The Cost of Overconfidence in Public Information

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Abstract

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Keywords: Overconfidence, Factors, Public Signals, Short-term Return Reversals

JEL codes: G02, G12.

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1. Introduction

The norm in the overconfidence literature is to model investor overconfidence in their private information (Hirshleifer et al. 1994; Daniel et al., 1998; Odean, 1998; Banerjee et al, 2009; Banerjee, 2011) or new public information such as earnings announcements (Barberis et al. 1998; Hong and Stein, 1999; Hirshleifer, 2001; Scheinkman and Xiong, 2003); this is because asset prices should not be affected by any information already known to investors. However, many studies in the asset pricing literature have reported that trading strategies based on publicly available information such as financial reports or past trading activity (henceforth, public information) can produce profits, even after considering risk.[1] If public information is not irrelevant to asset returns, then investors may also be overconfident about their abilities when they interpret this information. We explore this possibility to fill the gap in the literature.

Our purpose is to investigate if investors are overconfident about public information. If investors believe too strongly in public information, asset prices may be biased during their Bayesian updating process in a way similar to the effects of their belief in private information (Kyle and Wang, 1997; Odean, 1998; Daniel et al., 1998). However, the effects of investor overconfidence in public information on asset returns may not be the same as those of their overconfidence in private information or new public information. We investigate the characteristics of firms that are more easily affected by investor overconfidence in public information; further, we examine the extent to which stock prices are biased by the overconfidence and how fast these biases are subsequently reversed.

1 Public information (or public signals) in this study does not include "new public information" that has been used in event studies. It is historical information that is known to investors in the market. For surveys of studies that report hundreds of trading strategies based on publicly available information, see Agarwal et al. (2015), Harvey et al. (2016), McLean and Ponti (2016), and Green et al. (2017).

For these purposes, we analyze how investors respond to noisy signals about factors in linear factor models. If factors can explain stock returns (Fama and French 2015; Hou et al., 2015; Barillas and Shanken, 2018), signals about these factors are what investors use to update their prediction of stock returns. Overconfidence in firm-specific public information, such as firm-specific announcements or financial disclosures, would not be cross-sectionally comparable because of its idiosyncratic nature.

Lagged factors are used as public signals for the factors we test in this study, such as macroeconomic variables, firm characteristics factors, or factors from principal component analysis. They are noisy, but are available to all investors and thus serve our purpose better than firm-specific information, which is less likely to be disseminated to all investors in the market (Huberman and Regev, 2001; Hirshleifer et al., 2009; Engelberg and Parsons, 2011). Other sophisticated signals (i.e., less noisy signals) for the factors can be used, but they would not change our results on cross-sectional asset returns. We demonstrate that different signals change posterior expectations of factors without affecting cross-sectional difference in overconfidence.

We propose a procedure to measure overconfidence by observing the violation of Bayes' rule on what investors have learned in the past.[2] The posterior expectation in Bayesian updating (Daniel et al., 1998) consists of signals and responses to these signals for both rational and overconfident investors. If signals are the same, regardless of stocks, the difference between the two groups of investors arises from how they respond to the signals. Therefore, we estimate unexpected responses to signals by comparing *ex post* realized returns with posterior returns that investors expect when they process signals according to what they have learned from their

[2] Empirical studies have used various methods to investigate overconfidence in different context: e.g., volatility or trading volume (Odean, 1998; Barber and Odean, 2000; Grinblatt and Keloharju, 2009), laboratory experiments (Biais et al. 2005), the timing of option exercises (Malmendier and Tate, 2005), psychological profile (Grinblatt and Keloharju, 2009), survey data (Deaves et al., 2010; Merkle, 2017), or betting (Moskowitz, 2015). However, these methods do not show the detailed effects of investor overconfidence about publicly available information on cross-sectional asset returns.

experience. The *ex post* realized returns reflect investors' beliefs in signals and are thus affected by overconfidence biases, whereas the posterior expected returns represent *status quo* expectations, because these returns are what investors expect when they follow their experience. The difference between the two returns represents investors' over- or under-responses that are driven by their level of confidence in the signals.

For every month between January 1970 and June 2016, we estimate *status quo* expected returns (expected return predicted by signal, ERS) and responses to the ERSs (response to signal, RS) for non-penny and non-financial stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ. Investor overconfidence measured by RS and subsequent return reversals are analyzed using monthly Fama-MacBeth regression with individual stocks, as well as portfolios formed on ERS and RS. The empirical results are summarized below.

First, overconfidence in noisy public signals for factors is prevalent in equity markets. Investors' perceived precision of signals is, on average, twice as high as what investors have learned in the past; this is similar to the survey results of Merkle (2017). The proportion of contrarian responses to ERS is also significant: approximately one-third of stocks move in a direction that is opposite to what ERS suggests.

Second, and more interestingly, investors tend to be overconfident about the noisy public signals for old stocks, 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 are characteristics of mature firms that have long operating histories and are well known to investors and analysts (Benartzi et al., 1997; Berger and Udell, 1998; Grullon et al., 2002; De Angelo et al., 2006; Bulan et al., 2007; Bulan et al., 2010). The empirical results that mature firms are more likely to be affected by overconfidence in the noisy public signals are surprising because stocks that are difficult to value or arbitrage—typically small and illiquid stocks—are likely to be affected by behavioral biases (Baker and Wurgler, 2005; Kumar, 2009).

Third, most effects of overconfidence in the noisy public signals for factors are reversed during the following two months. Therefore, overconfidence in publicly available information is less likely to be responsible for anomalies, such as size or value (Banz, 1981; Rosenberg et al., 1985; Lakonishok et al., 1994; Daniel et al., 1998, 2001), that typically last for a considerable period after portfolio formation. Instead, the immediate return reversals are closely related to the short-term return reversals of Jegadeesh (1990) and Lehmann (1990). We find that almost half of the short-term return reversals can be explained by the return reversals following overconfidence in the noisy public signals.

Finally, the cost of overconfidence, which is calculated by return reversals following the formation of portfolios on ERS and RS, is statistically and economically significant. The Fama-French five-factor alphas of these hedge portfolios formed on the independent 5×5 sorts on ERS and RS range from 1.1% to 1.3% per month, depending on the portfolio formation methods and signals. The cost is not explained by the 14 popular factors in the literature, although it shows significant relationships with a few factors (i.e., momentum, idiosyncratic volatility, and investment to assets) that the literature associates with overconfidence (Jegadeesh and Titman, 2001; Daniel et al., 1998, 2001; Chuang and Lee, 2006; Cooper et al., 2008). Our empirical results are also robust under other conditions, including a bid-ask bounce, January effects, size and portfolio breakpoints, liquidity, learning periods, and prediction horizons.

Our empirical results indicate a clear difference in how overconfidence in public and private information or other behavioral biases such as sentiment affect cross-sectional asset pricing. Sentiment or overconfidence in private signals is more likely to affect stocks that are difficult to value or arbitrage and their effects on stock prices last for several months or even years (Baker and Wurgler, 2006; Kumar, 2009; Stambaugh et al., 2012; Antoniou et al., 2015). Moreover, investors are less likely to be overconfident about new public information (Hirshleifer, 2001; Moskowitz, 2015). However, for public signals, large positive or negative values of RS are more likely to be observed for mature firms, and the effects of the overconfidence bias disappear relatively quickly.

We suggest the overconfidence of investors who trade these stocks as an explanation for these empirical results. If market experts are more overconfident than novices (De Long et al., 1991; Griffin and Tversky, 1992; Odean, 1998), then the stocks that these experts trade are affected by their overconfidence in public information. In fact, Gompers and Metrick (2001), Bennett et al. (2003), and Yan and Zhang (2009) show that institutional investors prefer large stocks, value stocks, or stocks with a long listing history. In addition, the valuation of mature firms also appears to be relatively easy with fewer problems of information asymmetry between managers and investors (Easley and O'Hara, 2004); this makes investors over-place themselves, relative to others, when valuing mature firms (Benoît et al., 2015).

The short-term return reversals owing to overconfidence in public information are the cost of the irrationality that the overconfident experts should pay for over-responding to the signals (Arif et al., 2016). However, they are also the profit that rational investors earn from providing liquidity to the overconfident institutional investors who cause intense buying or selling. (Campbell et al., 1993; Nagel, 2012; Cheng, Hameed, Subrahmanyam, and Titman, 2014). Our results are consistent with the increase in short-term return reversals for stocks whose institutional holdings decrease (Cheng et al., 2014).

The rest of this paper is organized as follows. In Section 2, we propose a measure for investors' unexpected responses to public signals of factors. In Section 3, we report the empirical results for the characteristics of firms that show extremely large values of RS, and how stock returns respond to overconfidence. The cost of overconfidence is calculated in Section 4, together with the robustness of the results. Finally, Section 5 concludes.

2. Overconfidence in public signals and cross-sectional asset returns

2.1 Unexpected responses to public signals and biases in asset returns

To investigate the effects of overconfidence on cross-sectional asset returns, we focus on risk-adjusted returns. Suppose that the risk-adjusted return of asset *i* is explained by the following linear factor model:

$$r_{i,t+1}^{A}=\sum_{k=1}^{K}\beta_{i,k,t+1}f_{k,t+1}+\epsilon_{i,t+1}, \tag{1}$$

where $r_{i,t+1}^{A}=r_{i,t+1}-\beta_{i,m,t+1}r_{m,t+1}$, $r_{i,t+1}$ and $r_{m,t+1}$ are excess returns for asset i and the market, respectively; $f_{k,t+1}$ is a factor; and $\epsilon_{i,t+1}$ denotes an idiosyncratic shock, $\epsilon_{i,t+1}\sim N(0,\sigma_{\epsilon_{i,t+1}}^{2})$. At time *t*, investors receive noisy public signals for the factors (henceforth, noisy public signals), each of which appears as $s_{k,t}=\rho_k f_{k,t+1}+\varepsilon_{k,t}$ for a given scale parameter ρ_k, where $\varepsilon_{k,t}$ represents noise of factor k at time *t*. [3]

Upon receiving these K $s_{k,t}$s, investors apply Bayes' rule to update their prior beliefs and their posterior expectation of asset *i*'s risk-adjusted return is

$$E_t\left[r_{i,t+1}^{A}\middle|s_{1,t},\dots,s_{K,t}\right]=\sum_{k=1}^{K}\varphi_{i,k,t}s_{k,t}, \tag{2}$$

where $\varphi_{i,k,t}=\beta_{i,k,t+1}w_{k,t}$ and $w_{k,t}=\frac{\rho_k\sigma_{f_{k,t+1}}^{2}}{\rho_k^{2}\sigma_{f_{k,t+1}}^{2}+\sigma_{\varepsilon_{k,t}}^{2}}$ because $\frac{cov(r_{i,t+1}^{A},s_{k,t})}{var(s_{k,t})}s_{k,t}=\beta_{i,k,t+1}\frac{cov(f_{k,t+1},s_{k,t})}{var(s_{k,t})}s_{k,t}=\beta_{i,k,t+1}w_{k,t}s_{k,t}$. Therefore, for given noisy public signals, investors' expectation about individual asset returns can be decomposed into their posterior expectation

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[3] Typical assumptions for a linear factor model are applied, and factors and signals are assumed to be uncorrelated: $f_{k,t+1}\sim N\left(0,\sigma_{f_{k,t+1}}^{2}\right)$; $\varepsilon_{k,t}\sim N(0,\sigma_{\varepsilon_{k,t}}^{2})$; $cov(f_{k,t+1},f_{j,t+1})=cov(s_{k,t},s_{j,t})=cov(f_{k,t+1},\varepsilon_{k,t})=cov(r_{i,t+1}^{A},\varepsilon_{k,t})=0$; $var(s_{k,t})=\rho_k^{2}\sigma_{f_{k,t+1}}^{2}+\sigma_{\varepsilon_{k,t}}^{2}$; and $cov(s_{k,t},r_{i,t+1}^{A})=\rho_k\beta_{i,k,t+1}\sigma_{f_{k,t+1}}^{2}$.

of common factors, i.e., $E_t[f_{k,t+1}|s_{k,t}] = w_{k,t}s_{k,t}$, and cross-sectional responses to the expectation, i.e., $\beta_{i,k,t+1}$, which is not affected by the Bayesian updating. If investors had a noise-free signal $s_{k,t} = f_{k,t+1}$, then $E_t[f_{k,t+1}|s_{k,t}] = f_{k,t+1}$ because $\sigma^2_{\varepsilon_{k,t}} = 0$, $\rho_k = 1$. In general, however, we expect $1 > w_{k,t} > 0$ (or $\beta_{i,k,t+1} > \varphi_{i,k,t} > 0$) for any noisy signal.

The weight on $s_{k,t}$ in equation (2) is equivalent to the regression coefficient of asset i's $t+1$ risk-adjusted return on $s_{k,t}$, i.e.,

$$r^A_{i,t+1} = \sum_{k=1}^{K} \varphi_{i,k,t}s_{k,t} + \eta_{i,t+1}, \tag{3}$$

where $\eta_{i,t+1} \sim N(0, \sigma^2_{\eta,i,t})$. The term $\sum_{k=1}^{K} \varphi_{i,k,t}s_{k,t}$ is the expected return predicted by rational investors on the basis of the noisy public signals; it is referred to as the expected return predicted by signal (ERS) in this study.

