Momentum, Reversals, and Fund Manager Overconfidence

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This paper examines the role of investor overconfidence and self-attribution bias in explaining the momentum effect. We develop a novel measure of overconfidence based on characteristics and trading patterns of US equity mutual fund managers. Stocks held by more overconfident managers experience greater momentum profits and stronger return reversals than stocks held by less overconfident managers. The difference in momentum profits is not compensation for risk nor is it attributable to stock characteristics that influence momentum. Our results are consistent with Daniel, Hirshleifer, and Subrahmanyam (1998) who argue that momentum results from delayed overreaction caused by overconfidence and biased self-attribution.

In this paper, we examine whether investor overconfidence, combined with self-attribution bias, contributes to the momentum effect of Jegadeesh and Titman (1993). The momentum effect, or the tendency of recent winners to outperform recent losers over the subsequent 3 to 12 months, is the most prominent anomaly unexplained by the Fama-French three-factor model (Fama and French, 1996). Moreover, the momentum effect has been documented around the world (Rouwenhorst, 1998; Griffin, Ji, and Martin, 2003) across many asset classes (Asness, Moskowitz, and Pedersen, 2013) and remains significant after its initial discovery (Jegadeesh and Titman, 2001).

Although several theoretical and empirical papers offer rational explanations for the momentum effect, the literature has primarily focused on behavioral explanations due to the magnitude of momentum profits (Chui, Titman, and Wei, 2010).[1] For instance, Barberis, Shleifer, and Vishny (1998) and Hong and Stein (1999) propose models in which investors' conservatism and the slow diffusion of news cause initial under-reaction to information and lead to momentum. Alternatively, Daniel et al. (1998) develop a model in which investor overconfidence and biased self-attribution generate delayed overreaction to information and result in momentum. In this paper, we empirically examine the Daniel et al. (1998) explanation for the momentum effect.

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[1] Rational momentum models include Berk, Green, and Naik (1999), Johnson (2002), and Sagi and Seasholes (2007). As discussed in Chui et al. (2010), the biggest challenge for these models is to explain the magnitude of momentum profits without assuming extreme levels of risk aversion. Among empirical papers, Conrad and Kaul (1998) and Chordia and Shivakumar (2002) provide evidence that momentum is related to expected returns. However, Jegadeesh and Titman (2001), Grundy and Martin (2001), and Cooper, Gutierrez, and Hameed (2004) challenge the robustness of their findings.

Daniel et al. (1998) study an informed, but overconfident investor who overreacts to his private signal. If subsequent public information confirms this signal, it triggers further overreaction due to self-attribution bias resulting in stock price momentum. In the long run, as more information becomes available, prices gradually move to fundamentals reversing the initial overreaction. Thus, if overconfidence drives the momentum effect, we expect both short run momentum and long run reversal to be stronger for stocks predominantly owned by overconfident investors.

Several recent empirical papers offer evidence consistent with the hypothesis that overconfidence impacts momentum. Cooper, Gutierrez, and Hameed (2004) find that momentum profits exist only in periods following prolonged market gains. Although aggregate overconfidence should be greater following market gains, market state by itself is not a measure of overconfidence.[2] Chui et al. (2010) confirm that momentum profits are higher in countries with stronger individualism. While the authors argue that individualism is correlated with overconfidence and self-attribution bias, they acknowledge that " . . . it does not directly measure the behavioral biases suggested in the momentum literature." (p. 362). In this paper, we focus on the overconfidence of mutual fund managers and use it as a conditioning variable to provide evidence supporting the Daniel et al. (1998) hypothesis.[3]

To develop the overconfidence measure, we use a comprehensive sample of mutual fund managers. In developing the measure, we focus on mutual fund managers' overconfidence for four reasons. First, the psychology literature suggests that overconfidence should be stronger among professional investors (Heath and Tversky, 1991; Griffin and Tversky, 1992). In addition, Daniel et al. (1998) model overconfidence as an investor's overestimation of the precision of their private information and professional investors, such as mutual fund managers, are more likely to possess private information. Moreover, mutual funds hold a large and growing fraction of the US stock market. According to the Investment Company Institute Fact Book (2015), mutual funds held 24% of the US stock market at the end of 2014. Finally, detailed characteristics and holdings data are readily available for mutual funds and their managers.

However, overconfidence is not directly observable. To overcome this challenge, we construct an overconfidence index by combining six overconfidence and self-attribution bias proxies suggested in the prior literature. Specifically, our overconfidence index includes manager's gender, manager's tenure, portfolio turnover, portfolio concentration, prior performance, and idiosyncratic risk. The index approach has three distinct advantages. It is parsimonious, it reduces the noise associated with individual proxies, and, most importantly, it allows us to capture multiple dimensions of overconfidence and the self-attribution bias.

To provide robustness to the analysis, we construct two versions of the overconfidence index. The first version of the overconfidence index equally weights each of the six proxies. The second version of the index is the first principal component of the six proxies. Since overconfidence is a manager-level characteristic, while momentum is a stock-level anomaly, for each version of the index, we compute the stock-level overconfidence index as the weighted average overconfidence index of all fund managers who hold the stock, using the manager's holdings of the stock as a weight. We use the two resulting stock-level overconfidence indexes as conditioning variables in the analysis.

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[2] In a related paper, Asem and Tian (2010) find that momentum profits are stronger when markets continue in the same state than when they transition to a different state, thereby supporting Daniel et al. (1998) and rejecting Hong and Stein (1999), as well as Sagi and Seasholes (2007). However, once again, the continuation of the market state is not a direct measure of overconfidence.

[3] For ease of exposition, we use the term "overconfidence" to refer to "dynamic overconfidence due to self-attribution bias." Our overconfidence measure captures both overconfidence and the self-attribution bias.

