	(0.008)	0.004	(0.007)	**-0.078**	(0.016)
Asset Tangibility	**-0.042**	(0.018)	0.027	(0.015)	**0.020**	(0.010)	**-0.078**	(0.014)
Dividends	**-0.092**	(0.020)	0.025	(0.013)	0.013	(0.013)	**-0.184**	(0.021)
Profitability	**0.168**	(0.034)	-0.004	(0.025)	0.039	(0.029)	0.060	(0.038)
R-square	0.100		0.072		0.163		0.177	

Table 3 The dynamics of response-to-signal index

The market-wide indices of RS are calculated by cross-sectionally, aggregating individual RS values for the four signals. The indices are then regressed on excess market return (EMR), Fama-French's size (SMB) and book-to-market ratio (HML), momentum (MM), market volatility (M_VOL), credit spread (CS), term spread (TS), dividend yield (DY), one month ahead National Bureau of Economic Research recession dummy (NBERS), and Baker and Wurgler's (2006) sentiment index. EMR, SMB, HML and MM are obtained from Kenneth French's data library and the others from the Federal Reserve Bank of St. Louis. Monthly market volatility (M_VOL) is calculated by summing squared daily returns as in Schwert (1989). D_July, D_August, and D_September are dummy variables for July, August and September, respectively. The numbers in the round brackets represent the Newey-West standard errors and the bold numbers represent significance at the 5% level.

	Macroeconomic variables (MA)		Fama-French three factors and momentum (FFM)		Five PCA factors (PCA)		Seven firm characteristics (FC)	
A. Equally weighted RS index								
RS	**1.327**	(0.096)	**0.708**	(0.082)	**0.644**	(0.137)	**0.271**	(0.104)
C	0.855	(0.660)	**1.006**	(0.450)	0.522	(0.960)	**1.431**	(0.215)
EMR	-0.015	(0.019)	-0.026	(0.029)	0.002	(0.035)	-0.020	(0.019)
SMB	0.006	(0.028)	0.010	(0.060)	0.106	(0.060)	-0.032	(0.019)
HML	0.038	(0.035)	-0.045	(0.044)	0.009	(0.061)	-0.025	(0.021)
MM	**0.064**	(0.015)	0.004	(0.022)	0.013	(0.028)	0.008	(0.011)
M_VOL	0.043	(0.051)	-0.127	(0.065)	0.049	(0.074)	**-0.090**	(0.033)
CS	**-1.516**	(0.624)	-0.074	(0.423)	**-2.760**	(1.131)	**-0.371**	(0.183)
TS	0.029	(0.192)	**0.238**	(0.120)	**0.389**	(0.191)	0.037	(0.042)
DY	**0.692**	(0.230)	0.063	(0.150)	0.916	(0.323)	**0.139**	(0.061)
NBERS(t+1)	**-1.502**	(0.536)	**-0.850**	(0.373)	**-2.073**	(0.794)	-0.134	(0.189)
SENT_BW	**-0.446**	(0.171)	0.067	(0.109)	0.215	(0.278)	0.082	(0.054)
D_July							**-8.396**	(0.360)
D_August							**-1.332**	(0.096)
D_September							**-0.348**	(0.079)
AR(1)	**0.668**	(0.053)	**0.178**	(0.051)	**0.427**	(0.078)	**0.127**	(0.046)
R-square	0.638		0.134		0.330		0.870	
B. Value weighted RS index								
RS	**1.357**	(0.207)	**0.684**	(0.083)	**0.649**	(0.136)	**-0.008**	(0.112)
C	-0.166	(0.566)	**1.029**	(0.437)	0.587	(0.948)	**0.871**	(0.247)
EMR	-0.012	(0.021)	-0.020	(0.028)	0.013	(0.036)	-0.014	(0.015)
SMB	0.009	(0.030)	0.001	(0.047)	0.085	(0.056)	0.007	(0.019)
HML	0.059	(0.038)	-0.050	(0.043)	0.005	(0.061)	-0.009	(0.021)
MM	**0.082**	(0.021)	0.002	(0.026)	0.019	(0.028)	0.003	(0.011)
M_VOL	0.047	(0.048)	-0.135	(0.069)	0.011	(0.080)	-0.057	(0.033)
CS	**-1.378**	(0.546)	-0.131	(0.405)	**-2.679**	(1.053)	**-0.392**	(0.182)
TS	0.163	(0.153)	0.240	(0.123)	**0.425**	(0.189)	-0.005	(0.057)
DY	**0.949**	(0.190)	0.073	(0.146)	**0.898**	(0.304)	**0.210**	(0.070)
NBERS (t+1)	**-1.936**	(0.562)	**-0.728**	(0.363)	**-1.944**	(0.796)	-0.120	(0.203)
SENT_BW	**-0.535**	(0.153)	0.081	(0.098)	0.237	(0.273)	-0.029	(0.067)
D_July							**-8.561**	(0.452)
D_August							**-1.390**	(0.122)
D_September							**-0.336**	(0.094)
AR(1)	**0.506**	(0.055)	0.108	(0.065)	**0.380**	(0.093)	**0.165**	(0.040)
R-square	0.520		0.103		0.302		0.829	

Table 4 Explanation of cross-sectional returns by response-to-signal

The effects of RS and ERS of macroeconomic variables (MA) on the contemporaneous and one month ahead cross-sectional risk-adjusted returns are investigated using monthly Fama-MacBeth regressions from July 1967 to June 2011. Returns_BS and Returns_Others represent the components of the return explained by RS and ERS and the others, respectively. The six annual firm characteristics (ME/ME, Sales Growth, External Financing, Asset Tangibility, Dividends, and Profitability) are calculated at the end of June using accounting data for fiscal year-end in the previous year, as in Fama and French (1992), and are assumed to remain the same from July to June of the following year. Illiquidity is calculated as in Amihud (2002). Idiosyncratic volatility (IVol) is calculated as in Ang, Hodrick, Xing and Zhang (2006) using daily idiosyncratic errors from the Fama-French three factor model. The logarithmic values of volatility, Amihud illiquidity, turnover, and size are used because of their right tails. All explanatory variables are cross-sectionally standardized to have zero mean and unit variance, and then are winsorized at three standard deviations. The numbers in the round brackets represent the Newey-West standard errors and the bold numbers represent significance at the 5% level.