To explain how overconfident investors respond to the noisy public signals in practice, we introduce a response-to-signal (RS) variable $\delta_{i,t}$ to represent their perceived bias about the precision of signals (Daniel et al., 1998) such that the perceived variance of signal k appears as $var(s_{k,t})/\delta_{i,t}$ for these investors, rather than as $var(s_{k,t})$. The RS variable $\delta_{i,t}$ is set to be specific to asset i so that it measures investors' beliefs about the accuracy of signals for asset i.[4] With investors' perceived variance $var(s_{k,t})/\delta_{i,t}$ in the denominator of $w_{k,t}$, overconfident investors' response to the signal can be represented as $\varphi^b_{i,k,t} = \frac{cov(s_{k,t}, r^A_{i,t+1})}{var(s_{k,t})/\delta_{i,t}} = \delta_{i,t}\varphi_{i,k,t}$, and thus investors' posterior expectation becomes as follows:

$$E^b_t[r^A_{i,t+1}|s_{1,t}, \ldots, s_{K,t}] = \delta_{i,t}s^*_{i,t}, \tag{4}$$

[4] Other specifications for the RS variable are also possible. For example, the RS variable can be allowed to be specific to signal k ($\delta_{k,t}$) regardless of assets, or to both asset i and signal k ($\delta_{i,k,t}$). Because the purpose of this study is to investigate cross-sectional asset returns and firm characteristics of firms that are likely to be affected by investor overconfidence, $\delta_{i,t}$ is made specific to assets.

where b represents bias in the expectation and $s_{i,t}^* = \sum_{k=1}^{K} \varphi_{i,k,t} s_{k,t}$ is ERS.[5]

The RS variable describes the way that investors respond to ERS: i.e., rational behavior when $\delta_{i,t} = 1$, or an unexpected response depending on the value of $\delta_{i,t}$: i.e., $\delta_{i,t} > 1$ for overconfidence (over-precision) and $1 > \delta_{i,t} > 0$ for under-confidence (under-precision). As reported later (Table 1), a large number of stocks shows negative $\delta_{i,t}$s, suggesting that stock prices move in a direction opposite to what the signals suggest (ERS). Therefore, we take absolute values of $\delta_{i,t}$s to test investors' over- or under-confidence in the noisy public signals, regardless of whether these responses are for or against the signals. On the other hand, the signs of $\delta_{i,t}$s represent investors' behavior for or against signals, regardless of over- or under-confidence.

The decomposition of the posterior expectation $E_t^b\left[r_{i,t+1}^A \middle| s_{1,t}, \dots, s_{K,t}\right]$ into RS and ERS provides details of the effects of investors responses to public signals on asset returns. As in Figure 1, RS alone may not show a clear difference in cross-sectional asset returns since positive and negative biases in RS can be cancelled out. Therefore, in the empirical tests, the effects of overconfidence on cross-sectional asset returns are calculated by taking long and short positions in negatively biased and positively biased stocks, respectively.[6]

2.2 Estimation of responses to signals

[5] Rational investors do not affect prices as far as they are risk-averse, and thus asset prices are driven away from their rational values by overconfident investors. See Daniel et al. (1998) and Daniel and Hirshleifer (2015) for further explanations.

[6] The two extreme cases of overconfidence—over-responses for or against signals—are more likely to affect the posterior expectation than those of under-confidence; this is because $\delta_{i,t}$ is either positively or negatively unbounded.

One difficulty in the empirical tests is the identification of ERS and RS. If rational investors' responses ($\varphi_{i,k,t}s$) to signals ($s_{k,t}s$) were known, RS could be estimated using the following regression:

$$r_{i,t+1}^{A} = \alpha_{i,t} + \delta_{i,t} s_{i,t}^{*} + \eta_{i,t+1}. \tag{5}$$

However, neither the responses nor signals are directly observable.

To overcome this problem, we estimate $\varphi_{i,k,t}s$ under the assumption that rational investors form their expectation based on what they have learned in the past. When investors receive noisy public signals and predict returns, they implicitly or explicitly evaluate how returns have responded to the signals in the past, and then predict returns based on the return-signal relationship. Even though the past return-signal relationship is biased, rational investors are less likely to correct the bias because of the risks and costs associated with arbitrage trading (Barberis and Thaler, 2003). The return-signal relationship can be estimated by regressing $r_{i,t}^{A}$ on $s_{k,t-1}$s as in equation (3) using past data. The estimates of $\varphi_{i,k}$s reflect what investors have learned in the past, and thus $\hat{s}_{i,t}^{*} = \sum_{k=1}^{K} \hat{\varphi}_{i,k,t} s_{k,t}$ is the estimate of investors' posterior expectation at time *t* for the forecast of the $t + 1$ return.

For public signals about $f_{k,t+1}$s, we use lagged variables of the factors assuming that $f_{k,t}$ includes information for $f_{k,t+1}$: i.e., $s_{k,t} = f_{k,t} = \rho_k f_{k,t+1} + \varepsilon_{k,t}$. Certain factors—particularly macroeconomic ones (Ferson and Harvey, 1999)—are highly persistent, and thus current values include information about future outcomes. Other factors based on firm characteristics (Fama and French, 2015) or statistical approaches (Lehmann and Modest, 1988) are not as persistent as macroeconomic factors, but the past performance of factors is widely used to predict factor returns in practice (Baltussen et al., 2019).

Sophisticated models or additional information would not affect the cross-sectional difference in the unexpected responses because any change in ERS is market-wide and thus is not specific to individual assets. To see this, suppose another public signal $s^*_{k,t} = \rho^*_k f_{k,t+1} + \varepsilon^*_{k,t}$ where the composition of signal ($\rho^*_k f_{k,t+1}$) and noise ($\varepsilon^*_{k,t}$) is different from $s_{k,t}$. It can be easily proven that investors' responses ($\varphi^*_{i,k,t}s$) to these signals ($s^*_{k,t}s$) are affected by the same scale for all assets because $\varphi^*_{i,k,t} = \beta_{i,k,t+1} w^*_{k,t}$ where $w^*_{k,t} = \frac{\rho^*_k \sigma^2_{f_{k,t+1}}}{\rho^{*2}_k \sigma^2_{f_{k,t+1}} + \sigma^2_{\varepsilon^*_{k,t}}}$ is common to all assets. Therefore, in so far as $s_{k,t}$ is a market-wide common signal and $\rho_k \neq 0$, the cross-sectional relationship between asset returns and RSs remains unchanged. In the empirical tests, we use three types of noisy public signals to demonstrate the robustness of our results.

The details of the estimation process for ERS and RS are as follows. We first calculate risk-adjusted returns to focus on the relationship between signals and stock returns. Risk-adjusted returns for individual stocks are calculated using the past τ periods as follows:

$$\hat{r}^A_{i,t-s} = r_{i,t-s} - \hat{\beta}_i r_{m,t-s},\ \ s = \tau - 1, \ldots, 0, \tag{6}$$

where β_i is estimated using the past τ monthly returns. The second step is to estimate ERS at time t for the prediction of $\hat{r}^A_{i,t+1}$. Using lagged factor returns as noisy signals, the risk adjusted returns are regressed on the signals to estimate $\varphi_{i,k}$s:

$$\hat{r}^A_{i,t-s} = \sum_{k=0}^{K} \varphi_{i,k} f_{k,t-s-1} + \eta_{i,t-s}, \text{ where } f_{0,t-s-1} = 1 \text{ and } s = \tau - 1, \ldots, 0. \tag{7}$$

For investors who have learned this return-signal relationship, $\hat{s}^*_{i,t} = \sum_{k=0}^{K} \hat{\varphi}_{i,k,t} f_{k,t}$ is the estimate of ERS at time t for the prediction of $\hat{r}^A_{i,t+1}$. At the final stage, the response to ERS for stock i, δ_i, is estimated by adding one more recent observation ($\hat{s}^*_{i,t}$) to the τ observations in Equation (7):[7]

$$r_{i,t+1-s} = \alpha_i + \beta_i r_{m,t+1-s} + \delta_i \hat{s}^*_{i,t-s} + \eta_{i,t+1-s},\ \ s = \tau, \ldots, 0. \tag{8}$$

[7] A regression model obtained by adding the most recent observation to the regression equation in (7) is $\hat{r}^A_{i,t+1-s} = \alpha^A_i + \delta^A_i \hat{s}^*_{i,t-s} + \eta^A_{i,t+1-s}$, where $s_{0,t-s} = 1$ and $s = \tau, \ldots, 0$. The results obtained with this risk-adjusted return are not different from those reported using Equation (8).

Any deviation of δ_i from one represents under- or over-precision. The details of the timeline of the estimation procedure are given in Figure 2. These three steps are repeated for each stock, and then extreme estimates of RS and ERS are winsorized to three standard deviations from their means to minimize the impact of outliers. The procedure is repeated every month.

A few notes on the estimates of ERS ($\hat{s}^*_{i,t}$) and RS (δ_i). First, the estimates of ERS and RS are not biased, although they are noisy following multiple steps of regressions. The estimation errors in the first step are not correlated with the lagged signals, and thus the $\hat{\varphi}_{i,k}$ and $\hat{s}^*_{i,t}$ calculated with $\hat{\varphi}_{i,k}$ are not biased for investors who try to predict the t+1 return.[8] Second, using $\tau + 1$ observations rather than τ observations at the final stage, any adverse effect from omitting the most remote observation can be avoided. Third, 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 $t + 1$ is calculated using $\hat{\delta}_{i,t+1} = (\hat{\delta}_i - 1)\tau + \hat{\delta}_i$.

For ensuring robustness of the results, RS and ERS are estimated under different learning periods (τ) or forecasting horizons by changing the regression equations in the second and third steps as follows:

$$\hat{r}^A_{i,t-s} = \sum_{k=0}^{K} \varphi^h_{i,k} f_{k,t-h-s} + \eta_{i,t-s},\ \ s = \tau - 1, \dots, 0, \tag{9}$$

$$r_{i,t+h-s} = \alpha_i + \beta_i r_{m,t+h-s} + \delta_i \hat{s}^*_{i,t-s} + \eta_{i,t+h-s},\ \ s = \tau + h - 1, \dots, 0, \tag{10}$$

where $\varphi^h_{i,k}$ represents return response to the h-month-lagged noisy public signal, and $\hat{s}^*_{i,t-s} = \sum_{k=0}^{K} \hat{\varphi}^h_{i,k} f_{k,t-s}$. The default case is one-period- (month-)ahead forecast ($h = 1$) and $\tau = 60$ (60 months). We test forecasting horizons longer than one period, i.e., $h > 1$ and various learning periods, i.e., $\tau = 24$ to 84. In addition, the impact of new information arriving between times t and $t + 1$ can be evaluated using $h = 0$. In this case, investors are assumed

[8] This can be proved easily using the least squares estimation. For a discussion of econometric problems similar to this multi-step estimation, see Brennan et al. (1998).

to know the $t + 1$ factor realization $s_{k,t} = f_{k,t+1}$ (no noise) for the prediction of $r_{i,t+1}$, and thus the second and third steps appear as follows:

$$\hat{r}_{i,t-s}^{A} = \sum_{k=0}^{K} \varphi_{i,k} f_{k,t-s} + \eta_{i,t-s}, \; s = \tau - 1, \dots, 0, \tag{11}$$

$$r_{i,t+1-s} = \alpha_i + \beta_i r_{m,t+1-s} + \delta_i \hat{s}_{i,t+1-s}^{*} + \eta_{i,t+1-s}, \; s = \tau, \dots, 0, \tag{12}$$

where $\hat{s}_{i,t+1-s}^{*} = \sum_{k=0}^{K} \hat{\varphi}_{i,k} f_{k,t+1-s}$. The results of various cases are reported in the Appendix, and these are similar to those of the default case.

2.3 Return reversals subsequent to overconfidence in noisy public signals

In a cross-section, a portfolio formed on large positive (negative) $\hat{\delta}_{i,t}$s would seriously overstate (underestimate) the true value of the portfolio's RS, $\delta_{p,t}$. Forming portfolios on $\hat{\delta}_{i,t}$s causes large positive or negative sampling errors within portfolios, and thus the difference in $\hat{\delta}_{p,t}$ between high and low portfolios would be severely upward biased (Fama and MacBeth, 1973). Moreover, $\hat{\delta}_{i,t}$ may capture the rational response of time-varying factor loadings to the noisy public signals, as in Equation (2). A similar overstatement also appears in the estimates of ERS ($\hat{s}_{p,t-1}^{*}$) of the portfolios formed on $\hat{s}_{i,t-1}^{*}$.

Because of these problems, when portfolios are formed on $\hat{\delta}_{i,t}$ and $\hat{s}_{i,t-1}^{*}$, their values of $\hat{\delta}_{p,t}$s, $\hat{s}_{p,t-1}^{*}$s, and returns would show large pre-formation differences, but not all of these differences reflect investor overconfidence. Thus, following De Bondt and Thaler (1985), Barberis et al. (1998), Baker and Wurgler (2006), Chuang and Lee (2006), and many others, we investigate the effects of investor overconfidence on asset returns by observing post-formation return reversals of the portfolios formed on the estimates of $\hat{\delta}_{i,t}$ and $\hat{s}_{i,t-1}^{*}$. Furthermore, we investigate if the return reversals can be explained by a large number of popular factors reported in the literature.

The patterns of return reversals would show if the over-precision in the noisy public signals is related to various anomalies reported in the literature. In many behavioral finance studies, price distortions created by behavioral biases persist for months or even years, mainly because of the risks or restrictions in arbitrage trading (Shleifer and Vishny, 1997; Daniel et al., 1998). However, most of these studies focus on behavioral biases about private signals, rather than public signals; thus, it is possible that the results for the biases regarding public and private signals may differ.

3. Empirical evidence of overconfidence in public signals

3.1 Data and public signals

ERS and RS are calculated for common stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ from January 1970 to June 2016. 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. Penny 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 (minimum 24 monthly observations). The results for other learning periods—24, 36, 48, 72, and 84 months—are reported in Appendix B.

Three types of noisy public signals are tested for the robustness of the empirical results: macroeconomic variables (MA); five factors from principal component analysis (PCA); and two sets of factors formed on firm characteristics.[9] The macroeconomic variables are those that

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[9] In addition to the common factors formed on firm characteristics, we also tested various firm-specific characteristics, such as book-to-market ratio, asset growth, accruals, net stock issue, size, dividends, sales growth, profitability, investment, net operating assets, idiosyncratic volatility, and illiquidity. The main results remain

are frequently 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 five PCA factors are calculated as in Lehmann and Modest (1988) and Connor and Korajczyk (1988). They are calculated every month using the past sixty monthly returns of non-penny stocks larger than the NYSE 20th percentile to minimize the effects of a number of microcaps (Fama and French, 2008).[10] For the factors formed on firm characteristics, we use the Fama-French five factors (FF5) (Fama and French, 2015), and ten factors created according to the literature (10F). The nine factors, in addition to the excess market return in 10F, are accruals (Sloan, 1996), asset growth (Cooper et al., 2008), book-to-market ratio (Rosenberg et al., 1985; Fama and French, 1992, 1993), gross profitability (Novy-Marx, 2010), net operating assets (Hirshleifer et al., 2004), net stocks issues (Fama and French, 2008), size (Banz, 1981; Fama and French, 1992, 1993), momentum (Jegadeesh and Titman, 1995, 2001), and earnings surprises (Chan et al., 1996). Equally weighted top and bottom decile portfolios are used to create factor returns for each of these trading strategies. The performance of these portfolios is similar to that of those reported in the literature.[11]

3.2 Properties of RS and ERS

unchanged. The responses to these characteristics show strong seasonal patterns (i.e., negative responses) from July to September after annual accounting variables are updated in June. The detailed results can be obtained from the authors upon request.