We begin our empirical analysis by testing the relation between the momentum effect and manager overconfidence using a portfolio approach. Consistent with Daniel et al.'s (1998) predictions, we find that stocks with high stock-level overconfidence experience both stronger momentum and stronger reversal than stocks with low stock-level overconfidence. Interestingly, the stocks ranked in the lowest overconfidence tercile do not experience statistically significant momentum or reversal. The average monthly difference in momentum profits between stocks in the high and low stock-level overconfidence terciles ranges from 0.44%−0.49%, which is both economically and statistically significant. Similarly, the average monthly difference in return reversal between stocks in the high and low stock-level overconfidence terciles is between 0.26% and 0.28%. These differences are not compensation for risk, as the Fama-French three-factor model alphas are statistically significant and of similar magnitude to the raw returns. Moreover, in time-series analysis, we find that momentum profits are stronger when aggregate stock-level overconfidence is higher, even after controlling for the market state and aggregate liquidity.

We perform a set of robustness tests and find that our results are robust to controlling for several stock characteristics that impact momentum (size, book-to-market [BM], analyst coverage, turnover, and idiosyncratic volatility) in both portfolio and regression analyses. In addition, several of these robustness results are inconsistent with the reverse causality narrative in which overconfident investors are attracted to momentum stocks. Finally, we find that in the event of manager turnover, the stock holdings of more overconfident managers experience stronger momentum than the holdings of less overconfident managers. Taken together, our findings suggest that the momentum effect results from investor overconfidence and biased self-attribution.

Our paper contributes to two strands of the literature. First, we add to the literature regarding the momentum anomaly. A number of behavioral models attempt to explain short-term momentum and long-term reversal in stock returns, most notably Barberis et al. (1998), Hong and Stein (1999), and Daniel et al. (1998). In this paper, we examine the Daniel et al. (1998) hypothesis that overconfidence drives return continuation. Several prior studies (Daniel and Titman, 1999; Cooper et al., 2004; Asem and Tian, 2010; Chui et al., 2010) provide evidence that is suggestive of a link between overconfidence and momentum. By using fund managers' overconfidence as a conditioning variable, our paper offers more direct evidence that overconfidence, combined with biased self-attribution, impacts both short-term momentum and long-term reversal, consistent with Daniel et al. (1998).

In addition, our paper contributes to the literature regarding the implications of overconfidence for financial markets. Prior literature focuses on individual investors and establishes that overconfidence leads to excessive trading and poor investment performance (Barber and Odean, 2001, 2002; Grinblatt and Keloharju, 2009). Our paper is one of the first to consider overconfidence among mutual fund managers.[4] This topic has been largely unexplored as fund managers are traditionally viewed as immune to judgment biases. However, the psychology literature provides evidence that professionals tend to be more overconfident than laymen. In addition, the growth in funds' assets under management has increased their potential impact on asset prices. Our paper adds to the literature by developing a new measure of investor overconfidence and by empirically linking investor overconfidence to momentum and reversal in stock returns.

It is important to note that although our overconfidence measure is based on mutual fund managers' data, we do not claim that mutual fund managers are the only overconfident investors, nor should our results be taken to imply that only the overconfidence of mutual fund managers drives the momentum effect. Ideally, we would like to measure the level of overconfidence and

[4] Other studies that examine overconfidence among mutual fund managers include Choi and Lou (2010) and Putz and Ruenzi (2009).

self-attribution bias across all investors. However, overconfidence is a characteristic of people, not the market (Odean, 1998), and investor-level characteristics are generally not available for other classes of investors on a broad scale. In a way, our paper is analogous to several recent studies that use data on a subset of market participants to investigate market-wide phenomena. For example, Chen, Hong, and Stein (2002) examine the relation between breadth of ownership and subsequent stock returns, and they measure the breadth of ownership as the number of mutual funds holding a stock. Frazzini (2006) analyzes the relation between the disposition effect and postearnings announcement drift. He constructs a measure of capital gains overhang based on the portfolios of equity mutual funds. Verardo (2009) studies the impact of heterogeneous beliefs on the momentum effect and measures heterogeneous beliefs with dispersion in analyst forecasts.

I. Data and Sample Construction

We study a large sample of US equity mutual fund holdings from January 1984 to December 2014. The data for the study is derived from six sources. We obtain mutual fund holdings from the Thomson-Reuters (formerly CDA/Spectrum) Mutual Fund Holdings Database. Fund returns, monthly total net assets, turnover, and investment objectives come from the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database (CRSP MFBD, henceforth). Fund manager names and their beginning and ending dates are derived from the Morningstar Direct Database. Stock price, return, volume, and shares outstanding data are compiled from the CRSP Monthly Stock File. The book value of equity is pulled from the Compustat Industrial Annual File. The risk-free rate and the Fama and French (1993) factors are gleaned from Kenneth French's website.[5]

The Thomson database provides detailed equity holdings information for virtually all US mutual funds. There is no minimum survival requirement for the inclusion of a fund in the database. The data include the report date, the date at which the portfolio snapshot is taken, and the file date, a vintage date assigned by Thomson. The report date is more appropriate for our analysis. A difference between the report and the file date longer than 6 months indicates stale data and we exclude those cases. In addition, we discard about 0.25% of the cases for which the report date does not fall at the month end. Following Kacperczyk, Sialm, and Zheng (2008), we also remove funds with fewer than ten stock holdings or less than $5 million in total assets under management. Because Thomson adjusts shares held for stock splits as of the file date, we use a cumulative adjustment factor from CRSP and readjust shares to remove any adjustment that happened between the report and the file date.

Next, we combine the Thomson database with the CRSP MFDB using MFLINKS linking files from WRDS.[6] We use the Wharton Financial Institution Center Number (WFICN) to aggregate multiple share classes of the same fund as all share classes of the same fund are backed by the same portfolio of assets and have the same portfolio manager. In the analysis, we focus on US equity funds as holdings data for these funds are the most complete and reliable. To identify US equity funds, we follow the investment objective selection criteria from Kacperczyk et al. (2008). In addition, we exclude funds with an investment objective code of eight (metals) from the

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[6] Our MFLINKS data end in 2013. We extrapolate the MFLINKS data to 2014 by assuming that all of the funds that were active at the end of 2013 remain active with the same identifiers in 2014. This data extrapolation is expected to have minimal impact on our results.