A. Contemporaneous risk-adjusted returns

Risk Adjusted Return(t)	**0.255**	(0.101)	**0.255**	(0.101)	**0.255**	(0.101)	**0.255**	(0.101)	**0.255**	(0.101)
Number of Equities	1818		1818		1818		1818		1818	
Constant	**0.267**	(0.107)	**0.267**	(0.107)	**0.266**	(0.107)	**0.277**	(0.109)	**0.274**	(0.109)
ERS(t-1)			**-0.448**	(0.042)					**-0.711**	(0.057)
RS(t)					**-0.256**	(0.105)			0.143	(0.164)
RS(t)* ERS(t-1)							**6.368**	(0.188)	**7.054**	(0.208)
Momentum (t-12,t-2)	**-0.145**	(0.064)	0.017	(0.066)	**-0.122**	(0.062)	-0.117	(0.070)	-0.026	(0.058)
log_IVol	**0.533**	(0.094)	**0.498**	(0.093)	**0.509**	(0.093)	**0.384**	(0.072)	**0.376**	(0.068)
Log_Illiquidity	**2.503**	(0.183)	**2.765**	(0.185)	**2.521**	(0.180)	**2.464**	(0.147)	**2.289**	(0.137)
Log_Turnover	**1.872**	(0.089)	**1.954**	(0.091)	**1.859**	(0.088)	**1.561**	(0.069)	**1.479**	(0.067)
Log-ME	**1.854**	(0.168)	**2.063**	(0.169)	**1.867**	(0.166)	**1.834**	(0.128)	**1.703**	(0.127)
BE/ME	**0.289**	(0.045)	**0.291**	(0.045)	**0.289**	(0.044)	**0.345**	(0.035)	**0.299**	(0.034)
Sales Growth	-0.117	(0.076)	-0.120	(0.078)	-0.126	(0.076)	**-0.157**	(0.063)	**-0.162**	(0.064)
External Financing	**-0.291**	(0.029)	**-0.281**	(0.029)	**-0.289**	(0.028)	**-0.232**	(0.022)	**-0.222**	(0.022)
Asset Tangibility	**0.202**	(0.036)	**0.195**	(0.037)	**0.193**	(0.036)	**0.136**	(0.031)	**0.146**	(0.028)
Dividends	**0.715**	(0.047)	**0.712**	(0.047)	**0.699**	(0.046)	**0.556**	(0.037)	**0.555**	(0.034)
Profitability	**0.257**	(0.097)	**0.240**	(0.099)	**0.276**	(0.095)	-0.111	(0.086)	-0.008	(0.076)
R square	0.091		0.096		0.108		0.335		0.364	

B. One month ahead risk-adjusted returns

Risk Adjusted Return(t)	**0.428**	(0.106)	**0.428**	(0.106)	**0.428**	(0.106)	**0.428**	(0.106)	**0.428**	(0.106)
Number of Equities	1800		1800		1800		1800		1800	
constant	**0.446**	(0.114)	**0.446**	(0.114)	**0.445**	(0.114)	**0.440**	(0.114)	**0.440**	(0.114)
ERS(t-1)			0.056	(0.041)						
RS(t)			**0.059**	(0.018)						
RS(t)* ERS(t-1)					**-0.423**	(0.034)				
Returns_BS(t)									**-0.421**	(0.033)
Returns_Others(t)									**-0.639**	(0.049)
Returns(t)							**-0.779**	(0.057)		
Momentum (t-12,t-2)	**0.159**	(0.063)	0.119	(0.073)	0.128	(0.066)	0.070	(0.069)	0.075	(0.068)
log_IVol	**-0.309**	(0.042)	**-0.301**	(0.041)	**-0.311**	(0.042)	**-0.318**	(0.043)	**-0.317**	(0.043)
Log_Illiquidity	**0.412**	(0.120)	**0.407**	(0.119)	**0.558**	(0.114)	**1.086**	(0.105)	**1.078**	(0.105)
Log_Turnover	**0.253**	(0.046)	**0.252**	(0.045)	**0.306**	(0.045)	**0.496**	(0.044)	**0.495**	(0.044)
Log-ME	-0.187	(0.115)	-0.182	(0.115)	-0.041	(0.110)	**0.465**	(0.104)	**0.459**	(0.104)
BE/ME	**0.191**	(0.050)	**0.182**	(0.051)	**0.192**	(0.051)	**0.229**	(0.053)	**0.228**	(0.053)
Sales Growth	0.028	(0.083)	0.031	(0.082)	0.032	(0.083)	0.017	(0.084)	0.014	(0.084)
External Financing	**-0.238**	(0.029)	**-0.239**	(0.028)	**-0.241**	(0.029)	**-0.251**	(0.030)	**-0.250**	(0.029)
Asset Tangibility	0.026	(0.041)	0.030	(0.040)	0.026	(0.042)	0.028	(0.043)	0.026	(0.043)
Dividends	**0.121**	(0.042)	**0.118**	(0.042)	**0.121**	(0.043)	**0.131**	(0.044)	**0.129**	(0.043)
Profitability	**-0.331**	(0.142)	**-0.326**	(0.140)	**-0.308**	(0.143)	**-0.312**	(0.144)	**-0.314**	(0.143)
R square	0.059		0.063		0.062		0.067		0.068	

Table 5 Properties of portfolios sorted on the response-to-signal and unbiased expected return by signal

Twenty five portfolios are formed by two independent sorts on RS and lagged ERS of individual equities when the four macroeconomic variables (MA) are used as a signal. The numbers in the round brackets represent the Newey-West standard errors and the bold numbers represent significance at the 5% level.