[10] Three and seven PCA factors were tested but the main empirical results do not change.

[11] Despite the hundreds of characteristics reported in the literature, recent studies such as Green et al. (2017), Feng et al. (2017), and Barillas and Shanken (2018) show that the number of factors is less than 10. Our choice of factors is closely related to those identified in these studies.

Table 1 provides summary statistics of ERS ($\hat{s}_{i,t}^{*}$) and RS ($\hat{\delta}_{i,t+1}$) for the four noisy public signals. The properties of ERS are similar, regardless of the signals. ERS is, on average, over 0.5% per month and cross-sectionally disperse. Stocks with positive RS values are more common than those with negative RS values, but overconfidence in contrarian behavior is also widespread: approximately a third of stocks show negative RS values.

Investors appear to respond less to the ERSs estimated on the basis of signals available within the stock market, e.g., 10F and PCA.[12] However, despite this difference in the levels of RS, Appendix A shows that their properties are all positively and significantly correlated with each other. The results also show that investor overconfidence in noisy public signals increases when the economic outlook or stock market performance improves, whereas it plummets during crises. Investors are less likely to respond to the signals if they anticipate a recession or when they are pessimistic. As the results are similar, we report the main results with the macroeconomic variables to save space.

The average values of absolute RSs suggest that investors' perceived precision of their signals is approximately twice as high as what investors have learned in the past. Because $\delta_{i,t}$ measures investors' bias in the variance of noisy signal, the level of overprecision can be calculated by taking the square root of $|\hat{\delta}_{i,t}|$. For example, in the MA case, when the square root of 5.5. is taken, the outcome, 2.35, suggests that investors believe that the standard deviation of the noisy public signal is $\frac{1}{2.35}$ of what it was in the past. For the other signals whose average values of $|\hat{\delta}_{i,t}|$s range from 2.73 to 3.87, the level of overprecision varies from

[12] The difference may be owing to the endogeneity problem in these signals. For example, if some factors ($f_k s$) in 10F or PCA reflect overconfidence, investors' expectation ($s_{i,t}^{*} = \sum_{k=0}^{K} \varphi_{i,k} f_{k,t}$) is biased, which, in turn, affects $\delta_{i,t+1}$ because of the reversals following the behavioral biases.

1.6 to 2. Our estimates of overprecision, which range from 1.6 to 2.35, are close to the survey results of Merkle (2017), which range from 2 to 2.5.

3.3 Properties of RS and ERS with respect to firm characteristics

Previous studies on overconfidence in private signals or new public signals show that trading volume, volatility, and illiquidity are high for stocks that are affected by investor overconfidence.[13] In addition, Baker and Wurgler (2006), Kumar (2009), Stambaugh et al. (2012), and Antoniou et al. (2015) show that stocks whose valuation is difficult are more likely to be affected by behavioral biases. In particular, Baker and Wurgler (2006) find that small, young, high volatility, unprofitable, non-dividend-paying, extreme growth, and distressed stocks are affected by sentiment.

We investigate if these results hold for overconfidence in public signals. Absolute values of RS and ERS are used as a proxy for investor overconfidence and the magnitude of status quo expectation based on their past experience. As explanatory variables, we use the following eight firm characteristics in Baker and Wurgler (2006), in addition to trading volume, volatility, and illiquidity: size, age, book-to-market ratio, sales growth, external finance, asset tangibility, profitability, and dividends. These variables are standardized to have zero mean and unit variance, and then winsorized to three standard deviations to minimize the impact of outliers.

Table 2 reports the results of the monthly Fama-MacBeth regression for absolute values for RS and ERS. All results show that absolute values of RS and ERS are persistent. Moreover, the coefficients of turnover, volatility, and illiquidity are all positive and significant, indicating

[13] See, for example, Miller (1977), De Long et al. (1991), Kyle and Wang (1997), Odean (1998), Gervais and Odean (2001), Daniel et al. (1998, 2001), Scheinkman and Xiong (2003), Statman et al. (2006), Darrat et al. (2007), Chuang and Lee (2006), Kumar (2009), Campbell et al. (1993), Avramov et al. (2006), and Kumar (2009).

that RS becomes large either positively or negatively with these three variables; this is consistent with the results in previous studies. In addition, absolute values of RS are positively autocorrelated, as in the dynamic overconfidence in private signals (Daniel et al., 1998).

Properties of RS and ERS with respect to firm characteristics

The result in panel A of Table 2 show that investors are likely to over-respond to noisy public signals for old, large, value, and dividend-paying stocks, as well as stocks with tangible assets, little external financing, and low sales growth. This result holds when the absolute value of RS is regressed on each firm characteristic univariately, or when positive and negative RSs are investigated separately.[14]

The characteristics—old, 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 to investors and analysts (Bulan et al., 2007; Bulan et al., 2010; Damodaran, 2011). Mature firms do not rely on external financing because they have large cash flows and few investment opportunities (low growth) and thus are largely self-financing (Berger and Udell, 1998; De Angelo et al., 2006; Baker, 2009). According to Benartzi et al. (1997) and Grullon et al. (2002), mature firms pay more dividends, delivering information about their diminishing investment opportunities and thus declining earnings growth and profitability (Grullon et al., 2002; De Angelo et al., 2006; Damodaran, 2011).

The results in Panel B of Table 2, on the other hand, show that stocks whose valuations are highly subjective and difficult to arbitrage are more likely to show extreme positive or negative values of ERS. Absolute ERS increases for young, small, growth, and non-dividend

[14] The results are not reported but can be obtained upon request.

paying, as well as stocks with less tangible assets, large external financing, and high sales growth but low profitability.

Extreme values of RS are subsequently reversed more quickly than those of ERS. Compared with the results in Table 2 with $h = 1$ (one month), the results in Table 3 show that extreme values of RS found in mature firms disappear quickly: the coefficients with $h = 12$ become less than one tenth of those with $h = 1$, and most coefficients become insignificant as h increases to three years. However, extreme values of ERS are still more likely to be found for firms with valuation difficulties, even if the forecasting horizon increases to three years. These results indicate that the effects of overconfidence in noisy public signals on cross-sectional stock returns would not be persistent; the details of this result are discussed later.

Why is overconfidence found in mature stocks?

Why is overconfidence in public signals likely to be found in mature stocks, rather than in stocks difficult to price? We propose an explanation based on the characteristics of mature firms and the investors who trade these stocks.

First, the valuation of mature firms would appear to be relatively easy because of fewer problems of information asymmetry between managers and investors (Easley and O'Hara, 2004). The investment and financing patterns of these firms have settled down, and thus their risk and returns are stable over time; this results in investor overconfidence in public signals for the valuation of these firms (Damodaran, 2009). Institutional investors may believe that their pricing ability is better than that of others in valuing mature firms (Moore and Healy, 2008; Merkle, 2017), despite the difficulties in predicting stock prices.

Second, institutional investors are more overconfident than novices (De Long et al., 1991; Griffin and Tversky, 1992; Odean, 1998; Glaser et al., 2013), and their overconfidence is reflected strongly in 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 and value stocks, or stocks that have superior past performance and a long listing history; these characteristics are largely consistent with those of mature stocks.

Other rational explanations for unexpectedly large positive or negative RSs in mature firms are also possible. RS may capture the rational response to the change in characteristics or sensitivity, given that stock characteristics and their sensitivity to factors can change over time. The linear factor model that we use to investigate investor overconfidence may not capture the valuation of mature firms that are associated with a better information environment. For example, investors may rely more on in-depth fundamental analysis than factor models to predict the returns for such firms. We investigate these possibilities by observing reversals of risk-adjusted returns after they show large values of RS. Details of test results for return reversals follow in Section 4.

3.4 The effects of overconfidence on cross-sectional returns

The effects of overconfidence on cross-sectional stock returns are investigated using monthly Fama-MacBeth regressions of contemporaneous or one-month-ahead risk-adjusted returns on RS and ERS in the presence of various firm characteristic variables. In addition to the firm characteristics in Table 2, we add the momentum and idiosyncratic volatility (IVol) that is calculated, as in Ang et al (2006), because past performance or volatility may subsume the effects of overconfidence (Daniel and Hirshleifer, 2015). All explanatory variables are cross-sectionally standardized to have zero mean and unit variance and then winsorized to three standard deviations. The signs of the coefficients of the firm characteristics in Table 4 are consistent with the predictions in the literature.

The contemporaneous risk-adjusted returns ($r_{i,t} - \hat{\beta}_i r_{m,t}$) are significantly affected by RS and ERS. Panel A of Table 4 shows that the average R-squared value is only 0.06 when $\hat{\delta}_{it}$, $\hat{s}^*_{it-1}$, and $\hat{\delta}_{it}\hat{s}^*_{it-1}$ are excluded. 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 $\hat{\delta}_{it}\hat{s}^*_{it-1}$: a one-standard-deviation difference in $\hat{\delta}_{it}\hat{s}^*_{it-1}$ affects the risk-adjusted return by more than 7%, which is larger than that for other variables.

The large impact of $\hat{\delta}_{it}\hat{s}^*_{it-1}$ on the contemporaneous returns suggest that subsequent return reversals may not be trivial if they are driven by overconfidence in public signals. The results in panel B show that the effects of $\hat{\delta}_{it}\hat{s}^*_{it-1}$ on $r_{i,t+1} - \hat{\beta}_i r_{m,t+1}$ are significant, i.e., a one-standard-deviation change in these variables changes risk-adjusted returns by more than 0.43% in the month that follows. However, the return reversals after one month are not significant (not reported), indicating that most of the overconfidence bias is corrected without much delay.

These patterns of quick return reversals following overconfidence in public signals are further investigated with respect to the short-term return reversals (Jagedeesh, 1990; Lehmann, 1990). We first decompose returns into those attributable to RS and ERS ($Returns\_BS_{it}$) and those unrelated to them ($Return\_Others_{it}$), and then, one-month-ahead risk adjusted returns are cross-sectionally regressed on current returns (r_{it}) or these two return components. The two return components are calculated using the following cross-sectional regression:

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

where c_{kt} denotes the control variables in panel A of Table 4.

The coefficient of the lagged return in the fifth column in panel B indicates that a one-standard-deviation difference in the lagged return would lead to a subsequent return difference of 0.8%, 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 fourth column shows that a significant proportion of the short-term return reversals can be explained by investor overconfidence: a one-standard-deviation difference in Returns_BS_{it} and $\text{Returns\_Others}_{it}$ causes subsequent return differences of 0.46% and 0.64%, respectively. Investor overconfidence in public signals is one of the major reasons for the short-term return reversals.

4. The Cost of Overconfidence

The empirical results so far show that investor overconfidence in public signals affects stock returns after controlling various firm characteristics. However, the bias in stock returns due to the overconfidence may not be easy for arbitrageurs to exploit because of the quick return reversals and trading costs. Nonetheless, it still is costly for those over-responding to public signals. In this section, we investigate the cost of overconfidence in public signals by observing post-formation return reversals of the portfolios formed on the estimates of $\hat{\delta}_{i,t}$ and $\hat{s}^{*}_{i,t-1}$.

4.1 Portfolios formed on signal and response-to-signal

We form 25 portfolios by two independent 5x5 sorts on ERS ($\hat{s}^{*}_{it-1}$) and RS ($\hat{\delta}_{it}$) of individual equities to investigate cross-sectional biases in returns. These portfolios are rebalanced every month. The 25 RS-ERS sorted portfolios show large contemporaneous return differences between high- and low-RS portfolios, which range from -24.16% to 23.14% in the formation month for the low- and high-ERS portfolios, respectively (panel A1 of Table 5).

These return differences are robust to the Fama-French five factors: alphas of these high-low RS portfolios in panel A2 are not different from the raw returns in panel A1. As explained earlier, the contemporaneous return differences between the four extreme RS and ERS portfolios are large due to the regression phenomenon, the time-variation in factor loadings or firm characteristics, private information, or non-linearity in valuation, which are not captured by our estimation method. Despite these problems, portfolios formed on RS and ERS should not show subsequent return reversals unless RS contains investors' irrational responses to public signals.

Return reversals in the one to five months following the formation of the 25 portfolios are reported in panels B through F. The reversals in the first month are 1.84% and -0.87% per month for the low- and high-ERS portfolios (panel B1), respectively, and their alphas from the five-factor model are 1.7% and -0.72% per month (panel B2), respectively. In the two months following the month of portfolio formation, the aggregated return difference between high- and low-confidence portfolios is 2.26% (2.08% for alpha) per month for the low-ERS portfolios, whereas it is -0.82% (-0.58% for alpha) per month for the high-ERS portfolios. However, there is little evidence of reversals during months three to five following the month of portfolio formation.

The cumulative alphas of the four extreme portfolios following the formation of the RS-ERS portfolios show that the reversals following portfolio formation are prominent during the first month: the post-formation return differences between RS portfolios disappear after two months from the month of formation. The return dynamics of these portfolios are similar to the theoretical model proposed by Daniel et al. (1998), except that the return reversals occur quickly. The immediate return reversals indicate that the effects of overconfidence in public signals on stock returns are different from those of overconfidence in private information or new public information. Immediate return reversals are also observed for different learning periods or forecasting horizons (Appendix B).

The return reversals following overconfidence in public signals are consistent with the liquidity provision theory that explains short-term return reversals if the exogenous shocks or non-informational trading by institutional investors is triggered by their irrational responses to public signals. Overconfident experts may over-respond to signals (De Long et al., 1991; Griffin and Tversky, 1992; Odean, 1998), either positively or negatively, causing intense buying or selling. From this perspective, the return reversals following overconfidence are excess profits that rational investors earn by providing liquidity, but they may not be arbitraged away easily because of frequent (monthly) rebalancing and trading costs. However, the return reversals are certainly the cost of irrationality that these experts pay (Cheng et al., 2014; Arif et al., 2016). These results explain why short-term return reversals increase for stocks whose institutional holdings decrease (Cheng et al., 2014).