Thomson database. Finally, we remove index funds from our analysis as the investment decisions of index fund managers are not information sensitive and cannot display signs of managers' overconfidence. We use the fund name and character strings from Gil-Bazo and Ruiz-Verdu (2009) to identify and exclude index funds.

In order to obtain more reliable data on fund manager names and their beginning and ending dates, we link the Morningstar data with the CRSP/Thomson data using fund name-, CUSIP-, and ticker-based matching. The matching success rate is over 83%. Since the Morningstar Direct database is subject to survivorship bias prior to 1993 and since we cannot match all of the funds, we supplement manager data with information from various issues of the Morningstar Mutual Fund Sourcebook (Morningstar Mutual Fund Sourcebook, 1984–1995) and CRSP MFDB for funds that are available in CRSP/Thompson, but not in the Morningstar database.

Finally, we link each reported holding to the CRSP stock file using CUSIPs. We are able to link about 98.6% of the holdings from the Thomson database. In order for our stock sample to be comparable to those used in the prior momentum literature (Jegadeesh and Titman, 2001), we exclude all noncommon stocks (CRSP shrcd not 10 or 11) and all stocks priced below $5 or smaller than the NYSE smallest size decile on the portfolio formation date. Our final sample consists of 150,019 fund-quarter observations with 3,113 unique funds. These funds account for 347,441 stock-quarter observations.

II. Measuring Investor Overconfidence

A. Background, Motivation, and Variable Choice

Judgment biases are not directly observable making the measurement of overconfidence challenging. Prior literature suggests several proxies for overconfidence, which fall into two broad categories. The first category includes personal characteristics that the psychology literature has found to be related to overconfidence, such as gender (Lundeberg, Fox, and Puncochar, 1994; Barber and Odean, 2001). The second category relies on the behavior of overconfident investors derived from theoretical models. For instance, Odean (1998) finds that overconfident investors trade more actively and hold a larger position in the risky asset they have private information about than would rational investors. These predictions suggest that portfolio turnover, portfolio concentration, and portfolio risk can proxy for overconfidence. Barber and Odean (2001, 2002) find evidence that the portfolios of overconfident investors indeed exhibit higher turnover and greater risk. Goetzmann and Kumar (2008) conclude that overconfidence is related to underdiversification. Further, Gervais and Odean (2001) note that self-attribution bias leads to (increased) overconfidence as investors attribute good outcomes to their own ability and poor outcomes to external factors suggesting that prior performance can be a proxy for dynamic overconfidence.[7] Finally, because the self-attribution bias is more pronounced among young managers (Gervais and Odean, 2001; Choi and Lou, 2010), a manager's tenure should also be related to dynamic overconfidence.

However, none of these measures have received universal acceptance in the literature. To capture both overconfidence and the self-attribution bias, and to reduce the noise associated with individual measures, we combine the above measures into a composite overconfidence index. Specifically, our index contains the following six components:

[7] Prior literature suggests that past success makes both analysts (Hilary and Menzley, 2006) and CEOs (Billett and Qian, 2008; Libby and Rennekamp, 2012) overconfident about future performance.

- Manager gender: an indicator variable that is equal to one for funds with a solo, male manager and zero otherwise. We determine manager gender by matching the manager's first name to a names database constructed using several sources.[8] If a manager's first name can be used for both genders, we search the fund's website, prospectus, and various popular press sources to determine that manager's gender. We remove a small number of managers for who we cannot determine gender.
- Manager tenure: the number of months since a manager started managing the fund.
- Portfolio turnover: obtained from CRSP MFDB. CRSP portfolio turnover is defined as the ratio of annual sales or purchases, whichever is smaller, to total net assets. Since it uses a minimum of purchases or sales, this definition of turnover captures fund trading that is unrelated to investor inflows and redemptions.
- Portfolio concentration: measured by Herfindahl's (1950) concentration index. The index is the sum of the squared portfolio weights across all stocks in the portfolio. It takes a high value if the manager invests a large portion of the portfolio in a few stocks.
- Prior performance: prior 36-month four-factor alpha of the fund.
- Portfolio idiosyncratic risk: the standard deviation of the four-factor model residuals measured over past 36 months. The factors include the market factor, the size factor, the BM factor, and the momentum factor.[9]

Combining these variables into one index has three important advantages over using each in isolation. First, it reduces noise associated with individual measures and improves the power to measure overconfidence. In addition, it allows us to capture different dimensions of overconfidence and the self-attribution bias within one measure. In fact, in order to capture both overconfidence and the self-attribution bias, it is necessary to combine multiple measures as no individual proxy captures both phenomena. Moreover, it is parsimonious.

B. Index Construction

We use two approaches to combine the six components into an index. Our first approach to forming an overconfidence index (henceforth, OC Index) is similar to the approach that Gompers, Ishii, and Metrick (2003) use to construct their governance index. Specifically, each quarter, we rank managers into percentiles based on five components that are not indicator variables. For example, when ranking managers on turnover, the bottom 1% of the managers with the lowest turnover is assigned a score of 0.01. Similarly, the top 1% of the managers with the highest turnover is assigned a score of 1. The gender indicator remains zero-one. We then sum the scores on all six components. As a result, each component of the index receives the same weight. We term this specification of the index $OC\ Index^{EW}$. $OC\ Index^{EW}$ is a continuous variable that can take on values between 0.05 and 6. Each of the six components is formed so that it positively relates to the degree of overconfidence and the self-attribution bias. Accordingly, higher values correspond to a higher degree of overconfidence and biased self-attribution. To reduce noise, we use a one-year moving average of $OC\ Index^{EW}$.