A. Response to signal (RS)

		Expected return predicted by signal						
		Low	2	3	4	High	High-Low	
Response-to-signal	Low	-8.291	-8.184	-7.849	-8.006	-7.790	**-0.501**	(0.065)
	2	-1.172	-1.002	-0.893	-1.018	-1.204	**0.032**	(0.010)
	3	1.608	1.663	1.681	1.636	1.578	**0.030**	(0.007)
	4	4.185	4.192	4.180	4.186	4.171	0.014	(0.010)
	High	9.659	9.820	9.780	10.136	10.099	**-0.440**	(0.060)
	High-Low	**17.950**	**18.004**	**17.629**	**18.141**	**17.889**		
		(0.575)	(0.579)	(0.591)	(0.611)	(0.566)		

B. Expected return (ERS)

		Expected return predicted by signal						
		Low	2	3	4	High	High-Low	
Response-to-signal	Low	-6.447	-1.782	0.454	2.748	8.120	**14.567**	(0.559)
	2	-6.194	-1.669	0.456	2.653	7.652	**13.846**	(0.555)
	3	-5.734	-1.567	0.442	2.540	7.046	**12.780**	(0.480)
	4	-5.453	-1.553	0.436	2.510	6.835	**12.288**	(0.442)
	High	-5.154	-1.586	0.432	2.533	6.600	**11.754**	(0.424)
	High-Low	**1.293**	**0.196**	-0.021	**-0.216**	**-1.519**		
		(0.076)	(0.015)	(0.013)	(0.015)	(0.095)		

C. Size

		Expected return predicted by signal						
		Low	2	3	4	High	High-Low	
Response-to-signal	Low	2.542	3.482	3.486	3.251	2.214	**-0.328**	(0.044)
	2	2.284	3.041	3.191	2.920	2.124	**-0.160**	(0.034)
	3	2.148	2.700	2.987	2.766	2.129	-0.019	(0.033)
	4	2.161	2.754	3.015	2.806	2.148	-0.013	(0.035)
	High	2.318	2.997	3.133	2.866	2.117	**-0.201**	(0.044)
	High-Low	**-0.224**	**-0.485**	**-0.353**	**-0.385**	**-0.096**		
		(0.033)	(0.033)	(0.030)	(0.033)	(0.027)		

D. Book-to-Market

		Expected return predicted by signal						
		Low	2	3	4	High	High-Low	
Response-to-signal	Low	0.731	0.727	0.785	0.838	0.761	0.030	(0.009)
	2	0.772	0.777	0.796	0.776	0.721	**-0.051**	(0.009)
	3	0.762	0.813	0.796	0.731	0.678	**-0.084**	(0.008)
	4	0.750	0.811	0.784	0.739	0.695	**-0.055**	(0.011)
	High	0.747	0.769	0.759	0.787	0.747	**0.000**	(0.011)
	High-Low	**0.017**	**0.042**	**-0.026**	**-0.051**	**-0.014**		
		(0.008)	(0.006)	(0.007)	(0.009)	(0.008)		

E. Asset Tangibility

Response-to-signal	Expected return predicted by signal: Low	2	3	4	High	High-Low	
Low	29.575	33.822	34.656	32.562	26.787	**-2.789**	(0.703)
2	26.716	31.592	32.502	30.630	25.261	**-1.454**	(0.325)
3	25.648	29.452	30.830	28.679	25.192	-0.457	(0.383)
4	25.842	29.703	31.151	27.505	25.155	**-0.687**	(0.332)
High	26.772	30.848	31.604	30.149	26.409	-0.363	(0.476)
High-Low	**-2.803**	**-2.974**	**-3.052**	**-2.413**	**-0.377**		
	(0.553)	(0.508)	(0.331)	(0.417)	(0.307)		

F. Dividends

Response-to-signal	Expected return predicted by signal: Low	2	3	4	High	High-Low	
Low	1.325	3.126	3.260	2.730	1.076	**-0.249**	(0.058)
2	1.118	2.095	2.735	2.150	0.780	**-0.338**	(0.053)
3	0.882	1.864	2.161	1.747	0.786	-0.095	(0.053)
4	0.954	1.746	2.346	1.733	0.686	**-0.267**	(0.056)
High	0.939	1.962	2.564	1.991	0.900	-0.039	(0.054)
High-Low	**-0.385**	**-1.164**	**-0.696**	**-0.738**	**-0.175**		
	(0.037)	(0.062)	(0.057)	(0.049)	(0.038)		

G. Past Returns ($r_{t-2} \sim r_{t-12}$)

Response-to-signal	Expected return predicted by signal: Low	2	3	4	High	High-Low	
Low	0.152	1.340	1.330	1.342	3.269	**3.116**	(0.103)
2	-0.267	0.935	1.279	1.770	3.741	**4.007**	(0.092)
3	-0.569	0.577	1.276	2.151	4.194	**4.763**	(0.089)
4	-0.894	0.351	1.295	2.399	4.566	**5.460**	(0.100)
High	-1.408	0.114	1.316	2.629	5.051	**6.459**	(0.114)
High-Low	**-1.560**	**-1.225**	-0.014	**1.287**	**1.783**		
	(0.052)	(0.038)	(0.045)	(0.044)	(0.070)		

H. Profits

Response-to-signal	Expected return predicted by signal: Low	2	3	4	High	High-Low	
Low	8.969	11.925	11.549	10.715	9.243	0.273	(0.190)
2	8.211	10.644	11.110	11.086	9.801	**1.590**	(0.173)
3	7.394	10.150	11.042	11.259	9.627	**2.233**	(0.183)
4	7.677	10.004	11.097	11.177	9.759	**2.081**	(0.215)
High	7.788	10.503	11.168	11.017	9.683	**1.895**	(0.224)
High-Low	**-1.181**	**-1.422**	**-0.381**	**0.302**	**0.441**		
	(0.146)	(0.109)	(0.093)	(0.087)	(0.119)		

I. Sales Growth

Response-to-signal	Expected return predicted by signal: Low	2	3	4	High	High-Low	
Low	11.201	10.142	8.599	7.998	10.977	-0.225	(0.243)
2	10.797	9.624	9.307	9.786	12.886	**2.089**	(0.287)
3	10.968	8.794	9.303	11.068	13.828	**2.860**	(0.262)
4	11.003	9.173	9.316	10.985	13.193	**2.191**	(0.253)
High	10.810	9.774	9.500	9.789	12.138	**1.327**	(0.277)
High-Low	-0.391	**-0.368**	**0.901**	**1.791**	**1.161**		
	(0.213)	(0.157)	(0.172)	(0.113)	(0.178)		