4.2 The Cost of Overconfidence in Public Signals

We calculate the cost of investor overconfidence in public signals using the four extreme portfolios—high-RS high-ERS (HH), high-RS low-ERS (HL), low-RS high-ERS (LH), and low-RS low-ERS (LL) —from the two independent 5x5 sorts on ERS ($\hat{s}^{*}_{it-1}$) and RS ($\hat{\delta}_{it}$) in Table 5.[15] Using positive (negative) overconfidence biases for LL and HH (LH and HL) portfolios, we construct a hedge portfolio (RS_ERS) by taking long positions in negatively

[15] RS alone does not capture overconfidence. For example, the results in panel B2 of Table 5 show that when RS alone is considered to investigate return reversals, the average risk-adjusted return reversal of the five low RS portfolios is 0.08% per month in the month that follows, whereas that of the five high RS portfolios is 0.28%. The difference of 0.2% is not significant. The differences in the average risk-adjusted return reversal for the second to fifth months are all less than 0.1% per month. On the other hand, when ERS alone is considered, the differences in the average risk-adjusted return reversals of the five high and low ERS portfolios range from 0.18% to 0.39% per month in the five months following portfolio formation. However, the delayed response to signals is lower for other signals. When 10F is used, the differences between high and low ERS portfolios are all less than 0.1% per month.

biased HL and LH portfolios and short positions in positively biased HH and LL portfolios—that is, (HL+LH)/2-(LL+HH)/2—and calculate the following-month return of the hedge portfolio. The procedure is repeated every month. For comparison, we also report the return reversals of the low-minus-high decile portfolios formed on $\hat{\delta}_{it}\hat{s}^{*}_{it-1}$ (RS*ERS_D), r_{it} (Return_D), $\mathrm{Returns\_Others}_{it}$ (Returns_Others_D), and $\mathrm{Returns\_BS}_{it}$ (Returns_BS_D).[16]

The cost of overconfidence in public signals is large and significant. Panel A of Table 6 shows that the average return of RS_ERS is 1.35% per month during the sample period. It is still significant in the 2000s despite active arbitrage trading by institutional investors (Dichev et al., 2011; Green et al., 2017). The performance of Returns_BS_D and RS*ERS_D is 1.24% and 1.05% per month, respectively, which is similar to that of RS_ERS.

The cost of overconfidence (RS_ERS or Return_BS_D) after the 2000s shows a pattern that is different from that the cost calculated by other reasons (Returns_Others_D). The average short-term return reversal (Return_D) has decreased significantly from 2.71% for the 20 years from January 1970 to 1.09% from January 2000 onward, confirming a significant decrease in short-term return reversals as in Hameed and Mian (2014) and Cheng et al. (2014). When the short-term return reversal is decomposed into those due to Returns_BS_D and Returns_Others_D, it becomes clear that it is the return reversal from Returns_Others_D that becomes insignificant in the 2000s. For example, the return reversal contributed by Returns_Others_D is 0.49%; this is not statistically significant. On the other hand, the return reversals driven by overconfidence in public signals—either RS_RES or Return_BS_D—are still significant both statistically and economically.

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[16] The proportion of stocks used for the RS_ERS hedge portfolio is 4/25, which is close to 2/10 for Return_D, Returns_Others_D, and Returns_BS_D. The results with quintile portfolios are not different from those with decile portfolios in Table 6.

The changes in the performance of these hedge portfolios are notable when they are value weighted. The average return of RS_ERS decreases to 0.65% per month when portfolios are value weighted (panel B). Although overconfidence is more likely to occur for mature firms, the effects of overconfidence on stock returns appear to be stronger in small firms because they are calculated by combining RS and ERS, and extreme RS and ERS values are more likely to be found in small firms. Investors' over-responses to public signals for stocks difficult to value or arbitrage are not as strong as those for mature stocks, but they are amplified by the extreme ERSs of small stocks. Nevertheless, the bottom line is that the average return reversals of RS_ERS and Returns_BS_D are still large and significant at 0.46% and 0.65% per month, respectively, during the 2000s.

4.3 Robustness of overconfidence cost

The cost of overconfidence in public signals may be closely related to existing factors. It may be related to factors formed on the book-to-market ratio, size, and the momentum that can be explained by overconfidence in private signals (Daniel et al., 1998, 2001). Moreover, the cross-sectional analysis using individual stocks in Table 2 confirms that various firm characteristics are indeed associated with overconfidence in public signals. Therefore, we test whether the overconfidence factor (RS_ERS) can be explained by the 14 well-known factors in the literature.[17]

The cost of overconfidence is not subsumed by these 14 factors. The results in Table 7 show that the alphas of RS_ERS are still large and significant, i.e., from 1.14% to 1.25% per month, and their *t*-statistics are over 5, well above the level proposed by Harvey et al (2016).

[17] In addition to the ten factors used in 10F, four more firm characteristics factors are included for robustness—investment to assets (IA) (Chen and Zhang, 2010), return on assets (ROA) (Chen and Zhang, 2010), liquidity (Liq) (Amihud, 2002), and idiosyncratic volatility (IVol) (Ang et al., 2006). Top- and bottom-decile portfolios are used to calculate returns for each trading strategy. Portfolios are equally weighted.

The overconfidence factor calculated with value-weighted portfolios in the last column of the table is also robust to the existing factors, but is much smaller than those with equally weighted portfolios.

Interestingly, we find that some of the factors that are argued to be outcomes of overconfidence in private signals show statistically significant relationships with the cost of overconfidence in public signals.[18] For example, the overconfidence cost that measures return reversals subsequent to overreaction is negatively associated with momentum that reflects delayed overreactions (Jegadeesh and Titman, 2001). Idiosyncratic volatility shows negative coefficients because it increases with investor overconfidence (Tables 2; Daniel et al., 1998, 2001; Chuang and Lee, 2006). The positive coefficients of the investment to asset (IA) are consistent with the view that investors' over-response to firms' investment is subsequently reversed (Cooper et al., 2008).

The robustness of the overconfidence cost is further investigated with respect to different types of signals, bid-ask bounce, January effects, size and portfolio breakpoints, liquidity, learning periods, and forecasting horizons. The results reported in Appendix B show that the overconfidence cost is robust under these conditions.

5. Conclusions

We show that cross-sectional stock returns are affected by investor overconfidence in public signals, and these effects are then reversed quickly. The results show that overconfidence in market-wide common signals is not responsible for various anomalies in the stock market, most of which require that the effects of overconfidence last over longer horizons. The

[18] In unreported univariate regressions for each of the 14 factors, only momentum appears significant.

immediate return reversals following overconfidence in public signals explain approximately half of the short-term return reversals reported by Jagedeesh (1990) and Lehmann (1990). The reversals can be interpreted as a reward for rational investors who provide liquidity to overconfident investors (Campbell et al., 1993; Nagel, 2012). These results also explain why short-term return reversals increase for stocks whose institutional holdings decrease (Cheng et al., 2014). Short-term return reversals after intense trading by overconfident institutional investors (De Long et al., 1991; Griffin and Tversky, 1992; Odean, 1998) affect illiquid assets more than liquid assets and, thus, generate a larger compensation for more illiquid assets (Campbell et al., 1993; Avramov et al., 2006).

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

ERS and RS are calculated using non-financial common stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and NASDAQ from January 1970 to June 2016. Stocks whose prices are less than $1 at the time of the estimation are excluded, and the investors' learning period τ is set as 60 months. The macroeconomic variables (MA) are 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 the S&P500 index). Five factors from the principal component analysis (PCA5) are calculated, as in Connor and Korajczyk (1988), for the non-penny stocks larger than the NYSE 20th percentile. These factors are calculated every month using the past 60 monthly returns. Fama-French five factors (FF5) are obtained from Kenneth French's data library. Ten factors include the excess market return and nine firm characteristics factors. These factors are calculated for the top and bottom decile (equally weighted) portfolios formed on accruals (Sloan, 1996), asset growth (Cooper et al., 2008), book-to-market ratio (Rosenberg et al., 1985; Fama and French, 1992, 1993), gross profitability (Novy-Marx, 2010), net operating assets (Hirshleifer et al., 2004), net stocks issues (Fama and French, 2008), size (Banz, 1981; Fama and French, 1992, 1993), momentum (Jegadeesh and Titman, 1993, 2001), and earnings surprises (Chan et al., 1996). 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 signals.

	Macroeconomic variables (MA)	Ten factors (10F)	Five PCA factors (PCA)	Fama-French five factors (FF5)
Number of stocks	2,219	2,156	2,220	2,220
Number of Positive ERS	1,198	1,181	1,294	1,276
Number of Negative ERS	1,021	975	926	944
Number of Positive RS	1,502	1,529	1,700	1,593
Number of Negativive RS	717	627	520	627
Average value of ERS	0.550	0.514	0.587	0.573
(Standard error)	(0.047)	(0.079)	(0.069)	(0.053)
Average value of positive ERS	3.913	5.065	3.790	3.297
(Standard error)	(0.077)	(0.135)	(0.172)	(0.091)
Average value of negative ERS	-(3.428)	-(4.702)	-(3.327)	-(2.845)
(Standard error)	(0.062)	(0.116)	(0.153)	(0.069)
Average value of absolute ERS	3.746	5.007	3.693	3.182
(Standard error)	(0.068)	(0.121)	(0.159)	(0.076)
Average value of RS	1.312	0.460	0.682	0.961
(Standard error)	(0.097)	(0.072)	(0.139)	(0.075)
Average value of positive RS	5.085	2.299	2.977	3.509
(Standard error)	(0.066)	(0.022)	(0.051)	(0.054)
Average value of negative RS	-5.664	-3.042	-3.507	-4.032
(Standard error)	(0.119)	(0.091)	(0.176)	(0.118)
Average value of absolute RS	5.501	2.734	3.585	3.866
(Standard error)	(0.087)	(0.062)	(0.133)	(0.085)
R square value	0.075	0.194	0.124	0.084

Table 2 Properties of RS and ERS with respect to firm characteristics

The absolute values of response-to-signal (RS) and expected return predicted by signal (ERS) estimated with the three steps in Section 2 are cross-sectionally regressed on their own lagged values and other variables. Firm characteristic variables are age (the number of years since the firm's first appearance on CRSP), 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). Six-month gap is allowed for the availability of accounting variables for six firm characteristics (BE/ME, Sales Growth, External Financing, Asset Tangibility, Dividends, and Profitability). These variables 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. Volatility is calculated using daily returns in the month, and illiquidity is calculated as in Amihud (2002). Logarithmic values of volatility, Amihud illiquidity, turnover, and size are used because of their right tails. All explanatory variables except for the lagged dependent variable are standardized to have zero mean and unit variance and then are winsorized to three standard deviations to minimize the impact of outliers. The average 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 in the monthly Fama-MacBeth regression. The numbers inside the round brackets on the name of explanatory variables represents the numbers of lags. 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)		Ten factors (10F)		Fama-French five factors (FF5)		Five PCA factors (PCA)	
Average Number of Equities	1881		1882		1882		1882	
A. Absolute values of RS								
Absolute RS	**5.533**	(0.089)	**2.746**	(0.063)	**3.901**	(0.087)	**3.622**	(0.134)
constant	**3.869**	(0.132)	**2.230**	(0.099)	**3.100**	(0.124)	**2.677**	(0.209)
Absolute RS(-1)	**0.311**	(0.009)	**0.219**	(0.015)	**0.228**	(0.011)	**0.324**	(0.021)
ERS(-1)	**-0.120**	(0.021)	-0.009	(0.019)	**-0.062**	(0.013)	-0.013	(0.023)
Log_Volatility	**0.708**	(0.029)	**0.327**	(0.016)	**0.580**	(0.029)	**0.383**	(0.027)
Log_Illiquidity	**0.735**	(0.059)	**0.171**	(0.026)	**0.340**	(0.029)	**0.185**	(0.039)
Log_Turnover	**0.292**	(0.023)	**0.131**	(0.011)	**0.231**	(0.016)	**0.177**	(0.018)
Age(-1)	**0.221**	(0.016)	**0.079**	(0.010)	**0.158**	(0.016)	**0.120**	(0.018)
Log_ME(-1)	**0.862**	(0.058)	**0.250**	(0.025)	**0.491**	(0.034)	**0.293**	(0.041)
BE/ME	**0.116**	(0.018)	**0.058**	(0.008)	**0.099**	(0.013)	**0.055**	(0.014)
Sales Growth	**-0.173**	(0.028)	**-0.081**	(0.017)	**-0.141**	(0.029)	**-0.094**	(0.023)
External Financing	**-0.035**	(0.009)	0.004	(0.006)	**-0.038**	(0.008)	**-0.017**	(0.008)
Asset Tangibility	**0.087**	(0.014)	**0.058**	(0.008)	**0.047**	(0.012)	**0.049**	(0.011)
Dividends	**0.359**	(0.018)	**0.157**	(0.010)	**0.243**	(0.015)	**0.169**	(0.014)
Profitability	**0.115**	(0.030)	**0.069**	(0.014)	**0.143**	(0.027)	0.017	(0.035)
R-square	0.149		0.125		0.109		0.198	

	Macroeconomic variables (MA)		Ten factors (10F)		Fama-French five factors (FF5)		Five PCA factors (PCA)	
Average Number of Equities	1881		1822		1882		1882	
A. Absolute values of ERS								
ERS	**3.588**	(0.068)	**4.773**	(0.118)	**3.048**	(0.075)	**3.543**	(0.154)
constant	**1.310**	(0.079)	**3.851**	(0.149)	**2.072**	(0.081)	**2.685**	(0.204)
Absolute ERS(-1)	**0.664**	(0.011)	**0.217**	(0.007)	**0.356**	(0.012)	**0.308**	(0.011)
RS(-1)	0.014	(0.008)	**0.087**	(0.013)	**0.070**	(0.011)	**0.041**	(0.013)
Log_Volatility	**0.269**	(0.019)	**0.514**	(0.034)	**0.280**	(0.021)	**0.400**	(0.043)
Log_Illiquidity	**0.311**	(0.044)	**0.216**	(0.078)	**0.192**	(0.062)	**0.213**	(0.083)
Log_Turnover	**0.272**	(0.024)	**0.290**	(0.040)	**0.201**	(0.035)	**0.241**	(0.052)
Age(-1)	**-0.085**	(0.009)	**-0.320**	(0.020)	**-0.165**	(0.009)	**-0.208**	(0.016)
Log_ME(-1)	0.075	(0.033)	**-0.341**	(0.058)	**-0.126**	(0.044)	**-0.179**	(0.068)
BE/ME	**-0.040**	(0.008)	**-0.212**	(0.019)	**-0.127**	(0.010)	**-0.148**	(0.016)
Sales Growth	**0.129**	(0.022)	**0.436**	(0.046)	**0.281**	(0.026)	**0.295**	(0.039)
External Financing	**0.039**	(0.006)	**0.146**	(0.017)	**0.095**	(0.007)	**0.116**	(0.015)
Asset Tangibility	**-0.011**	(0.005)	**-0.074**	(0.015)	**-0.044**	(0.006)	**-0.052**	(0.009)
Dividends	**-0.040**	(0.008)	**-0.315**	(0.014)	**-0.182**	(0.009)	**-0.210**	(0.012)
Profitability	**-0.135**	(0.025)	**-0.398**	(0.061)	**-0.233**	(0.039)	**-0.254**	(0.066)
R-square	0.580		0.214		0.302		0.269	

Table 3 Properties of the expected return predicted by signal and response to signal with respect to firm characteristics for different forecasting horizons

Risk-adjusted return $\hat{r}^{A}_{i,t+1-s}$ is first regressed on $f_{k,t+1-s-h}$ to estimate $\hat{\varphi}_{i,k}$s; these are, then, used to obtain δ_i in the second equation.