In addition, we follow an approach similar to Baker and Wurgler (2006) and use principal component analysis to determine the weight of each individual measure in the index. Specifically,

[8] The sources include a popular names list published by the US Social Security Administration for years 1980 to 2014 and websites: www.babynameguide.com, and babynamesworld.parentsconnect.com.

[9] Given that two of the index components require 36 months of data to estimate, those measures are specific to the fund rather than the fund manager in order to preserve the sample size. Our results are qualitatively similar if we use manager-specific measures.

we first standardize all of the continuous variables by quarter to remove trends. We then construct *OC Index*^{PCW} as the first principal component of the above six measures estimated on the full panel. The first principal component explains approximately 25% of the sample variance. Panel A of Table I presents the expected signs of the factor loadings and the actual factor loadings for the six components. All of the loadings have the expected signs. Portfolio concentration has the highest loading (0.53) followed by portfolio risk (0.50), prior performance (0.28), gender (0.24), portfolio turnover (0.18), and tenure (−0.06). Similar to *OC Index*^{EW}, we use a one-year moving average.

Panel B of Table I reports the time-series average of the cross-sectional descriptive statistics and the correlation coefficients for *OC Index*^{EW}, *OC Index*^{PCW}, and the six components. The average value of *OC Index*^{EW} is 3.02 by construction and the standard deviation is 0.83. The average value (standard deviation) of *OC Index*^{PCW} is 0.01 (0.95). An average manager in our sample turns 7% of his portfolio over each month (84% per year), which is consistent with prior studies (Chen, Jegadeesh, and Wermers, 2000). The average tenure of managers in our sample is 5.35 years. Approximately 48% of our sample funds are managed by solo, male managers.

Turning to the correlations, individual overconfidence measures are not highly correlated, consistent with the idea that they capture different dimensions of overconfidence (self-attribution bias), as well as the nonoverconfidence related component. For example, the highest correlation coefficient is between portfolio risk and portfolio concentration (0.30), followed by correlation coefficients between turnover and portfolio risk (0.20), turnover and tenure (−0.16), and prior performance and risk (0.10). The remaining correlation coefficients are all below 0.10. Magnitudes of these correlation coefficients suggest that combining individual overconfidence measures into the index should significantly improve the measurement of overconfidence and the self-attribution bias when compared to any individual measure.

The two specifications of the OC Index are highly correlated with the average correlation coefficient of 0.70. However, they do exhibit some important differences. For example, *OC Index*^{EW} has the highest correlations with gender (0.59), portfolio risk (0.52), and tenure (−0.36), while *OC Index*^{PCW} has the highest correlations with portfolio risk (0.74), portfolio concentration (0.47), and portfolio turnover (0.34). These differences suggest that *OC Index*^{EW} and *OC Index*^{PCW} indeed capture different dimensions of overconfidence and the self-attribution bias.[10] Thus, using both specifications should provide robustness to the analysis.

III. Empirical Results

While overconfidence is a manager-level characteristic, momentum is a stock-level anomaly. To transform the manager-level overconfidence index to a firm-level overconfidence index (henceforth OCI), we compute the weighted average overconfidence index of fund managers that hold the stock using their holdings as weights.[11] Because we use two specifications of the OC Index, this procedure provides us with two stock-level measures, *OCI*^{EW} and *OCI*^{PCW}. These are the two measures that we use as conditioning variables in all of our further tests.

Table II reports the descriptive statistics and average correlation coefficients for the two measures and various firm characteristics. The characteristics include firm size, BM ratio,

[10] In Section IV.A, we discuss potential alternative interpretations of the OC Index. In the appendix, we examine whether the OC Index captures overreaction behavior similar to that suggested by Daniel et al. (1998).

[11] For illustrative purposes, imagine that only two fund managers, X and Y, hold shares of Stock ABC. Manager X holds 500,000 shares of ABC and has an OC Index of 5. Manager Y holds 200,000 shares of ABC and has an OC Index of 3. As such, the OCI for Stock ABC will be (500,000 $\times$ 5 + 200,000 $\times$ 3)/(700,000) = 4.43.

Table I. Descriptive Statistics–OC Index

The table presents summary statistics for measures of fund managers' overconfidence and self-attribution bias. Portfolio turnover is the minimum of buys or sells during a given year divided by the fund's total net assets, as available in CRSP MFDB. Portfolio Concentration is constructed following the approach in Herfindahl (1950) as the sum of the squared portfolio weights across all of the stocks in the portfolio. Prior performance is a fund's four-factor alpha estimated from monthly net returns over the prior 36 months. Portfolio risk is the standard deviation of residuals from the market model estimated over the prior 36 months. Male is an indicator variable for solo male managers. *Tenure* is the number of months since the manager started managing the fund. *OC Index*^{EW} is the sum of the percentile ranks of the above six overconfidence and self-attribution bias proxies. *OC Index*^{PCW} is the weighted sum of the above six proxies, where weights are obtained using principal component analysis. Specifically, each quarter, we standardize the continuous variables to remove trends. We then estimate the first principal component and use the factor loadings as weights. Panel A summarizes the output of the principal component analysis. Panel B presents descriptive statistics for the two OC indexes and six components. Mean is the time-series mean of the cross-sectional average value. Stdev is the time-series mean of the cross-sectional standard deviation. *P*10 is the time-series mean of the cross-sectional 10% cutoff. *P*90 is the time-series mean of the cross-sectional 90% cutoff. Average cross-sectional correlations are the time-series means of the cross-sectional correlation coefficients.