J. Idiosyncratic volatility

Response-to-signal	Expected return predicted by signal: Low	2	3	4	High	High-Low	
Low	8.093	3.663	3.275	3.384	6.449	**-1.643**	(0.205)
2	7.438	3.946	3.262	3.671	6.415	**-1.023**	(0.158)
3	7.807	4.486	3.484	4.267	7.054	**-0.753**	(0.154)
4	8.135	4.461	3.553	4.425	7.612	**-0.523**	(0.188)
High	8.895	4.470	3.673	4.848	9.111	0.216	(0.266)
High-Low	**0.802**	**0.808**	**0.398**	**1.464**	**2.661**		
	(0.170)	(0.097)	(0.068)	(0.097)	(0.164)		

Table 6 Returns of the twenty five portfolios sorted on the response-to-signal and unbiased expected return by signal

The contemporaneous and subsequent five month returns of twenty five portfolios formed by two independent sorts on RS and lagged ERS of individual equities are reported. The alphas are estimated in the presence of Fama-French three factors and momentum. The numbers in the round brackets represent the Newey-West standard errors and the bold numbers represent significance at the 5% level.

		Expected return predicted by signal						
		Low	2	3	4	High	High-Low	
A1. Contemporaneous returns								
Response-to-signal	Low	12.367	9.690	1.684	-6.166	-8.586	**-20.953**	(0.606)
	2	3.051	4.408	0.854	-2.440	-1.889	**-4.939**	(0.320)
	3	-2.095	0.547	0.485	0.424	2.795	**4.890**	(0.170)
	4	-5.711	-1.937	0.491	2.804	6.881	**12.591**	(0.427)
	High	-10.955	-4.982	1.287	7.509	15.277	**26.231**	(1.040)
	High-	**-23.321**	**-14.672**	-0.397	**13.675**	**23.863**		
	Low	(0.756)	(0.548)	(0.739)	(0.651)	(0.885)		
B1. Returns one month later								
Response-to-signal	Low	-0.129	0.380	1.016	1.456	1.744	**1.874**	(0.150)
	2	0.535	0.588	0.924	1.196	1.305	**0.770**	(0.143)
	3	1.040	0.942	0.915	0.890	1.015	-0.024	(0.176)
	4	1.392	1.015	0.832	0.820	1.136	-0.256	(0.204)
	High	1.723	1.179	0.764	0.773	0.864	**-0.859**	(0.213)
	High-	**1.852**	**0.800**	-0.252	**-0.682**	**-0.880**		
	Low	(0.165)	(0.123)	(0.137)	(0.152)	(0.161)		
C1. Returns two month later								
Response-to-signal	Low	0.665	0.759	1.084	1.033	1.304	**0.639**	(0.144)
	2	0.861	0.870	1.000	1.102	1.196	**0.335**	(0.133)
	3	1.033	0.956	0.902	0.983	1.246	0.213	(0.178)
	4	1.025	0.937	0.859	0.961	1.309	0.284	(0.182)
	High	1.233	0.919	0.980	0.991	1.388	0.154	(0.222)
	High-	**0.568**	0.161	-0.104	-0.042	0.084		
	Low	(0.174)	(0.124)	(0.107)	(0.116)	(0.140)		

	Expected return predicted by signal						
	Low	2	3	4	High	High-Low	
A2. Contemporaneous alphas							
Low	11.907	9.161	1.065	-6.692	-9.207	**-21.114**	(0.617)
2	2.539	3.928	0.278	-3.045	-2.581	**-5.120**	(0.327)
3	-2.643	0.037	-0.103	-0.283	2.067	**4.710**	(0.188)
4	-6.295	-2.492	-0.134	2.126	6.125	**12.421**	(0.430)
High	-11.566	-5.534	0.656	6.787	14.473	**26.039**	(1.086)
High-	**-23.473**	**-14.695**	-0.409	**13.479**	**23.680**		
Low	(0.809)	(0.585)	(0.811)	(0.691)	(0.895)		
B2. Alphas one month later							
Low	-0.632	-0.157	0.362	0.831	0.981	**1.613**	(0.166)
2	0.038	0.038	0.288	0.539	0.550	**0.513**	(0.153)
3	0.553	0.448	0.286	0.222	0.243	-0.310	(0.181)
4	0.983	0.498	0.218	0.121	0.337	**-0.646**	(0.202)
High	1.299	0.713	0.182	0.093	0.031	**-1.268**	(0.216)
High-	**1.932**	**0.870**	-0.180	**-0.739**	**-0.950**		
Low	(0.181)	(0.125)	(0.136)	(0.174)	(0.150)		
C2. Alphas two month later							
Low	0.173	0.194	0.503	0.431	0.560	**0.387**	(0.150)
2	0.358	0.304	0.392	0.438	0.469	0.110	(0.136)
3	0.652	0.429	0.295	0.344	0.553	-0.099	(0.168)
4	0.656	0.452	0.233	0.327	0.485	-0.171	(0.180)
High	0.908	0.428	0.360	0.239	0.531	-0.377	(0.203)
High-	**0.735**	0.234	-0.144	-0.193	-0.029		
Low	(0.171)	(0.127)	(0.117)	(0.112)	(0.149)		

		Expected return predicted by signal						
		Low	2	3	4	High	High-Low	
D1. Returns three month later								
Response-to-signal	Low	0.845	0.849	0.993	0.940	1.185	**0.339**	(0.162)
	2	0.887	0.903	0.969	1.056	1.319	**0.432**	(0.147)
	3	0.876	0.960	1.006	1.023	1.151	0.275	(0.151)
	4	0.898	0.884	0.932	1.072	1.219	0.321	(0.156)
	High	0.765	0.766	0.978	1.052	1.497	**0.732**	(0.178)
	High-Low	-0.080	-0.083	-0.016	0.112	**0.313**		
		(0.132)	(0.112)	(0.108)	(0.113)	(0.145)		
E1. Returns four month later								
Response-to-signal	Low	0.905	0.776	1.133	1.000	1.160	0.255	(0.158)
	2	0.934	0.874	0.940	1.213	1.202	0.268	(0.158)
	3	1.133	0.932	0.956	0.962	1.260	0.127	(0.202)
	4	1.035	0.820	0.913	0.994	1.326	0.291	(0.195)
	High	0.902	0.796	0.907	0.986	1.237	0.334	(0.180)
	High-Low	-0.003	0.020	**-0.226**	-0.013	0.076		
		(0.137)	(0.112)	(0.110)	(0.121)	(0.138)		
F1. Returns five month later								
Response-to-signal	Low	0.945	0.714	1.057	1.023	1.258	**0.313**	(0.151)
	2	1.094	0.908	0.951	1.137	1.280	0.186	(0.139)
	3	0.720	1.028	0.882	1.018	1.171	**0.451**	(0.163)
	4	0.977	0.928	0.848	1.002	1.132	0.155	(0.164)
	High	0.982	0.781	0.787	0.997	1.086	0.105	(0.203)
	High-Low	0.037	0.067	**-0.270**	-0.027	-0.172		
		(0.124)	(0.117)	(0.102)	(0.103)	(0.125)		