$\hat{r}^{A}_{i,t-s} = \sum_{k=0}^{K} \varphi^{h}_{i,k} f_{k,t-h-s} + \eta_{i,t-s},\ \ s = \tau - 1, \dots, 0,$

$r_{i,t+h-s} = \alpha_i + \beta_i r_{m,t+h-s} + \delta_i \hat{s}^{*}_{i,t-s} + \eta_{i,t+h-s},\ \ s = \tau + h - 1, \dots, 0,$

where $\hat{s}^{*}_{i,t-s} = \sum_{k=0}^{K} \hat{\varphi}^{h}_{i,k} f_{k,t-s}$. For this h-month-ahead forecasting, the estimates of RS and ERS from the regression are average values of $\hat{\delta}_{i,t+h}$ and $\hat{s}^{*}_{i,t}$ for h months. The absolute values of the estimates are then regressed on firm characteristics lagged at h months in the presence of their lagged variables and other control variables. A six-month gap is allowed for the availability of accounting variables for six firm characteristics (BE/ME, Sales Growth, External Financing, Asset Tangibility, Dividends, and Profitability). The accounting variables 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. The numbers inside the round brackets on the name of explanatory variables represents the numbers of lags. The numbers in the round brackets represent the Newey-West standard errors and the bold numbers represent significance at the 5% level.

Forecasting Horizon (*h*)	12		24		36			12		24		36	
Number of stocks	1509		1155		909			1501		1150		905	
	A. Absolute values of RS							**B. Absolute values of ERS**					
RS	**1.753**	(0.022)	**1.464**	(0.014)	**1.289**	(0.010)	ERS	**3.921**	(0.091)	**4.230**	(0.095)	**4.248**	(0.088)
constant	**0.549**	(0.022)	**0.383**	(0.013)	**0.313**	(0.011)	constant	**0.578**	(0.053)	**0.464**	(0.035)	**0.451**	(0.037)
abs(RS(-1))	**0.693**	(0.007)	**0.739**	(0.008)	**0.757**	(0.008)	abs(ERS(-1))	**0.867**	(0.009)	**0.896**	(0.009)	**0.901**	(0.008)
ERS(-1)	**-0.009**	(0.002)	**-0.008**	(0.002)	0.000	(0.001)	RS(-1)	**-0.008**	(0.004)	-0.011	(0.003)	-0.002	(0.004)
Log_Volatility	**0.017**	(0.002)	0.002	(0.002)	0.000	(0.001)	Log_Volatility	**0.153**	(0.018)	**0.119**	(0.012)	**0.121**	(0.014)
Log_Illiquidity	**0.068**	(0.008)	**0.009**	(0.004)	-0.001	(0.003)	Log_Illiquidity	**0.158**	(0.035)	**0.082**	(0.020)	**0.056**	(0.021)
Log_Turnover	**0.037**	(0.003)	**0.008**	(0.002)	-0.001	(0.001)	Log_Turnover	**0.141**	(0.021)	**0.093**	(0.012)	**0.100**	(0.017)
Age(-*h*)	**0.013**	(0.002)	**0.008**	(0.001)	**0.006**	(0.001)	Age(-*h*)	**-0.018**	(0.004)	-0.004	(0.004)	-0.005	(0.004)
Log_ME(-*h*)	**0.056**	(0.007)	**0.007**	(0.003)	-0.002	(0.003)	Log_ME(-*h*)	**0.045**	(0.019)	**-0.010**	(0.017)	**-0.031**	(0.016)
BE/ME(-*h*)	**0.007**	(0.002)	**0.005**	(0.002)	-0.001	(0.001)	BE/ME(-*h*)	-0.007	(0.007)	**-0.012**	(0.006)	0.003	(0.005)
Sales Growth(-*h*)	**-0.016**	(0.004)	-0.005	(0.004)	-0.003	(0.002)	Sales Growth(-*h*)	**0.073**	(0.018)	**0.025**	(0.012)	0.017	(0.013)
External Financing(-*h*)	-0.002	(0.001)	-0.002	(0.001)	0.000	(0.001)	External Financing(-*h*)	**0.014**	(0.006)	0.004	(0.004)	0.006	(0.004)
Asset Tangibility(-*h*)	0.003	(0.002)	0.002	(0.001)	-0.001	(0.001)	Asset Tangibility(-*h*)	**-0.009**	(0.004)	0.005	(0.004)	**-0.008**	(0.004)
Dividends(-*h*)	**0.020**	(0.003)	**0.007**	(0.002)	0.000	(0.001)	Dividends(-*h*)	**-0.016**	(0.005)	**-0.010**	(0.005)	0.002	(0.006)
Profitability(-*h*)	-0.002	(0.005)	-0.005	(0.003)	-0.002	(0.002)	Profitability(-*h*)	**-0.049**	(0.014)	**-0.070**	(0.015)	**-0.050**	(0.011)
R-square	0.500		0.565		0.594		R-square	0.808		0.845		0.855	

Table 4 Explanation of cross-sectional returns by response-to-signal and expected return by 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 January 1970 to June 2016. Returns_BS and Returns_Others represent the components of the return explained by RS and ERS, and others, respectively. A six-month gap is allowed for the availability of accounting variables for six firm characteristics (BE/ME, Sales Growth, External Financing, Asset Tangibility, Dividends, and Profitability). These variables 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 the July to June period of the following year. Illiquidity is calculated as in Amihud (2002). Idiosyncratic volatility (IVol) is calculated as in Ang et al. (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 they are winsorized to 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)	**0.305**	(0.104)	**0.305**	(0.104)	**0.305**	(0.104)	**0.305**	(0.104)	**0.305**	(0.104)
Number of Equities	1879		1879		1879		1879		1879	
constant	**0.324**	(0.112)	**0.324**	(0.112)	**0.324**	(0.112)	**0.360**	(0.114)	**0.359**	(0.114)
ERS(t-1)			**-0.300**	(0.043)					**-0.702**	(0.062)
RS(t)					**-0.307**	(0.108)			**0.360**	(0.179)
RS(t)* ERS(t-1)							**7.327**	(0.211)	**8.058**	(0.238)
Momentum (t-12,t-2)	**0.142**	(0.064)	**0.234**	(0.068)	**0.166**	(0.063)	0.084	(0.068)	**0.147**	(0.055)
Log_IVol(t-1)	**-0.302**	(0.042)	**-0.316**	(0.042)	**-0.312**	(0.041)	**-0.211**	(0.031)	**-0.192**	(0.030)
Log_Illiquidity(t-1)	**0.280**	(0.138)	**0.490**	(0.131)	**0.297**	(0.135)	**1.020**	(0.137)	**0.648**	(0.102)
Log_Turnover(t-1)	**0.198**	(0.050)	**0.259**	(0.050)	**0.189**	(0.048)	**0.354**	(0.050)	**0.223**	(0.036)
Age(t-1)	**0.065**	(0.022)	**0.065**	(0.022)	**0.064**	(0.022)	**0.045**	(0.019)	**0.066**	(0.016)
Log_ME(t-1)	**-0.314**	(0.128)	-0.131	(0.119)	**-0.290**	(0.126)	0.420	(0.116)	0.133	(0.093)
BE/ME	**0.140**	(0.048)	**0.143**	(0.048)	**0.139**	(0.048)	**0.223**	(0.037)	**0.175**	(0.035)
Sales Growth	0.118	(0.093)	0.123	(0.094)	0.105	(0.093)	0.089	(0.082)	0.088	(0.077)
External Financing	**-0.182**	(0.024)	**-0.177**	(0.024)	**-0.182**	(0.025)	**-0.163**	(0.023)	**-0.155**	(0.023)
Asset Tangibility	0.025	(0.040)	0.024	(0.040)	0.022	(0.039)	0.008	(0.032)	0.020	(0.027)
Dividends	**0.143**	(0.039)	**0.147**	(0.039)	**0.135**	(0.039)	**0.125**	(0.032)	**0.127**	(0.028)
Profitability	**-0.326**	(0.131)	**-0.341**	(0.131)	**-0.294**	(0.128)	**-0.569**	(0.118)	**-0.446**	(0.106)
R square	0.060		0.064		0.076		0.334		0.363	

B. One month ahead risk-adjusted returns

Risk Adjusted Return(t+1)	**0.297**	(0.103)	**0.297**	(0.103)	**0.297**	(0.103)	**0.297**	(0.103)	**0.297**	(0.103)
Number of Equities	1857		1857		1857		1857		1857	
constant	**0.317**	(0.111)	**0.316**	(0.111)	**0.314**	(0.111)	**0.309**	(0.111)	**0.309**	(0.111)
ERS(t-1)			0.026	(0.041)						
RS(t)			**0.071**	(0.019)						
RS(t)* ERS(t-1)					**-0.433**	(0.037)				
Returns_BS(t)							**-0.455**	(0.038)		
Returns_Others(t)							**-0.644**	(0.054)		
Returns(t)									**-0.796**	(0.063)
Momentum (t-12,t-2)	**0.138**	(0.064)	0.102	(0.072)	0.092	(0.068)	0.030	(0.070)	0.026	(0.071)
Log_IVol(t)	**-0.303**	(0.042)	**-0.298**	(0.041)	**-0.310**	(0.042)	**-0.334**	(0.043)	**-0.335**	(0.043)
Log_Illiquidity(t)	**0.249**	(0.138)	**0.254**	(0.136)	**0.431**	(0.130)	**1.042**	(0.117)	**1.043**	(0.117)
Log_Turnover(t)	**0.182**	(0.049)	**0.186**	(0.049)	**0.240**	(0.049)	**0.437**	(0.049)	**0.436**	(0.049)
Age(t)	**0.061**	(0.022)	**0.060**	(0.022)	**0.056**	(0.022)	0.046	(0.023)	0.047	(0.023)
Log_ME(t)	**-0.320**	(0.128)	**-0.307**	(0.126)	-0.143	(0.120)	**0.432**	(0.107)	**0.432**	(0.107)
BE/ME	**0.139**	(0.048)	**0.133**	(0.049)	**0.142**	(0.049)	**0.179**	(0.051)	**0.180**	(0.051)
Sales Growth	0.169	(0.095)	0.172	(0.096)	0.164	(0.094)	0.159	(0.094)	0.165	(0.095)
External Financing	**-0.181**	(0.025)	**-0.181**	(0.024)	**-0.182**	(0.025)	**-0.190**	(0.025)	**-0.192**	(0.025)
Asset Tangibility	0.025	(0.040)	0.028	(0.039)	0.024	(0.040)	0.022	(0.041)	0.023	(0.041)
Dividends	**0.138**	(0.039)	**0.135**	(0.039)	**0.140**	(0.039)	**0.150**	(0.040)	**0.150**	(0.040)
Profitability	**-0.342**	(0.131)	**-0.346**	(0.129)	**-0.323**	(0.130)	**-0.328**	(0.131)	**-0.329**	(0.132)
R square	0.060		0.064		0.063		0.070		0.068	

Table 5 Returns of the 25 portfolios sorted on the response-to-signal and unbiased expected return by signal

The contemporaneous and subsequent five month returns of 25 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 five factors. 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	14.039	10.007	2.760	-4.938	-8.386	**-22.425**	(0.643)
	2	3.714	4.678	1.468	-1.647	-1.680	**-5.393**	(0.366)
	3	-1.415	1.005	0.933	0.796	2.848	**4.263**	(0.170)
	4	-4.919	-1.237	0.848	2.833	6.772	**11.690**	(0.360)
	High	-10.123	-4.038	1.257	6.656	14.756	**24.879**	(0.940)
	High-Low	**-24.162**	**-14.044**	**-1.503**	**11.595**	**23.142**		
		(0.775)	(0.563)	(0.760)	(0.650)	(0.794)		
B1. Returns one month later								
Response-to-signal	Low	0.329	0.768	1.384	1.830	1.994	**1.665**	(0.149)
	2	0.943	1.051	1.207	1.503	1.560	**0.618**	(0.135)
	3	1.450	1.270	1.228	1.273	1.289	-0.161	(0.156)
	4	1.650	1.356	1.225	1.170	1.356	-0.294	(0.169)
	High	2.167	1.646	1.148	1.091	1.127	**-1.040**	(0.235)
	High-Low	**1.838**	**0.877**	-0.236	**-0.739**	**-0.867**		
		(0.176)	(0.137)	(0.148)	(0.133)	(0.165)		
C1. Returns two month later								
Response-to-signal	Low	1.002	1.150	1.409	1.490	1.611	**0.609**	(0.127)
	2	1.133	1.215	1.366	1.309	1.481	**0.348**	(0.111)
	3	1.296	1.343	1.295	1.367	1.526	0.229	(0.155)
	4	1.319	1.186	1.243	1.299	1.572	0.253	(0.162)
	High	1.420	1.288	1.341	1.243	1.670	0.250	(0.204)
	High-Low	**0.418**	0.138	-0.068	**-0.247**	0.059		
		(0.153)	(0.119)	(0.113)	(0.111)	(0.128)		