Panel A. Constructing OC_INDEX^{PCW} *Using Principal Component Analysis*

Variable	**Expected Sign**	**Factor Loading**
Portfolio turnover	+	0.18***
Portfolio concentration	+	0.53***
Prior performance	+	0.28***
Portfolio risk	+	0.50***
Male	+	0.24***
Tenure	−	−0.06***

Panel B. Descriptive Statistics for the OC Index and Components

					Average Cross-Sectional Correlations							
	Mean	**Stdev**	***P*10**	***P*90**	***OC_Index***^{EW}	***OC_Index***^{PCW}	**Turnover**	**Herfindahl**	**Tenure**	***PriPerf***	**Risk**	**Male**
OC_Index^{EW}	3.02	0.83	1.96	4.10	1.00							
OC_Index^{PCW}	0.01	0.95	−1.00	1.14	0.70***	1.00						
Turnover	0.07	0.07	0.02	0.14	0.34***	0.34***	1.00					
Herfindahl	0.03	0.02	0.01	0.04	0.34***	0.47***	−0.01***	1.00				
Tenure	64.21	55.84	13.15	136.45	−0.36***	−0.14***	−0.16***	0.05***	1.00			
PriPerf	0.09	0.36	−0.30	0.51	0.28***	0.23***	0.01	0.04***	0.07***	1.00		
Risk	0.02	0.01	0.01	0.02	0.52***	0.74***	0.20***	0.30***	−0.05***	0.10***	1.00	
Male	0.48	0.47	0.00	1.00	0.59***	0.27***	0.04***	0.08***	−0.02***	0.01	0.08***	1.00

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Table II. Descriptive Statistics–OCI

The table presents summary statistics for stock-level overconfidence measures and various stock characteristics. Stock-level overconfidence measures are OCI^{EW} and OCI^{PCW}. OCI^{EW} (OCI^{PCW}) is the weighted average $OC\ Index^{EW}$ ($OC\ Index^{PCW}$) of the fund managers holding the stock, where the weight is the number of shares held in the stock at the end of the quarter. $OC\ Index^{EW}$ is the sum of the percentile ranks of six overconfidence and self-attribution bias proxies. $OC\ Index^{PCW}$ is the weighted sum of six overconfidence and self-attribution bias proxies, where the weights are obtained using principal component analysis. $RET_{i;t-5,t}$ is the prior 6-month stock return. *SIZE* is the market capitalization in billions of dollars. BM is the book-to-market ratio. *RESNA* is the residual analyst coverage defined as a residual from a regression of log(1+ #of analysts) on firm size. *TURN* is the prior 6-month average ratio of volume to shares outstanding in excess of the average turnover of the exchange on which the stock trades. *Mean* is the time-series mean of cross-sectional average values. Stdev is the time-series mean of cross-sectional standard deviations. *P*10 is the time-series mean of the cross-sectional 10% cutoff. *P*90 is the time-series mean of the cross-sectional 90% cutoff. Average cross-sectional correlations are the time-series means of cross-sectional correlation coefficients.

					Average Cross-Sectional Correlations						
	Mean	Stdev	*P*10	*P*90	OCI^{EW}	OCI^{PCW}	$RET_{i;t-5,t}$	*SIZE*	BM	*RESNA*	*TURN*
OCI^{EW}	2.70	0.51	2.04	3.32	1.00						
OCI^{PCW}	−0.28	0.53	−0.87	0.34	0.87***	1.00					
$RET_{i;t-5,t}$	0.12	0.35	−0.21	0.47	0.05***	0.06***	1.00				
SIZE ($ billions)	3.54	12.60	0.18	6.73	−0.07***	−0.07***	−0.04***	1.00			
BM	0.64	0.52	0.19	1.14	−0.14***	−0.13***	0.06***	−0.06***	1.00		
RESNA	0.07	0.93	−1.30	1.08	0.07***	0.05***	−0.00	−0.07***	−0.10***	1.00	
TURN	0.07	0.49	−0.32	0.55	0.26***	0.25***	0.05***	−0.06***	−0.10***	0.14***	1.00

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

residual analyst coverage, and stock turnover. Please refer to Section III.C for detailed definitions of these variables. OCI^{EW} and OCI^{PCW} are highly correlated with an average correlation coefficient of 0.87. OCI^{EW} (OCI^{PCW}) does not exhibit a strong correlation with prior 6-month returns. The correlation coefficient is 0.05 (0.06). More importantly, neither OCI^{EW} nor OCI^{PCW} exhibit strong correlations with the other stock characteristics related to the momentum effect. Specifically, the correlation coefficient between OCI^{EW} and size is −0.07, between OCI^{EW} and the BM ratio is −0.14, between OCI^{EW} and residual analyst coverage is 0.07, and between OCI^{EW} and turnover is 0.26. Similarly, the correlation coefficient between OCI^{PCW} and size is −0.07, between OCI^{PCW} and the BM ratio is −0.13, between OCI^{PCW} and residual analyst coverage is 0.05, and between OCI^{PCW} and turnover is 0.25. These results suggest that stock-level overconfidence is distinct from the other stock characteristics that influence the strength of the momentum effect.

A. Overconfidence and Return Momentum

To determine whether overconfidence impacts momentum, each quarter, we sort all stocks into independent portfolios by one of two stock-level overconfidence measures and the prior 6-month returns. Since our analysis requires double and triple sorting, we sort stocks into terciles to avoid having undiversified portfolios that can create large standard errors in our test statistics. We rebalance the portfolios quarterly due to the availability of mutual fund holdings data. Quarterly rebalancing also mitigates the issue raised by Lesmond, Schill, and Zhou (2002) and Korajczyk and Sadka (2002) who argue that momentum profits are not realizable, as the strategy requires frequent trading in high trading cost securities. Following Jegadeesh and Titman (2001), we focus on 6-month formation/6-month holding strategy and compute equal-weighted returns for each portfolio.[12]