	Expected return predicted by signal						
	Low	2	3	4	High	High-Low	
D2. Alphas three month later							
Low	0.350	0.207	0.409	0.323	0.479	0.129	(0.169)
2	0.454	0.327	0.375	0.425	0.585	0.131	(0.139)
3	0.442	0.438	0.420	0.392	0.454	0.012	(0.162)
4	0.511	0.340	0.367	0.462	0.516	0.005	(0.206)
High	0.430	0.323	0.384	0.318	0.650	0.219	(0.170)
High-Low	0.081	0.116	-0.025	-0.006	0.170		
	(0.125)	(0.112)	(0.116)	(0.096)	(0.136)		
E2. Alphas foud month later							
Low	0.378	0.161	0.495	0.399	0.504	0.126	(0.169)
2	0.428	0.254	0.373	0.618	0.569	0.141	(0.152)
3	0.739	0.380	0.381	0.366	0.556	-0.183	(0.219)
4	0.591	0.347	0.335	0.385	0.624	0.033	(0.213)
High	0.476	0.350	0.317	0.273	0.424	-0.052	(0.163)
High-Low	0.098	0.189	-0.178	-0.126	-0.080		
	(0.137)	(0.113)	(0.123)	(0.125)	(0.128)		
F2. Alphas five month later							
Low	0.425	0.091	0.452	0.434	0.531	0.106	(0.152)
2	0.590	0.334	0.362	0.515	0.643	0.053	(0.140)
3	0.236	0.505	0.315	0.446	0.543	**0.307**	(0.153)
4	0.539	0.404	0.259	0.407	0.430	-0.110	(0.146)
High	0.509	0.279	0.204	0.319	0.320	-0.189	(0.186)
High-Low	0.084	0.188	**-0.248**	-0.114	-0.211		
	(0.121)	(0.118)	(0.113)	(0.102)	(0.116)		

Table 7 Performance of portfolios formed on response to signal and unbiased expected return by signal

Using the four extreme portfolios from the two independent sorts on ERS ($\hat{s}^*_{it-1}$) and RS ($\hat{\delta}_{it}$), i.e., high-RS high-ERS (HH), high-RS low-ERS (HL), low-RS high-ERS (LH), and low-RS low-ERS (LL), I form a hedge portfolio (RS_ERS) as (HL+LH-LL-HH)/2 and report the performance of the return reversals following the formation. The return reversals of the low-minus-high decile portfolios formed on r_{it} (Return_D), $\text{Returns\_Others}_{it}$ (Returns_Others_D), and Returns_BS_{it} (Returns_BS_D) are also reported. These portfolios are formed with non-financial and non-penny stocks ($1) when the four macroeconomic variables (MA) are used as a signal. The alphas are estimated in the presence of Fama-French three factors and momentum. The numbers in the round brackets represent the Newey-West standard errors and the bold numbers represent significance at the 5% level.

		A. Equally weighted portfolios				B. Value weighted portfolios			
		RS_ERS	Return_BS_D	Return_Others_D	Return_D	RS_ERS	Return_BS_D	Return_Others_D	Return_D
Portfolio Returns	July 1967 ~ June 2011	**1.234**	**1.321**	**1.315**	**2.680**	**0.810**	**0.639**	-0.160	0.413
		(0.148)	(0.142)	(0.203)	(0.294)	(0.144)	(0.166)	(0.227)	(0.246)
	July 1967 ~ December 1989	**1.430**	**1.471**	**1.871**	**3.087**	**1.003**	**0.975**	0.296	**0.902**
		(0.183)	(0.172)	(0.239)	(0.335)	(0.174)	(0.227)	(0.267)	(0.292)
	January 1990 ~ December 1999	**1.232**	**1.117**	**0.704**	**2.719**	0.475	-0.111	**-1.026**	-0.771
		(0.254)	(0.246)	(0.341)	(0.629)	(0.323)	(0.304)	(0.421)	(0.577)
	January 2000 ~ June 2011	**0.852**	**1.205**	0.759	**1.852**	**0.726**	0.634	-0.299	0.487
		(0.355)	(0.352)	(0.475)	(0.676)	(0.328)	(0.337)	(0.562)	(0.543)
Alphas of Portfolio Returns	July 1967 ~ June 2011	**1.324**	**1.457**	**1.403**	**2.924**	**0.880**	**0.713**	0.004	**0.572**
		(0.171)	(0.163)	(0.241)	(0.349)	(0.169)	(0.186)	(0.266)	(0.239)
	July 1967 ~ December 1989	**1.641**	**1.674**	**2.019**	**3.121**	**1.197**	**1.325**	**0.699**	**1.226**
		(0.177)	(0.185)	(0.214)	(0.295)	(0.186)	(0.266)	(0.224)	(0.271)
	January 1990 ~ December 1999	**1.493**	**1.411**	**0.953**	**3.484**	0.690	0.093	-0.666	0.171
		(0.268)	(0.269)	(0.295)	(0.682)	(0.371)	(0.368)	(0.435)	(0.450)
	January 2000 ~ June 2011	**0.878**	**1.299**	1.044	**2.248**	**0.717**	0.573	-0.013	0.695
		(0.338)	(0.339)	(0.541)	(0.729)	(0.362)	(0.315)	(0.606)	(0.598)

Table 8 Performance of overconfidence factor with respect to other factors in the literature

Using the four extreme portfolios from the two independent sorts on ERS ($\hat{s}^*_{it-1}$) and RS ($\hat{\delta}_{it}$), i.e., high-RS high-ERS (HH), high-RS low-ERS (HL), low-RS high-ERS (LH), and low-RS low-ERS (LL), I form a hedge portfolio (RS_ERS) as (HL+LH-LL-HH)/2 and regress the return reversals of the portfolio on various factors formed on firm characteristics: hedge portfolio returns form on 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), net stocks issues (NSI) (Fama and French, 2008), 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). These factors are calculated with non-financial and non-penny stocks ($1). The numbers in the round brackets represent the Newey-West standard errors and the bold numbers represent significance at the 5% level.