	Expected return predicted by signal						
	Low	2	3	4	High	High-Low	
A2. Contemporaneous alphas							
Low	12.861	8.841	1.786	-5.819	-9.366	**-22.227**	(0.660)
2	2.569	3.457	0.376	-2.635	-2.750	**-5.319**	(0.380)
3	-2.531	-0.150	-0.209	-0.285	1.717	**4.248**	(0.196)
4	-5.973	-2.336	-0.371	1.658	5.583	**11.556**	(0.386)
High	-11.069	-5.148	-0.048	5.376	13.410	**24.479**	(0.981)
High-Low	**-23.930**	**-13.989**	**-1.834**	**11.195**	**22.776**		
	(0.807)	(0.616)	(0.764)	(0.659)	(0.817)		
B2. Alphas one month later							
Low	-0.803	-0.355	0.190	0.591	0.783	**1.586**	(0.161)
2	-0.188	-0.100	0.016	0.315	0.390	**0.579**	(0.142)
3	0.324	0.100	0.049	0.138	0.177	-0.147	(0.190)
4	0.560	0.164	0.073	0.044	0.299	-0.262	(0.218)
High	0.901	0.519	-0.009	-0.063	0.065	**-0.836**	(0.335)
High-Low	**1.704**	**0.874**	-0.199	**-0.654**	**-0.718**		
	(0.229)	(0.160)	(0.145)	(0.152)	(0.204)		
C2. Alphas two month later							
Low	-0.123	-0.002	0.296	0.333	0.435	**0.558**	(0.131)
2	-0.046	0.021	0.204	0.151	0.366	**0.412**	(0.125)
3	0.182	0.202	0.146	0.237	0.474	0.292	(0.187)
4	0.239	0.030	0.070	0.197	0.490	0.251	(0.241)
High	0.250	0.120	0.156	0.070	0.570	0.320	(0.283)
High-Low	**0.373**	0.121	-0.140	**-0.264**	0.135		
	(0.187)	(0.139)	(0.148)	(0.124)	(0.171)		

		Expected return predicted by signal						
		Low	2	3	4	High	High-Low	
D1. Returns three month later								
Response-to-signal	Low	1.204	1.256	1.285	1.393	1.437	0.232	(0.147)
	2	1.173	1.257	1.309	1.358	1.588	**0.415**	(0.117)
	3	1.164	1.285	1.313	1.396	1.467	**0.303**	(0.132)
	4	1.170	1.195	1.299	1.429	1.490	**0.320**	(0.127)
	High	1.103	1.162	1.295	1.419	1.855	**0.752**	(0.164)
	High-Low	-0.101	-0.094	0.010	0.026	**0.419**		
		(0.127)	(0.114)	(0.110)	(0.119)	(0.129)		
E1. Returns four month later								
Response-to-signal	Low	1.237	1.257	1.293	1.422	1.564	**0.327**	(0.135)
	2	1.284	1.167	1.353	1.456	1.534	0.251	(0.137)
	3	1.410	1.273	1.327	1.345	1.548	0.138	(0.151)
	4	1.223	1.173	1.350	1.342	1.547	**0.325**	(0.146)
	High	1.291	1.096	1.248	1.366	1.696	**0.405**	(0.177)
	High-Low	0.054	-0.161	-0.046	-0.057	0.132		
		(0.131)	(0.114)	(0.106)	(0.110)	(0.126)		
F1. Returns five month later								
Response-to-signal	Low	1.230	1.174	1.303	1.364	1.577	**0.346**	(0.132)
	2	1.332	1.174	1.368	1.460	1.591	**0.259**	(0.119)
	3	1.106	1.298	1.280	1.364	1.528	**0.422**	(0.123)
	4	1.305	1.237	1.227	1.315	1.456	0.151	(0.149)
	High	1.351	1.259	1.263	1.328	1.539	0.188	(0.178)
	High-Low	0.121	0.085	-0.039	-0.037	-0.037		
		(0.118)	(0.120)	(0.108)	(0.099)	(0.115)		

	Expected return predicted by signal						
	Low	2	3	4	High	High-Low	
D2. Alphas three month later							
Low	0.053	0.085	0.132	0.171	0.260	0.207	(0.165)
2	0.058	0.067	0.149	0.182	0.487	**0.429**	(0.137)
3	0.060	0.143	0.144	0.287	0.396	**0.336**	(0.161)
4	0.149	0.075	0.144	0.321	0.405	0.255	(0.170)
High	-0.016	0.022	0.119	0.237	0.714	**0.730**	(0.220)
High-Low	-0.069	-0.063	-0.012	0.066	**0.454**		
	(0.158)	(0.114)	(0.117)	(0.131)	(0.132)		
E2. Alphas four month later							
Low	0.045	0.081	0.059	0.263	0.479	**0.434**	(0.132)
2	0.068	-0.038	0.183	0.332	0.452	**0.384**	(0.139)
3	0.301	0.108	0.165	0.266	0.511	0.210	(0.176)
4	0.138	0.054	0.201	0.208	0.493	0.355	(0.193)
High	0.084	-0.047	0.106	0.215	0.565	**0.481**	(0.210)
High-Low	0.039	-0.128	0.047	-0.049	0.086		
	(0.148)	(0.127)	(0.104)	(0.122)	(0.136)		
F2. Alphas five month later							
Low	0.073	0.030	0.118	0.170	0.400	**0.327**	(0.138)
2	0.183	0.003	0.145	0.279	0.498	**0.316**	(0.128)
3	-0.024	0.137	0.106	0.247	0.511	**0.535**	(0.138)
4	0.166	0.102	0.089	0.216	0.448	0.282	(0.157)
High	0.081	0.071	0.129	0.175	0.484	**0.403**	(0.191)
High-Low	0.008	0.041	0.011	0.005	0.084		
	(0.130)	(0.120)	(0.112)	(0.100)	(0.106)		

Table 6 Performance of portfolios formed on response to signal and expected return by signal

Using the four extreme portfolios from the two independent 5x5 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), we form a hedge portfolio (RS_ERS) as (HL+LH-LL-HH)/2 and report the performance of return reversals following its formation. RS*ERS_D represents a hedge portfolio of the top and bottom decile portfolios formed on $\hat{\delta}_{it}\hat{s}^{*}_{it-1}$. The performance of 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 five factors. 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							
	January 1970 ~ June 2016		January 1970 ~ December 1989		January 1990 ~ December 1999		January 2000 ~ June 2016		January 1970 ~ June 2016		January 1970 ~ December 1989		January 1990 ~ December 1999		January 2000 ~ June 2016	
A. Equally weighted portfolios																
RS_ERS	**1.353**	(0.147)	**1.844**	(0.203)	**1.105**	(0.237)	**0.907**	(0.251)	**1.211**	(0.201)	**1.800**	(0.225)	**0.982**	(0.277)	**0.788**	(0.315)
RS*ERS_D	**1.050**	(0.140)	**1.471**	(0.194)	**1.016**	(0.238)	**0.559**	(0.250)	**0.932**	(0.183)	**1.404**	(0.208)	**0.969**	(0.249)	0.421	(0.306)
Return_D	**1.917**	(0.215)	**2.713**	(0.305)	**1.692**	(0.353)	**1.090**	(0.372)	**1.838**	(0.298)	**2.489**	(0.294)	**1.439**	(0.347)	**1.166**	(0.509)
Return_BS_D	**1.238**	(0.148)	**1.673**	(0.208)	**0.948**	(0.229)	**0.887**	(0.266)	**1.133**	(0.202)	**1.676**	(0.226)	**0.874**	(0.256)	**0.796**	(0.336)
Return_Others_D	**1.173**	(0.174)	**1.897**	(0.255)	**0.855**	(0.311)	0.489	(0.264)	**1.060**	(0.232)	**1.716**	(0.266)	**0.588**	(0.293)	0.478	(0.340)
B. Value weighted portfolios																
RS_ERS	**0.654**	(0.124)	**1.054**	(0.162)	0.171	(0.274)	**0.461**	(0.213)	**0.534**	(0.168)	**0.904**	(0.199)	-0.119	(0.234)	0.425	(0.257)
RS*ERS_D	**0.432**	(0.166)	**0.934**	(0.249)	0.013	(0.352)	0.079	(0.251)	0.304	(0.203)	**0.931**	(0.316)	-0.201	(0.369)	-0.009	(0.276)
Return_D	**0.397**	(0.198)	**0.882**	(0.289)	-0.287	(0.402)	0.225	(0.360)	0.269	(0.243)	**0.689**	(0.334)	-0.736	(0.385)	0.243	(0.399)
Return_BS_D	**0.612**	(0.153)	**0.926**	(0.224)	-0.072	(0.314)	**0.647**	(0.248)	**0.391**	(0.186)	**0.787**	(0.285)	-0.393	(0.342)	0.459	(0.245)
Return_Others_D	0.001	(0.193)	0.389	(0.273)	-0.387	(0.349)	-0.235	(0.370)	-0.099	(0.232)	0.225	(0.315)	**-0.845**	(0.337)	-0.252	(0.407)

Table 7 The cost of overconfidence with respect to other factors in the literature

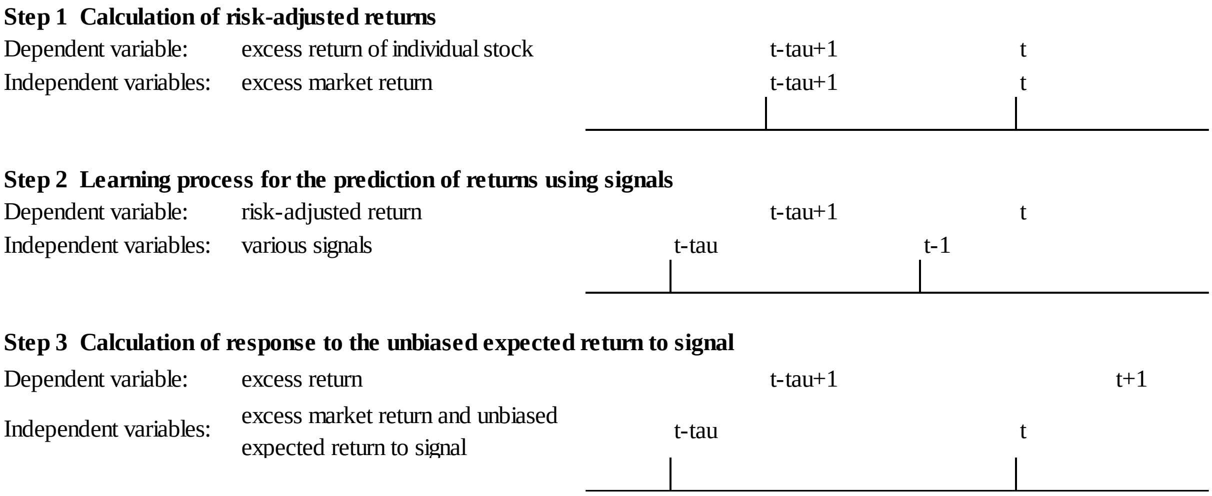
Using the four extreme portfolios from the two independent 5x5 sorts on ERS ($\hat{s}^{*}_{it-1}$) and RS ($\hat{\delta}_{it}$), i.e., high-RS high-ERS (HH), high-RS low-ERS (HL), low-RS high-ERS (LH), and low-RS low-ERS (LL), we form a hedge portfolio (RS_ERS) as (HL+LH-LL-HH)/2 and regress the return reversals of the portfolio on various factors formed on firm characteristics: hedge portfolio returns form on accruals (Acc) (Sloan, 1996), asset growth (AG) (Cooper et al., 2008), book-to-market ratio (BEME) (Rosenberg et al., 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 et al., 2004), net stocks issues (NSI) (Fama and French, 2008), return on assets (ROA) (Chen and Zhang, 2010), earnings surprises (ESUR) (Chan et al., 1996), liquidity (Liq) (Amihud, 2002), size (ME) (Banz, 1981; Fama and French, 1992, 1993), momentum (Mom) (Jegadeesh and Titman, 1993, 2001), and idiosyncratic volatility (IVol) (Ang et al., 2006). These factors are calculated using the top and bottom equally weighted decile portfolios formed 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.