Table III reports the average monthly portfolio returns. The full sample average monthly return to the momentum strategy is 0.36% ($t = 1.85$). This return is lower than that reported in previous studies due to disappearance of momentum in the post 2001 period (Chordia, Subrahmanyam, and Tong, 2014). When examining the overconfidence portfolios, we find that momentum profits are an insignificant 0.16% ($t = 0.99$) per month for the low OCI^{EW} portfolio, marginal 0.30% ($t = 1.76$) for the middle OCI^{EW} portfolio, and significant 0.60% ($t = 3.05$) for the high OCI^{EW} portfolio. The difference in momentum profits between the high and low OCI^{EW} portfolios is 0.44% ($t = 3.74$) per month or 5.28% per year, which is highly economically significant. When examining OCI^{PCW}, we find that the momentum profit is insignificant for low and middle OCI^{PCW} portfolios, but significant at 0.63% ($t = 3.14$) for the high OCI^{PCW} portfolio. The difference in momentum profits between the high and low OCI^{PCW} portfolios is highly statistically and economically significant at 0.49% ($t = 3.90$) amounting to 5.88% annually. The similarity of the results using OCI measures suggests that our findings are robust to alternative specifications of the OC Index.

To determine whether the difference in momentum profits between high- and low-OCI portfolios is compensation for risk, we estimate the Fama-French (1993) three-factor model for the monthly series of momentum overconfidence portfolio returns in excess of the risk-free rate. The dependent variables are the excess returns for portfolios of past losers, past winners, and the momentum profits in each of the overconfidence groups. In addition, we estimate the same time-series regression for the difference in momentum profits between the high- and low-overconfidence groups. We report the estimated coefficients in Table IV.

[12] In unreported analysis, we confirm that baseline momentum results are robust to using alternative momentum strategies.

Table III. Momentum Profits Across Overconfidence Portfolios–Raw Returns

Each quarter, we sort all CRSP common stocks with a share price no less than \$5 and larger than the smallest NYSE size decile into independent terciles based on their past 6-month return and their stock-level overconfidence measure. The stock-level overconfidence measure is either OCI^{EW} or OCI^{PCW}. OCI^{EW} (OCI^{PCW}) is the weighted average $OC\ Index^{EW}$ ($OC\ Index^{PCW}$) of fund managers holding the stock, where weight is the number of shares held in the stock at the end of the quarter. $OC\ Index^{EW}$ is the sum of the percentile ranks of six overconfidence and self-attribution bias proxies. $OC\ Index^{PCW}$ is the weighted sum of the six overconfidence and self-attribution bias proxies, where weights are obtained using principal component analysis. *OC*1 (*OC*3) is a tercile containing stocks with the lowest (highest) value of the stock-level overconfidence measure. *PR*1 (*PR*3) is a tercile containing past loser (winner) stocks. The table reports the average raw monthly returns over the subsequent 6 months for each of the nine portfolios, the average momentum returns for three overconfidence portfolios, and the average difference in momentum returns between high and low OCI portfolios. Reported returns are expressed in percentages. *t*-statistics (in parentheses) are based on Newey-West (1987) standard errors robust to heteroskedasticity and autocorrelation up to three lags. The numbers in brackets represent the average number of stocks in a portfolio.

		OCI^{EW}				OCI^{PCW}			
Prior Return	**All Stocks**	***OC*1 (low)**	***OC*2 (med)**	***OC*3 (high)**	***OC*3–*OC*1 (hi-low)**	***OC*1 (low)**	***OC*2 (med)**	***OC*3 (high)**	***OC*3–*OC*1 (hi-low)**
*PR*1	0.84**	0.99***	0.90***	0.66*		1.01***	0.97***	0.67*	
	(2.56)	(3.27)	(2.70)	(1.68)		(3.26)	(2.97)	(1.70)	
		[283]	[283]	[279]		[278]	[287]	[282]	
*PR*2	1.13***	1.19***	1.12***	1.02***		1.18***	1.18***	1.03***	
	(4.60)	(5.04)	(4.29)	(3.30)		(4.87)	(4.62)	(3.26)	
		[325]	[292]	[224]		[324]	[295]	[223]	
*PR*3	1.21***	1.15***	1.20***	1.26***		1.15***	1.22***	1.30***	
	(4.00)	(4.21)	(4.00)	(3.40)		(4.22)	(4.10)	(3.46)	
		[244]	[270]	[311]		[248]	[265]	[312]	
*PR*3–*PR*1	0.36*	0.16	0.30*	0.60***	0.44***	0.15	0.25	0.63***	0.49***
	(1.85)	(0.99)	(1.76)	(3.05)	(3.74)	(0.93)	(1.52)	(3.14)	(3.90)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Table IV. Momentum Profits Across Overconfidence Portfolios–Risk Adjusted Returns

Each quarter, we sort all CRSP common stocks with a share price no less than \$5 and larger than the smallest NYSE size decile into independent terciles based on their past 6-month return and their stock-level overconfidence measure. The stock-level overconfidence measure is either OCI^{EW} or OCI^{PCW}. OCI^{EW} (OCI^{PCW}) is the weighted average $OC\ Index^{EW}$ ($OC\ Index^{PCW}$) of fund managers holding the stock, where the weight is the number of shares held in the stock at the end of the quarter. $OC\ Index^{EW}$ is the sum of the percentile ranks of six overconfidence and self-attribution bias proxies. $OC\ Index^{PCW}$ is the weighted sum of the six overconfidence and self-attribution bias proxies, where the weights are obtained using principal component analysis. *OC*1 (*OC*3) is a tercile containing stocks with the lowest (highest) value of the stock-level overconfidence measure. *PR*1 (*PR*3) is a tercile containing past loser (winner) stocks. The table reports the Fama-French (1993) three-factor model coefficients for each of the nine portfolios, for the momentum returns in each OCI tercile, and for the difference in momentum returns between *OC*3 and *OC*1. Reported alpha estimates are expressed in percentages. *t*-statistics (in parentheses) are based on Newey-West (1987) standard errors robust to heteroskedasticity and autocorrelation up to three lags.