	Macroeconomic variables (MA)		Fama-French three factors and momentum (FFM)		Five PCA factors (PCA)		Seven firm characteristics (FC)	
C	**1.474**	(0.179)	**1.549**	(0.189)	**1.369**	(0.188)	**1.259**	(0.175)
EMR	0.064	(0.045)	0.063	(0.049)	0.021	(0.053)	0.068	(0.047)
RET_ACC	-0.071	(0.095)	-0.074	(0.088)	-0.129	(0.098)	**-0.068**	(0.072)
RET_AG	-0.164	(0.114)	-0.068	(0.117)	-0.164	(0.125)	-0.091	(0.097)
RET_BEME	0.069	(0.060)	0.065	(0.056)	-0.017	(0.065)	0.076	(0.051)
RET_ESUR	-0.029	(0.080)	-0.047	(0.082)	-0.043	(0.082)	-0.023	(0.072)
RET_FP	0.005	(0.084)	0.036	(0.098)	0.130	(0.093)	0.061	(0.076)
RET_GP	0.051	(0.063)	0.025	(0.062)	0.081	(0.072)	0.022	(0.066)
RET_IA	**0.412**	(0.133)	**0.328**	(0.137)	**0.344**	(0.153)	**0.293**	(0.111)
RET_IVOL	-0.091	(0.063)	-0.096	(0.069)	-0.114	(0.083)	-0.150	(0.061)
RET_LIQ	0.007	(0.069)	-0.015	(0.069)	-0.071	(0.077)	0.048	(0.070)
RET_ME	-0.070	(0.081)	-0.022	(0.088)	0.033	(0.099)	-0.144	(0.083)
RET_MOM	**-0.175**	(0.043)	**-0.180**	(0.043)	**-0.116**	(0.052)	**-0.145**	(0.038)
RET_NOA	-0.076	(0.113)	-0.170	(0.131)	-0.085	(0.139)	-0.120	(0.096)
RET_NSI	**-0.184**	(0.084)	-0.172	(0.092)	-0.065	(0.091)	-0.064	(0.079)
RET_OSC	0.039	(0.088)	-0.060	(0.087)	-0.066	(0.083)	0.019	(0.075)
RET_ROA	0.151	(0.087)	0.163	(0.083)	0.150	(0.086)	**0.145**	(0.061)
R Square	0.245		0.247		0.227		0.261	

Table 9 Robustness Tests

The portfolios are formed in various ways on RS_ERS. The performance of portfolios from different signals (panel A) and formation methods (panel B), for January and non-January (panel C), various universe or breakpoints (panel D), liquidity levels (panel E), learning periods (panel F), and forecasting horizons (panel G) are reported. The breakpoint between microcaps and small and large stocks is the 20% of the NYSE. The numbers in the round brackets represent the Newey-West standard errors and the bold numbers represent significance at the 5% level.

	Portfolio Returns								Alphas of Portfolio Returns							
	July 1967 ~ June 2011		July 1967 ~ December 1989		January 1990 ~ December 1999		January 2000 ~ June 2011		July 1967 ~ June 2011		July 1967 ~ December 1989		January 1990 ~ December 1999		January 2000 ~ June 2011	
A. RS_ERS portfolios for various signals																
MA	**1.366**	(0.134)	**1.564**	(0.179)	**1.143**	(0.209)	**1.173**	(0.305)	**1.441**	(0.138)	**1.694**	(0.177)	**1.329**	(0.213)	**1.231**	(0.285)
FFM	**1.418**	(0.152)	**1.721**	(0.183)	**1.108**	(0.271)	**1.097**	(0.354)	**1.505**	(0.155)	**1.804**	(0.179)	**1.368**	(0.255)	**1.158**	(0.309)
PCA	**1.244**	(0.156)	**1.567**	(0.217)	**1.157**	(0.257)	**0.689**	(0.292)	**1.348**	(0.168)	**1.610**	(0.208)	**1.338**	(0.241)	**0.854**	(0.276)
FC	**1.179**	(0.154)	**1.459**	(0.213)	**0.933**	(0.169)	**0.845**	(0.350)	**1.188**	(0.158)	**1.393**	(0.217)	**1.017**	(0.189)	**0.851**	(0.306)
B. Return reversals skipping the first day in the holding month																
Return_BS_D	**0.937**	(0.125)	**1.130**	(0.156)	**0.495**	(0.212)	**0.946**	(0.293)	**1.057**	(0.142)	**1.319**	(0.175)	**0.722**	(0.243)	**1.044**	(0.286)
RS_ERS	**0.808**	(0.109)	**1.073**	(0.150)	0.275	(0.168)	**0.753**	(0.227)	**0.905**	(0.118)	**1.243**	(0.154)	**0.440**	(0.174)	**0.787**	(0.219)
C. RS_ERS portfolios in January and non-January																
January	**3.951**	(0.673)	**4.542**	(0.856)	**3.494**	(0.805)	**3.248**	(1.834)	**2.577**	(0.474)	**2.353**	(0.636)	**3.465**	(0.755)	**1.692**	(1.065)
Non-January	**1.131**	(0.126)	**1.299**	(0.169)	**0.930**	(0.208)	**0.976**	(0.285)	**1.202**	(0.129)	**1.516**	(0.182)	**1.192**	(0.206)	**0.909**	(0.278)
D. RS_ERS portfolios for various breakpoints and universe																
NYSE Breakpoints	**1.246**	(0.129)	**1.489**	(0.172)	**0.990**	(0.208)	**0.993**	(0.271)	**1.317**	(0.132)	**1.633**	(0.166)	**1.152**	(0.211)	**1.062**	(0.244)
Microcaps	**1.972**	(0.204)	**2.085**	(0.307)	**1.851**	(0.270)	**1.857**	(0.408)	**2.041**	(0.205)	**2.095**	(0.320)	**2.123**	(0.249)	**1.842**	(0.379)
Small and large stocks	**0.964**	(0.134)	**1.297**	(0.159)	0.364	(0.259)	**0.834**	(0.272)	**0.958**	(0.145)	**1.448**	(0.152)	0.487	(0.253)	**0.789**	(0.271)
All Stocks	**1.299**	(0.128)	**1.434**	(0.172)	**1.189**	(0.209)	**1.132**	(0.284)	**1.356**	(0.129)	**1.565**	(0.169)	**1.345**	(0.212)	**1.164**	(0.250)
Non-penny (5$)	**0.958**	(0.123)	**1.259**	(0.154)	0.373	(0.223)	**0.877**	(0.256)	**1.038**	(0.127)	**1.402**	(0.151)	**0.523**	(0.199)	**0.969**	(0.242)
E. RS_ERS portfolios for various breakpoints and universe																
Illiquid stocks	**1.754**	(0.177)	**1.935**	(0.259)	**1.540**	(0.298)	**1.586**	(0.370)	**1.889**	(0.184)	**2.064**	(0.260)	**1.977**	(0.319)	**1.543**	(0.377)
Liquid Stocks	**0.957**	(0.146)	**1.256**	(0.159)	**0.340**	(0.291)	**0.909**	(0.342)	**0.996**	(0.168)	**1.371**	(0.143)	**0.516**	(0.288)	**1.018**	(0.350)