	Equally Weighted RS_RES Portfolio Returns								Value-Weighted RS_RES Portfolio	
	Macroeconomic variables (MA)		Ten factors (10F)		Fama-French five factors (FF5)		Five PCA factors (PCA)		Macroeconomic variables (MA)	
constant	**1.251**	(0.191)	**1.143**	(0.243)	**1.251**	(0.230)	**1.136**	(0.207)	**0.529**	(0.223)
EMR	0.001	(0.000)	0.000	(0.000)	0.001	(0.000)	0.001	(0.001)	0.001	(0.001)
RET_ACC	-0.032	(0.093)	-0.135	(0.099)	-0.021	(0.096)	-0.074	(0.102)	-0.085	(0.122)
RET_AG	-0.138	(0.137)	-0.121	(0.120)	-0.166	(0.139)	-0.185	(0.131)	-0.172	(0.122)
RET_BEM	0.088	(0.062)	0.015	(0.066)	0.011	(0.064)	0.045	(0.057)	0.067	(0.071)
RET_GP	0.007	(0.057)	0.048	(0.072)	-0.032	(0.078)	-0.018	(0.063)	0.045	(0.061)
RET_IA	0.254	(0.148)	**0.295**	(0.141)	0.216	(0.145)	0.252	(0.150)	0.309	(0.164)
RET_IVOL	-0.151	(0.082)	**-0.189**	(0.084)	-0.125	(0.091)	**-0.217**	(0.106)	-0.105	(0.102)
RET_LIQ	-0.035	(0.116)	-0.050	(0.125)	-0.016	(0.133)	-0.010	(0.139)	-0.117	(0.129)
RET_ME	0.028	(0.127)	0.021	(0.133)	0.098	(0.146)	-0.039	(0.151)	0.074	(0.141)
RET_MOM	**-0.179**	(0.054)	**-0.220**	(0.054)	**-0.169**	(0.056)	**-0.174**	(0.057)	-0.129	(0.067)
RET_NOA	-0.044	(0.089)	-0.075	(0.113)	0.024	(0.102)	-0.026	(0.092)	-0.088	(0.099)
RET_NSI	-0.134	(0.077)	-0.096	(0.079)	-0.008	(0.074)	0.027	(0.079)	-0.126	(0.091)
RET_ROA	0.197	(0.100)	0.080	(0.118)	0.197	(0.116)	0.144	(0.106)	0.082	(0.096)
RET_ESUR	0.058	(0.082)	0.144	(0.100)	-0.053	(0.094)	-0.044	(0.088)	0.119	(0.098)
R Square	0.183		0.203		0.199		0.168		0.129	

Figure 1 Biases in Asset Returns by Overconfidence ($\delta_{i,t}$) Conditional on Expected Return Predicted by Signal ($s^*_{i,t}$)

		Expected Return Predicted by Signal	
		$s^*_{i,t} < 0$	$s^*_{i,t} > 0$
Response to Signals	$\delta_{i,t} < -1$	positive bias (contrarian-overconfidence)	negative bias (contrarian-overconfidence)
	$1 > \delta_{i,t} > -1$	Under-response to signal	
	$\delta_{i,t} > 1$	negative bias (momentum-overconfidence)	positive bias (momentum-overconfidence)

Figure 2 The Timeline for the Estimation of RS and ERS



Appendix A. Dynamics of Response to Signals

The overall level of investors' responses to signals is analyzed using aggregated individual $\hat{\delta}_{i,t}$s. For each month, individual $\hat{\delta}_{i,t}$s are cross-sectionally aggregated to calculate a market-wide index of RS. The difference between value-weighted and equally weighted RS indices is negligible; they are highly correlated, with a minimum Spearman correlation of 0.9. The Spearman rank correlation coefficients between the four RS variables are all positive and significant. For equally weighted RS indices, the correlation coefficients range from 0.22 (between MA and FF5) to 0.56 (between 10F and PCA).

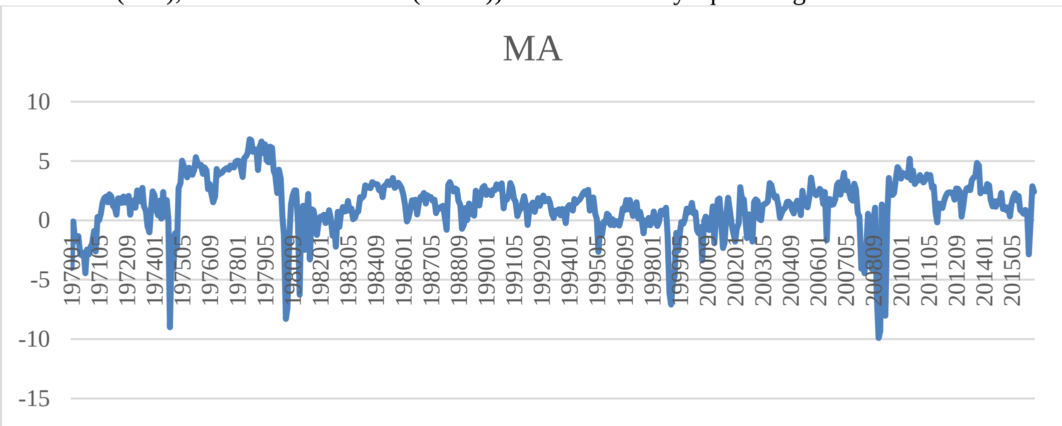
The market-wide RS indices change substantially over time. In the four signals reported in B1, the indices are negatively skewed: investors' response to ERS plummets during crises, e.g., after the first Oil Shock in 1974, the early 1980s, from the Russian Crisis in 1998 to the early 2000s, and the recent financial crisis. During the 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.

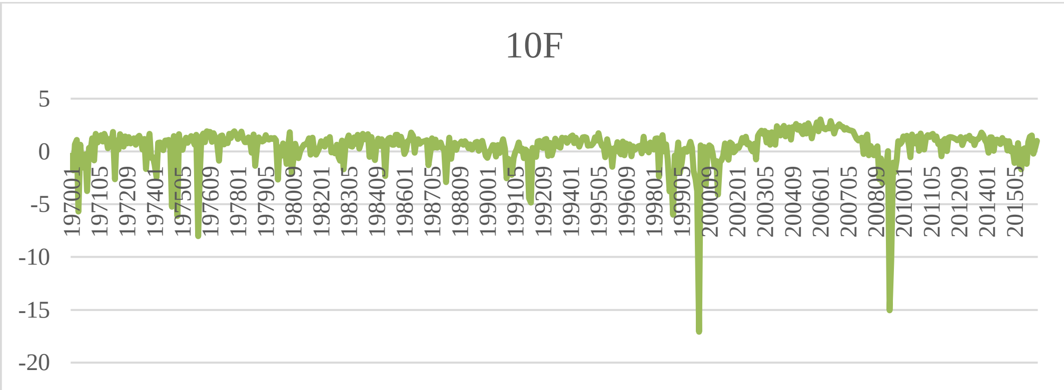
The overall levels of responses to signals increase as the economic outlook or stock market performance improves. The results in B2 show that RS increases with dividends (DY). Investors' responses to signals also increase when the term spread (TS) increases; this is because the term spread predicts economic outlook (Wheelock and Wohar, 2009). On the other hand, poor performance (EMR) lowers investors' response to signals. The one-month-ahead NBER recession dummy is significant at the 5% level in most cases, indicating that investors are less likely to respond to signals when they anticipate a recession. Similarly, the RS indices tend to decrease as the credit spread (CS) increases (Philippon, 2009).

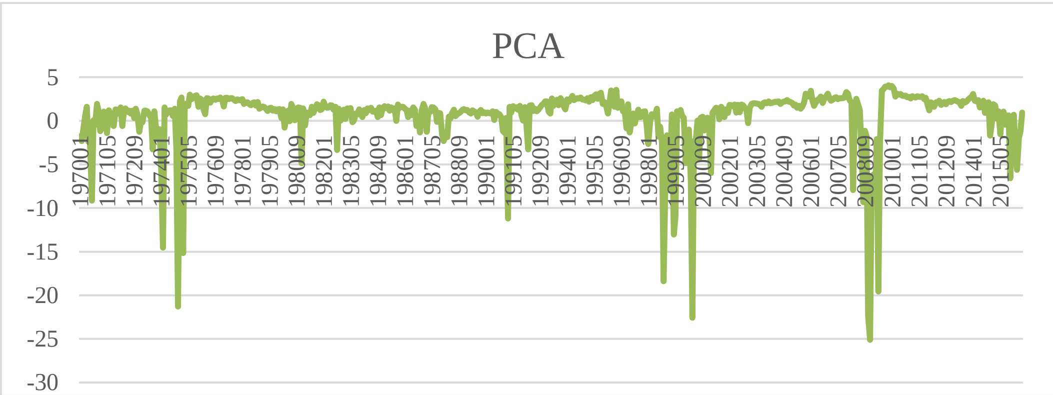
None of the RS indices except for MA shows significant coefficients of the Baker and Wurgler (2006) sentiment index. In the MA case, investors are less likely to consider information when their decision is under the influence of sentiment. This negative relationship, however, does not suggest that the effects of overconfidence on asset pricing are negatively associated with those of sentiment. In fact, the dynamics of overconfidence measured by absolute RS are not correlated with those of sentiment, despite the difference in the firm characteristics that are affected by sentiment and overconfidence: the correlation coefficients between the two dynamics are close to zero for both value- and equally weighted indices, having value of -0.03 and 0.04, respectively. The relationship between overconfidence and sentiment is often low or even negative, despite their similarities (Larrick et al., 2007).

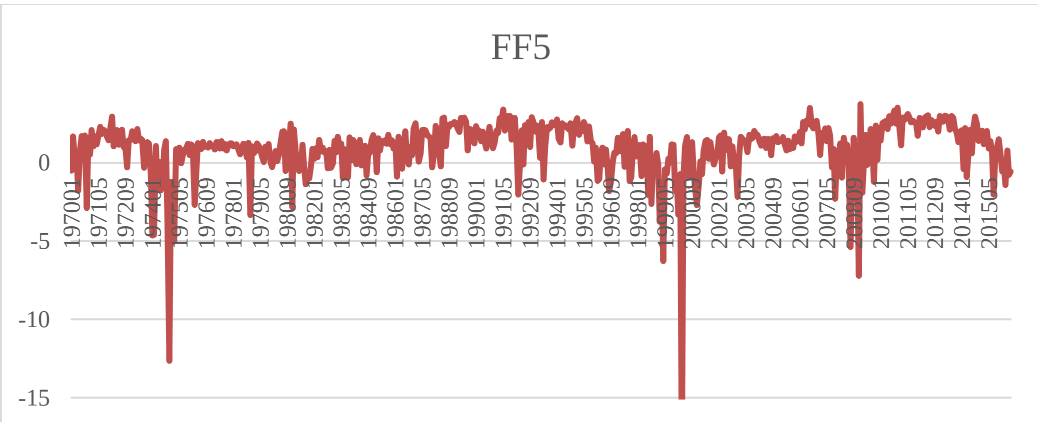
A1 Response to signal for various signals

The time series of the responses to the four signals (i.e., macroeconomic variables (MA), Fama-French five factors (FF5), ten factors (10F), and five PCA factors (PCA5)) are calculated by equal weights on the individual RS values.









A2 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), profitability (RMW), investment (CMA), 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, RMW, and CMA 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). 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)		Ten factors (10F)		Five PCA factors (PCA)		Fama-French five factors (FF5)	
Equally weighted RS index								
RS	**1.312**	(0.097)	**0.460**	(0.072)	**0.682**	(0.139)	**0.961**	(0.074)
C	**1.568**	(0.566)	**0.954**	(0.460)	0.891	(0.874)	**1.058**	(0.452)
EMR	**-0.031**	(0.011)	-0.010	(0.023)	-0.033	(0.031)	**-0.048**	(0.016)
SMB	-0.010	(0.019)	0.043	(0.026)	0.060	(0.040)	-0.002	(0.023)
HML	-0.007	(0.018)	-0.029	(0.032)	-0.021	(0.037)	**-0.124**	(0.027)
RMW	0.011	(0.025)	-0.051	(0.032)	-0.077	(0.050)	**-0.076**	(0.033)
CMA	0.047	(0.035)	0.005	(0.055)	-0.020	(0.068)	0.082	(0.050)
M_VOL	-0.007	(0.032)	-0.032	(0.042)	-0.044	(0.083)	**-0.105**	(0.041)
CS	**-1.953**	(0.269)	-0.614	(0.350)	**-2.378**	(0.500)	-0.288	(0.226)
TS	0.139	(0.106)	0.010	(0.108)	0.452	(0.235)	**0.377**	(0.104)
DY	**0.684**	(0.159)	0.148	(0.121)	**0.839**	(0.311)	0.141	(0.124)
NBER(t+1)	**-1.820**	(0.249)	**-0.828**	(0.344)	**-2.440**	(0.503)	**-0.982**	(0.308)
SENT_BW	**-0.417**	(0.167)	-0.016	(0.131)	0.284	(0.265)	0.132	(0.142)
AR(1)	**0.663**	(0.025)	**0.367**	(0.021)	**0.365**	(0.024)	**0.306**	(0.026)
R-square	0.626		0.182		0.292		0.229	

Value weighted RS index								
RS	**1.361**	(0.111)	**0.442**	(0.071)	**0.713**	(0.141)	**0.973**	(0.079)
C	0.710	(0.554)	0.817	(0.459)	0.774	(0.885)	**1.055**	(0.453)
EMR	**-0.031**	(0.015)	-0.006	(0.019)	-0.027	(0.032)	**-0.067**	(0.016)
SMB	-0.002	(0.027)	0.037	(0.023)	0.060	(0.039)	0.015	(0.026)
HML	0.011	(0.030)	-0.061	(0.033)	-0.015	(0.041)	**-0.144**	(0.026)
RMW	0.010	(0.038)	**-0.070**	(0.030)	-0.091	(0.052)	**-0.099**	(0.035)
CMA	0.049	(0.043)	0.041	(0.053)	-0.039	(0.072)	0.089	(0.047)
M_VOL	-0.012	(0.049)	-0.031	(0.042)	-0.061	(0.088)	**-0.121**	(0.038)
CS	**-2.107**	(0.355)	-0.566	(0.369)	**-2.198**	(0.505)	0.060	(0.248)
TS	**0.311**	(0.134)	0.009	(0.105)	**0.487**	(0.217)	**0.366**	(0.098)
DY	**1.005**	(0.173)	0.152	(0.147)	**0.833**	(0.319)	0.038	(0.131)
NBER (t+1)	**-2.240**	(0.314)	-0.467	(0.321)	**-2.404**	(0.494)	**-0.739**	(0.317)
SENT_BW	**-0.460**	(0.191)	0.006	(0.144)	0.223	(0.279)	0.083	(0.137)
AR(1)	**0.504**	(0.028)	**0.413**	(0.019)	**0.349**	(0.024)	**0.300**	(0.028)
R-square	0.493		0.196		0.273		0.194	

Appendix B. Robustness of the overconfidence factor

Signals other than macroeconomic variables

The main empirical results are reported for the macroeconomic variables. We investigate if similar results can be obtained when investors use other signals, such as firm characteristics or other factors from stock returns. The results for the Fama-French five factors, the ten factors, and five PCA factors in Table B1 show that the return reversals are similar to those for the macroeconomic variables. Alphas are over 1.1% per month and are significant for the entire sample period, and more importantly, are still significant during the 2000s. Figure B1 shows cumulative returns of the overconfidence factor for the four signals. The overconfidence factor performs poorly when RS_ERS portfolios are value-weighted. However, it performs well when the portfolios are equally weighted, despite poor performance of other factors over the past 10 years owing to the increase in arbitrage trading (Chan et al., 2005; Lo, 2008; Green et al., 2017). The overconfidence factors are significantly correlated with each other despite their difference: the Spearman rank correlations range from 0.22 (between MA and FF5) to 0.56 (between 10F 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 month following that of portfolio formation; then, 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 et al., 1997; Hameed and Mian, 2014). To evaluate the effects of bid-ask bounce on the return reversals owing to overconfidence, we exclude the return of the first day in the month following that of formation, as in Jegadeesh (1990) and Hameed and Mian (2014). Table B1 shows that although the return reversals owing to overconfidence decrease, the alphas are still significant during the sub-periods. The bid or ask prices at the end of the month of formation are not critical for the return reversals following overconfidence.