		OCI^{EW}				OCI^{PCW}			
		Alpha	**mktrf**	**smb**	**hml**	**Alpha**	**mktrf**	**smb**	**hml**
*OC*1	*PR*1	0.12	1.07***	0.55***	0.49***	0.10	1.09***	0.56***	0.54***
		(0.99)	(23.55)	(4.39)	(5.01)	(0.85)	(25.21)	(4.76)	(5.37)
	*PR*2	0.45***	0.89***	0.38***	0.48***	0.41***	0.91***	0.39***	0.50***
		(5.51)	(38.31)	(6.49)	(9.30)	(4.92)	(33.73)	(6.10)	(9.33)
	*PR*3	0.41***	0.93***	0.75***	0.31***	0.38***	0.94***	0.72***	0.34***
		(4.92)	(34.81)	(21.04)	(5.14)	(4.55)	(33.22)	(21.19)	(5.82)
	*PR*3–*PR*1	0.29*	−0.14**	0.20	−0.18	0.29*	−0.15**	0.16	−0.20
		(1.81)	(−2.27)	(1.30)	(−1.27)	(1.80)	(−2.52)	(1.10)	(−1.44)
*OC*2	*PR*1	−0.01	1.20***	0.57***	0.30***	0.05	1.18***	0.54***	0.30***
		(−0.08)	(27.05)	(4.28)	(2.95)	(0.43)	(26.50)	(3.94)	(2.95)
	*PR*2	0.34***	1.00***	0.37***	0.36***	0.40***	0.99***	0.37***	0.37***
		(4.35)	(39.22)	(5.02)	(5.92)	(4.98)	(39.83)	(5.61)	(5.94)
	*PR*3	0.44***	1.04***	0.63***	0.15**	0.43***	1.03***	0.64***	0.19**
		(5.31)	(37.62)	(20.29)	(2.07)	(5.68)	(35.95)	(19.38)	(2.62)
	*PR*3–*PR*1	0.45***	−0.16	0.06	−0.15	0.38**	−0.16**	0.09	−0.11
		(2.68)	(−2.61)	(0.41)	(−0.94)	(2.31)	(−2.53)	(0.64)	(−0.68)
*OC*3	*PR*1	−0.21	1.29***	0.69***	−0.11	−0.22	1.29***	0.72***	−0.14
		(−1.51)	(24.18)	(4.77)	(−0.81)	(−1.55)	(21.75)	(5.15)	(−1.02)
	*PR*2	0.27***	1.08***	0.56***	−0.01	0.26***	1.08***	0.59***	−0.04
		(3.79)	(44.03)	(9.68)	(−0.24)	(3.50)	(41.07)	(9.71)	(−0.67)
	*PR*3	0.54***	1.12***	0.82***	−0.27***	0.55***	1.13***	0.83***	−0.31***
		(4.86)	(34.52)	(17.97)	(−3.96)	(4.64)	(32.35)	(18.19)	(−4.49)
	*PR*3–*PR*1	0.75***	−0.17	0.13	−0.16	0.77***	−0.16**	0.11	−0.17
		(3.76)	(−2.58)	(0.76)	(−0.20)	(3.91)	(−2.30)	(0.69)	(−0.88)
*OC*3–*OC*1	*PR*3–*PR*1	0.46***	−0.03	−0.07	0.02	0.49***	−0.01	−0.05	0.03
		(3.61)	(−0.80)	(−1.51)	(0.29)	(3.70)	(−0.13)	(−1.00)	(0.45)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

The magnitudes of factor loadings on the mktrf, smb, and hml factors are between those reported by Jegadeesh and Titman (2001) and Lee and Swaminathan (2000). Turning to the main results, we find that momentum return alphas increase from 0.29% ($t = 1.81$) per month for low OCI^{EW} to 0.75% ($t = 3.76$) per month for the high OCI^{EW} portfolio. The alpha for the difference between the high and low OCI^{EW} portfolios is highly economically significant at 0.46% ($t = 3.61$) per month. Moreover, this estimate of alpha is close to the average raw return difference reported in Table III. The results for the OCI^{PCW} measure are very similar. Specifically, momentum return alphas increase from 0.29% ($t = 1.80$) for low OCI^{PCW} to 0.77% ($t = 3.91$) for the high OCI^{PCW} portfolio, producing a highly significant difference of 0.49% ($t = 3.70$). Overall, our results suggest that the momentum profit differential between high- and low-OCI stocks is not a compensation for the risk captured by the Fama-French (1993) model.

B. Overconfidence and Return Reversals

Our results thus far are strongly consistent with the Daniel et al. (1998) proposition that momentum results from dynamic overconfidence due to self-attribution bias. In particular, the difference in momentum profits between high- and low-OCI portfolios is between 0.44% and 0.49% per month, which is highly economically and statistically significant. Another important proposition is that momentum profits will reverse in the long run as more information becomes available and the market corrects the mispricing. Therefore, we expect the reversal to be stronger for those stocks with more overconfident investors.

To test this proposition, we sort stocks into independent portfolios based on their prior 6-month returns and OCI and examine returns for the 24-month period from month $t + 13$ to month $t + 36$. Table V reports the average monthly portfolio returns from this strategy. High-OCI portfolios exhibit very strong and economically significant reversals of −0.32% per month ($t = -3.64$) for OCI^{EW} and −0.34% ($t = -3.61$) for the OCI^{PCW} measure. In contrast, low-OCI portfolios do not exhibit statistically nor economically meaningful reversals. The difference in return reversals between high- and low-OCI portfolios is statistically significant at −0.26% per month ($t = -4.39$) for OCI^{EW} and −0.28% ($t = -3.94$) for the OCI^{PCW} measure.