	Portfolio Returns								Alphas of Portfolio Returns							
	July 1967 ~ June 2011		July 1967 ~ December 1989		January 1990 ~ December 1999		January 2000 ~ June 2011		July 1967 ~ June 2011		July 1967 ~ December 1989		January 1990 ~ December 1999		January 2000 ~ June 2011	
F. RS_ERS portfolios for different learning periods																
12 Months	**0.916**	(0.140)	**1.226**	(0.205)	**0.626**	(0.208)	**0.562**	(0.266)	**1.000**	(0.133)	**1.257**	(0.196)	**0.831**	(0.182)	**0.795**	(0.289)
24 Months	**1.294**	(0.137)	**1.620**	(0.195)	**1.008**	(0.196)	**0.903**	(0.270)	**1.418**	(0.152)	**1.759**	(0.208)	**1.085**	(0.202)	**0.968**	(0.280)
36 Months	**1.366**	(0.139)	**1.554**	(0.200)	**1.327**	(0.235)	**1.031**	(0.272)	**1.502**	(0.152)	**1.676**	(0.216)	**1.507**	(0.281)	**1.140**	(0.257)
48 Months	**1.242**	(0.132)	**1.429**	(0.164)	**1.012**	(0.214)	**1.078**	(0.315)	**1.319**	(0.135)	**1.546**	(0.167)	**1.308**	(0.206)	**1.089**	(0.263)
60 Months	**1.366**	(0.134)	**1.564**	(0.179)	**1.143**	(0.209)	**1.173**	(0.305)	**1.441**	(0.138)	**1.694**	(0.177)	**1.329**	(0.213)	**1.231**	(0.285)
72 Months	**1.240**	(0.136)	**1.454**	(0.181)	**1.108**	(0.241)	**0.937**	(0.300)	**1.335**	(0.142)	**1.591**	(0.173)	**1.321**	(0.243)	**1.008**	(0.268)
84 Months	**1.298**	(0.147)	**1.528**	(0.187)	**1.046**	(0.261)	**1.068**	(0.328)	**1.396**	(0.157)	**1.646**	(0.185)	**1.339**	(0.246)	**1.132**	(0.317)
G. RS_ERS portfolios for different forecasting horizons																
Contemporaneous explanation	**1.473**	(0.154)	**1.562**	(0.192)	**1.341**	(0.257)	**1.415**	(0.361)	**1.579**	(0.153)	**1.694**	(0.179)	**1.522**	(0.268)	**1.468**	(0.350)
Two month ahead forecasting																
One month later	**1.052**	(0.151)	**1.297**	(0.177)	**0.734**	(0.289)	**0.848**	(0.355)	**1.198**	(0.153)	**1.426**	(0.164)	**1.001**	(0.304)	**0.996**	(0.312)
Two month later	-0.150	(0.123)	-0.245	(0.156)	-0.237	(0.243)	0.114	(0.288)	0.006	(0.129)	-0.066	(0.159)	0.163	(0.238)	0.209	(0.261)
Three month ahead forecasting																
One month later	**0.773**	(0.154)	**0.913**	(0.174)	**0.720**	(0.296)	0.546	(0.370)	**0.936**	(0.150)	**1.143**	(0.171)	**1.144**	(0.210)	**0.535**	(0.263)
Two month later	**-0.322**	(0.128)	**-0.330**	(0.150)	-0.443	(0.263)	-0.203	(0.312)	-0.112	(0.138)	-0.098	(0.145)	0.104	(0.191)	-0.069	(0.269)
Three mnonth later	**-0.400**	(0.117)	**-0.433**	(0.145)	**-0.462**	(0.243)	-0.283	(0.265)	-0.233	(0.119)	**-0.285**	(0.135)	-0.023	(0.231)	-0.193	(0.280)
Four month ahead forecasting																
One month later	**0.769**	(0.189)	**1.074**	(0.241)	0.496	(0.346)	0.411	(0.398)	**0.982**	(0.191)	**1.164**	(0.195)	**1.159**	(0.308)	0.674	(0.366)
Two month later	-0.062	(0.149)	0.082	(0.170)	-0.349	(0.317)	-0.096	(0.332)	0.221	(0.174)	**0.303**	(0.152)	0.306	(0.274)	0.225	(0.366)
Three mnonth later	**-0.374**	(0.131)	-0.279	(0.176)	-0.407	(0.262)	-0.531	(0.260)	-0.118	(0.114)	-0.087	(0.150)	-0.020	(0.255)	-0.327	(0.239)
Four month later	**-0.270**	(0.114)	-0.251	(0.153)	-0.295	(0.228)	-0.287	(0.254)	-0.062	(0.128)	-0.118	(0.160)	-0.004	(0.234)	-0.138	(0.274)