Return reversals excluding January

The return reversals are known to be strong in January (Jegadeesh, 1990; Hameed and Mian, 2014), mainly owing to tax-loss selling (George and Hwang, 2004). Table B1 shows that the average return reversals following 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 0.71% per month in the 2000s.

Moreover, RS does not exhibit any particular pattern around January for all three signals (details not reported). Therefore, the overconfidence factor is not entirely attributable to tax-loss selling.

Robustness to breakpoints, size, and illiquidity

ERS of mature stocks is less extreme than that of stocks that are difficult to value or arbitrage, and thus, the overconfidence factor, obtained from the two independent sorts on RS and ERS, may be affected by these characteristics. A few tests are performed to investigate the extent of the return reversals caused by a large number of small stocks. First, when the portfolios are formed with small and large stocks (larger than the bottom 20% stocks of NYSE), the average return reversals are lower than those using microcaps. However, they are still significant. For example, the average return reversal in the 2000s for portfolios formed with small and large stocks is 0.63%. 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. Return reversals of illiquid stocks are also affected significantly by overconfidence (Avramov et al., 2006; Kumar, 2009). Using the median of the Amihud illiquidity measure as the breakpoint, we calculate the return reversals from liquid and illiquid stocks, and then investigate their performance. The results show that although return reversals become smaller when only liquid stocks are used to form portfolios, the return reversals from liquid stocks is 0.9% per month and are significant. Therefore, the return reversals following overconfidence are also significant in liquid stocks, while overconfidence is stronger in illiquid stocks.

Learning periods

Investors have been assumed to predict future returns based on their experiences during the previous 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 equal to 24, 36, 48, 72, and 84 to investigate the differences in the performance of the overconfidence factor. The results in Table B1 show that the return reversals are similar across these periods. The effects of overconfidence on asset returns is the strongest at $\tau = 36$.

Trends of return reversals following overconfidence

Return reversals for the four months after portfolio formation are calculated by setting the forecasting horizon to one month. The results show that the risk-adjusted returns are economically and statistically significant in the first month after formation, but are not significant for the three months that follow, except for the significant negative alphas in the third month. When 10F is tested instead of MA, the results (not reported) show that alphas are not significant from the second to fourth month after portfolio formation. These results confirm that most of the return reversals following investor overconfidence are observed in the month that follows, and do not show a medium-term price momentum.

Prediction horizon

The large difference in RS, ERS, and contemporaneous returns in Tables 6 and 7 may be affected by the 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) on 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 new information at time t. Contemporaneous ERS can minimize the possibility that unexpected large RSs may arise on the arrival of new information. The results in Table B1 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 month of formation.

Finally, we also test return reversals when the forecasting horizon increases: h=2, 3, and 4 in equations (9) and (10). When investors predict returns over longer horizons, rather than just one-month-ahead returns, investors would not over-respond to signals as much as they do for one-month-ahead forecasting; this is because the predictability of these signals decreases with an increase in the forecasting horizon. To investigate this possibility, investors are assumed to predict returns two, three, and four months ahead in the second and third step of the RS and ERS estimation. All three cases reported in Table B1 show that the return reversals are less severe, indicating that investor overconfidence in signals decreases when forecasting horizon increases. Moreover, return reversals arise in the first month after portfolio formation. Alphas are not significant after the first month during the entire sample period or other sub-periods. Therefore, the cross-sectional bias in the stock prices is corrected immediately after the overconfidence, regardless of the forecasting horizons.

Table B1 Robustness of overconfidence factor

The portfolios are formed in various ways. The performance of portfolios from different signals and formation methods, for January and non-January, various universe or breakpoints, liquidity levels, learning periods, and contemporaneous ERS are reported. The breakpoint between microcaps and small and large stocks is the 20% of the NYSE. The alphas are estimated in the presence of Fama-French five 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.

	Portfolio Returns								Alphas of Portfolio Returns							
	January 1970 ~ June 2016		January 1970 ~ December 1989		January 1990 ~ December 1999		January 2000 ~ June 2016		January 1970 ~ June 2016		January 1970 ~ December 1989		January 1990 ~ December 1999		January 2000 ~ June 2016	
RS_ERS portfolios for various signals																
MA	**1.353**	(0.147)	**1.844**	(0.203)	**1.105**	(0.237)	**0.907**	(0.251)	**1.211**	(0.201)	**1.800**	(0.225)	**0.982**	(0.277)	**0.788**	(0.315)
10F	**1.204**	(0.144)	**1.664**	(0.213)	**1.075**	(0.247)	**0.724**	(0.245)	**1.120**	(0.188)	**1.808**	(0.285)	**0.828**	(0.247)	**0.655**	(0.296)
FF5	**1.219**	(0.140)	**1.700**	(0.194)	**0.909**	(0.204)	**0.824**	(0.250)	**1.109**	(0.198)	**1.499**	(0.193)	**0.636**	(0.242)	**0.774**	(0.331)
PCA	**1.211**	(0.160)	**1.720**	(0.232)	**1.095**	(0.308)	**0.664**	(0.241)	**1.131**	(0.214)	**1.682**	(0.251)	**0.857**	(0.323)	**0.658**	(0.314)
Return reversals skipping the first day in the holding month																
Return_BS_D	**0.893**	(0.132)	**1.310**	(0.186)	**0.344**	(0.202)	**0.721**	(0.231)	**0.798**	(0.178)	**1.328**	(0.205)	0.277	(0.201)	**0.666**	(0.290)
RS_ERS	**0.884**	(0.111)	**1.327**	(0.175)	**0.313**	(0.165)	**0.694**	(0.162)	**0.792**	(0.140)	**1.352**	(0.196)	0.210	(0.166)	**0.656**	(0.214)
RS_ERS portfolios in January and non-January																
January	**3.741**	(0.638)	**4.383**	(0.862)	**3.626**	(1.104)	**3.052**	(1.317)	**2.750**	(0.638)	**2.133**	(1.004)	**2.932**	(1.844)	**2.803**	(1.080)
Non-January	**1.133**	(0.137)	**1.613**	(0.193)	**0.875**	(0.217)	**0.705**	(0.228)	**0.941**	(0.197)	**1.719**	(0.233)	**0.649**	(0.222)	**0.363**	(0.311)
RS_ERS portfolios for various breakpoints and universe																
Microcaps	**2.050**	(0.201)	**2.372**	(0.294)	**2.135**	(0.354)	**1.610**	(0.349)	**1.985**	(0.230)	**2.243**	(0.329)	**2.053**	(0.404)	**1.622**	(0.367)
Small and Large Stocks	**0.933**	(0.128)	**1.400**	(0.165)	**0.499**	(0.225)	**0.629**	(0.225)	**0.782**	(0.168)	**1.326**	(0.213)	0.302	(0.213)	0.472	(0.272)
All Stocks	**1.378**	(0.142)	**1.789**	(0.198)	**1.244**	(0.234)	**0.963**	(0.245)	**1.239**	(0.192)	**1.740**	(0.218)	**1.140**	(0.272)	**0.869**	(0.303)
Non-penny (5$)	**0.934**	(0.133)	**1.416**	(0.183)	**0.478**	(0.226)	**0.626**	(0.220)	**0.799**	(0.180)	**1.407**	(0.225)	0.290	(0.222)	0.512	(0.271)
RS_ERS portfolios for various breakpoints and universe																
Illiquid stocks	**1.719**	(0.187)	**2.233**	(0.248)	**1.430**	(0.350)	**1.272**	(0.352)	**1.591**	(0.229)	**2.048**	(0.277)	**1.331**	(0.404)	**1.144**	(0.360)
Liquid Stocks	**0.904**	(0.141)	**1.316**	(0.167)	0.424	(0.284)	**0.696**	(0.262)	**0.754**	(0.200)	**1.158**	(0.217)	0.175	(0.280)	0.659	(0.336)

	Portfolio Returns								Alphas of Portfolio Returns							
	January 1970 ~ June 2016		January 1970 ~ December 1989		January 1990 ~ December 1999		January 2000 ~ June 2016		January 1970 ~ June 2016		January 1970 ~ December 1989		January 1990 ~ December 1999		January 2000 ~ June 2016	
RS_ERS portfolios for different learning periods																
24 Months	**1.372**	(0.156)	**1.911**	(0.223)	**1.014**	(0.245)	**0.937**	(0.260)	**1.224**	(0.192)	**1.753**	(0.242)	**0.978**	(0.291)	**0.813**	(0.306)
36 Months	**1.444**	(0.155)	**1.881**	(0.228)	**1.354**	(0.270)	**0.970**	(0.256)	**1.344**	(0.205)	**1.839**	(0.227)	**1.284**	(0.320)	**0.934**	(0.337)
48 Months	**1.312**	(0.141)	**1.674**	(0.194)	**1.234**	(0.232)	**0.919**	(0.249)	**1.166**	(0.190)	**1.620**	(0.229)	**1.157**	(0.272)	**0.765**	(0.302)
72 Months	**1.291**	(0.155)	**1.799**	(0.215)	**1.166**	(0.236)	**0.750**	(0.272)	**1.164**	(0.210)	**1.710**	(0.236)	**1.028**	(0.280)	0.665	(0.346)
84 Months	**1.275**	(0.158)	**1.724**	(0.214)	**1.165**	(0.247)	**0.799**	(0.282)	**1.130**	(0.218)	**1.584**	(0.229)	**0.992**	(0.270)	**0.725**	(0.361)
Performance over one month when forecasting horizon is one month																
One month	**1.353**	(0.147)	**1.844**	(0.203)	**1.105**	(0.237)	**0.907**	(0.251)	**1.211**	(0.201)	**1.800**	(0.225)	**0.982**	(0.277)	**0.788**	(0.315)
Two month	0.179	(0.114)	0.139	(0.133)	0.037	(0.226)	0.315	(0.236)	0.119	(0.153)	0.098	(0.173)	0.010	(0.223)	0.233	(0.271)
Three month	**-0.260**	(0.102)	**-0.397**	(0.142)	-0.293	(0.191)	-0.074	(0.199)	**-0.262**	(0.118)	**-0.411**	(0.159)	-0.287	(0.194)	-0.048	(0.191)
Four month	-0.039	(0.108)	-0.268	(0.155)	0.075	(0.197)	0.170	(0.210)	-0.023	(0.123)	-0.265	(0.150)	0.224	(0.217)	0.138	(0.224)
Contemporaneous explanation																
	1.371	(0.136)	**1.738**	(0.186)	**1.159**	(0.229)	**1.054**	(0.240)	**1.261**	(0.185)	**1.704**	(0.190)	**1.076**	(0.258)	**0.932**	(0.295)
Remote forecasting horizon																
Two month ahead forecasting (*h*=2)																
One month	**0.964**	(0.157)	**1.260**	(0.199)	**0.687**	(0.265)	**0.774**	(0.308)	**0.864**	(0.213)	**1.121**	(0.205)	**0.600**	(0.299)	**0.729**	(0.383)
Two month	-0.168	(0.128)	**-0.334**	(0.139)	-0.063	(0.260)	-0.030	(0.270)	-0.183	(0.185)	**-0.371**	(0.174)	-0.170	(0.258)	0.037	(0.299)
Three month ahead forecasting (*h*=3)																
One month	**0.625**	(0.170)	**0.673**	(0.182)	0.508	(0.318)	0.638	(0.352)	**0.507**	(0.254)	**0.547**	(0.228)	0.322	(0.324)	0.615	(0.437)
Two month	-0.202	(0.139)	**-0.385**	(0.168)	-0.311	(0.301)	0.085	(0.265)	-0.235	(0.210)	-0.516	(0.194)	-0.284	(0.308)	0.186	(0.341)
Three month	**-0.317**	(0.134)	**-0.607**	(0.174)	-0.361	(0.307)	0.061	(0.230)	**-0.368**	(0.172)	**-0.702**	(0.173)	-0.335	(0.296)	**0.125**	(0.266)
Four month ahead forecasting (*h*=4)																
One month	**0.654**	(0.179)	**0.838**	(0.216)	0.449	(0.322)	0.556	(0.352)	**0.581**	(0.277)	**0.605**	(0.236)	0.386	(0.328)	0.671	(0.476)
Two month	0.039	(0.154)	0.060	(0.179)	-0.175	(0.319)	0.143	(0.295)	-0.001	(0.235)	-0.058	(0.195)	-0.125	(0.286)	0.257	(0.391)
Three month	-0.209	(0.124)	-0.283	(0.159)	-0.332	(0.257)	-0.044	(0.256)	-0.249	(0.175)	-0.294	(0.170)	-0.209	(0.222)	0.035	(0.309)
Four month	-0.088	(0.136)	-0.242	(0.187)	-0.082	(0.240)	0.094	(0.278)	-0.120	(0.155)	-0.283	(0.181)	0.133	(0.229)	0.250	(0.309)

Figure B1 Cumulative returns of hedge portfolios formed on signal and response

From the twenty five portfolios by the two independent sorts on ERS ($\hat{s}^*_{it-1}$) and RS ($\hat{\delta}_{it}$), the cumulative returns of the following portfolios are calculated: 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 and RS_ERS (HL+LH-LL-HH)/2. The figure report cumulative returns form January 1970 to June 2016 for six hedge portfolios (MA, FF5, 10F, PCA5, and equal and value weights for each of these portfolios). Cumulative returns of the CRSP value weighted market portfolio are reported for the comparison purpose.