Figure 1 Time line showing estimation procedure of the unbiased expected return by signal and response to signal

Step 1 Calculation of risk-adjusted returns
Dependent variable: excess return of individual stock
Independent variable: excess market return

Step 2 Learning process for the prediction of returns using signals
Dependent variable: risk-adjusted return
Independent variables: various signals

Step 3 Calculation of response to the unbiased expected return by signal
Dependent variable: excess return
Independent variables: excess market return and unbiased expected return by signal

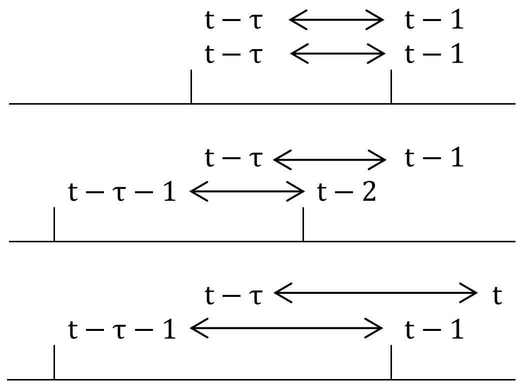

Figure 2 Response to signal for various signals

The time series of the responses to the four signals (i.e., macroeconomic variables (MA), Fama-French three factors and momentum (FFM), five PCA factors (PCA), and seven firm characteristics (FC)) are calculated by equal weights on the individual RS values. The large negative RS values in the seven firm characteristics (FC) occur at July, August, and September when annual accounting variables are updated.

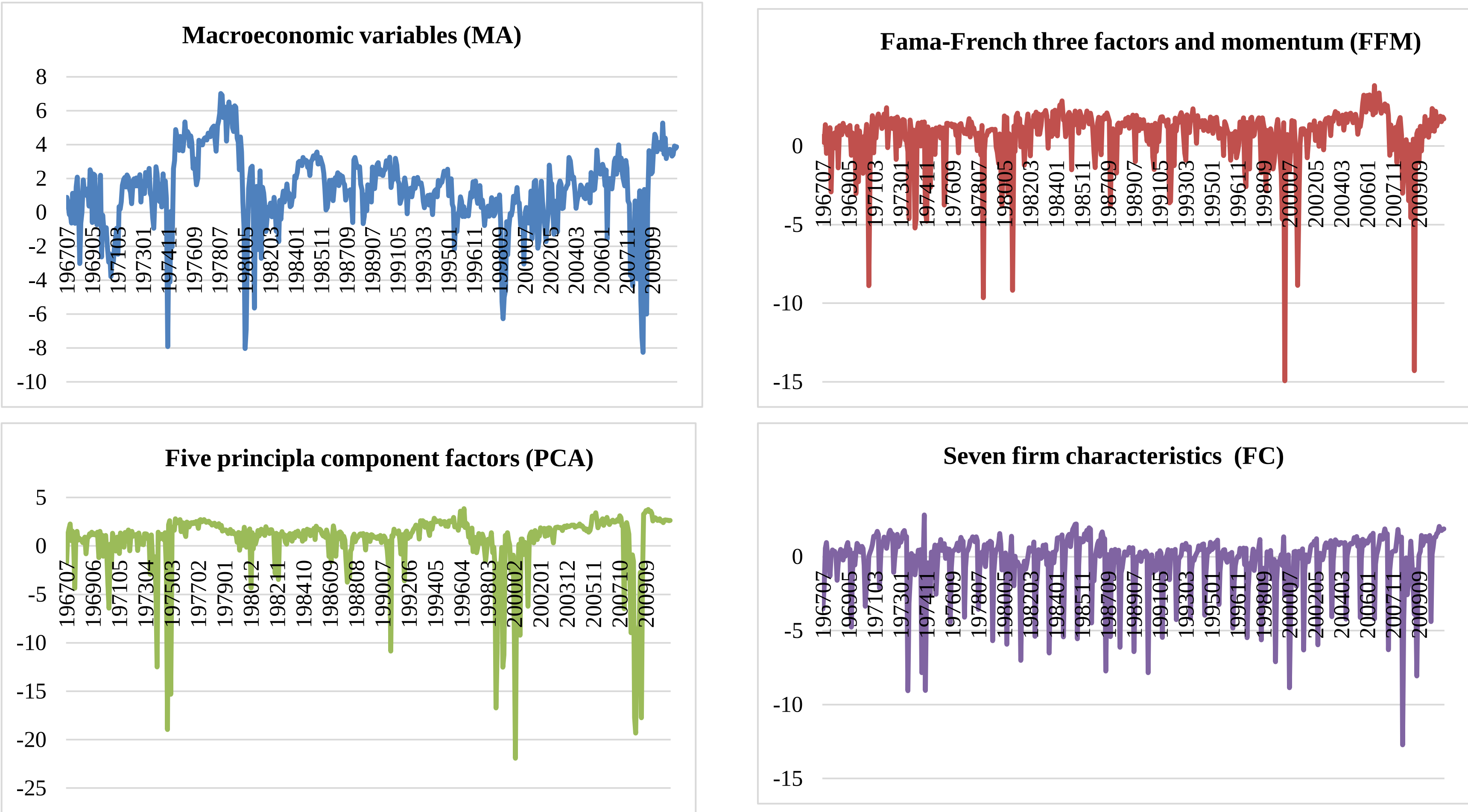

Figure 3 Dynamics of returns at the formation month and subsequent months.

From the twenty five portfolios by the two independent sorts on ERS ($\hat{s}^*_{it-1}$) and RS ($\hat{\delta}_{it}$), I calculate the cumulative alphas of the four portfolios: high-RS high-ERS (HH), high-RS low-ERS (HL), low-RS high-ERS (LH), and low-RS low-ERS (LL), as well as HL-LL and HH-LH. The alphas are calculated with the Fama-French three factors and momentum.