For robustness, Table VI reports the Fama-French three-factor model coefficients. Consistent with the prior literature (Fama and French, 1996), accounting for the three factors subsumes return reversals making intercepts insignificant for low and medium OCI portfolios. However, high-OCI portfolios continue exhibiting strong return reversals even after accounting for the three factors. The intercept estimates for the difference in return reversals between high- and low-OCI portfolios are statistically significant at −0.27% per month ($t = -4.89$) for the OCI^{EW} measure and −0.28% ($t = -4.30$) for the OCI^{PCW} measure. More importantly, the intercept estimates are of similar magnitude as the raw return estimates reported in Table V. These results suggest that the differential in return reversals between high and low OCI stocks is not compensation for the risk. Overall, our findings are consistent with both key Daniel et al. (1998) propositions.

C. Overconfidence, Momentum, and Stock Characteristics

The prior literature establishes significant relations between stock return momentum and certain stock characteristics. For instance, Hong, Lim, and Stein (2000) and Jegadeesh and Titman (2001) find that return momentum is stronger in small stocks. Hong et al. (2000) also link return momentum to analyst coverage. Daniel and Titman (1999) demonstrate that momentum profits are higher for low BM (i.e., growth) stocks. Lee and Swaminathan (2000) document a positive relation between return momentum and stock turnover.

Table V. Reversal Across Overconfidence Portfolios–Raw Returns

Each quarter, we sort all CRSP common stocks with a share price no less than \$5 and larger than the smallest NYSE size decile into independent terciles based on their past 6-month return and their stock-level overconfidence measure. The stock-level overconfidence measure is either OCI^{EW} or OCI^{PCW}. OCI^{EW} (OCI^{PCW}) is the weighted average *OC Index*^{EW} (*OC Index*^{PCW}) of fund managers holding the stock, where weight is the number of shares held in the stock at the end of the quarter. *OC Index*^{EW} is the sum of the percentile ranks of the six overconfidence and self-attribution bias proxies. *OC Index*^{PCW} is the weighted sum of the six overconfidence and self-attribution bias proxies, where weights are obtained using principal component analysis. *OC*1 (*OC*3) is a tercile containing stocks with the lowest (highest) value of the stock-level overconfidence measure. *PR*1 (*PR*3) is a tercile containing past loser (winner) stocks. The table reports average raw monthly returns over 24 months from $t + 13$ to $t + 36$ for the nine portfolios for the strategy of buying winners and selling losers across three OCI portfolios, and for the difference in momentum strategy between high and low OCI portfolios. Reported returns are expressed in percentages. Reported t-statistics (in parentheses) are based on Newey-West (1987) standard errors robust to heteroskedasticity and autocorrelation up to 21 lags.

		OCI^{EW}				OCI^{PCW}			
Prior Return	All Stocks	*OC*1 (low)	*OC*2 (med)	*OC*3 (high)	*OC*3–*OC*1 (hi-low)	*OC*1 (low)	*OC*2 (med)	*OC*3 (high)	*OC*3–*OC*1 (hi-low)
*PR*1	1.35***	1.30***	1.32***	1.41***		1.30***	1.36***	1.48***	
	(4.45)	(4.31)	(4.08)	(3.81)		(4.15)	(4.07)	(3.78)	
*PR*2	1.23***	1.24***	1.22***	1.24***		1.22***	1.23***	1.28***	
	(4.92)	(4.95)	(4.55)	(4.09)		(4.68)	(4.52)	(4.07)	
*PR*3	1.16***	1.24***	1.19***	1.09***		1.23***	1.21***	1.14***	
	(3.92)	(4.39)	(3.94)	(3.13)		(4.25)	(3.93)	(3.13)	
*PR*3–*PR*1	−0.19***	−0.06	−0.13*	−0.32***	−0.26***	−0.06	−0.15*	−0.34***	−0.28***
	(−2.63)	(−0.86)	(−1.76)	(−3.64)	(−4.39)	(−0.89)	(−1.89)	(−3.61)	(−3.94)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

To examine the incremental power of OCI in explaining stock return momentum, we use triple sorts. In particular, we compute momentum returns for stocks sorted independently on the past 6-month returns, stock OCI, and one of the following characteristics: firm size, BM ratio, residual analyst coverage, and turnover. Firm size is the market capitalization in the month prior to the return preranking period. BM is the ratio of book equity to market equity, constructed following Kayhan and Titman (2007). Residual analyst coverage is constructed following Hong et al. (2000) as the residual from a regression of ln(1 + number of analysts) on ln(size) in the month prior to the portfolio preranking period. Turnover is the average ratio of monthly share volume to the number of shares outstanding in excess of the exchange average turnover over the 6 month period prior to the portfolio formation.[13] In addition to raw returns, we estimate intercepts from time-series regressions of the difference in momentum profits between high- and low-OCI portfolios on the Fama-French (1993) three factors to verify that these profits are not compensation for risk.

For brevity, Table VII reports only the intercepts from the analysis. The first three columns report results for the full sample without conditioning on overconfidence. Consistent with prior studies, we find that momentum profits are strongest for small stocks (Hong et al., 2000; Jegadeesh and Titman, 2001), growth stocks (Daniel and Titman, 1999), low analyst coverage stocks (Hong et al., 2000), and high turnover stocks (Lee and Swaminathan, 2000). The next three columns

[13] The Nasdaq volume is different than the NYSE or AMEX volume due to double counting of dealer trades. We first divide the turnover of Nasdaq stocks by two and then compute the average turnover by exchange. Finally, we subtract the average exchange turnover from the stock turnover to obtain the excess turnover used in our tests.

Table VI. Reversal Across Overconfidence Portfolios–Risk Adjusted Returns

Each quarter, we sort all CRSP common stocks with a share price no less than \$5 and larger than the smallest NYSE size decile into independent terciles based on their past 6-month return and their stock-level overconfidence measure. The stock-level overconfidence measure is either OCI^{EW} or OCI^{PCW}. OCI^{EW} (OCI^{PCW}) is a weighted average *OC Index*^{EW} (*OC Index*^{PCW}) of fund managers holding the stock, where weight is the number of shares held in the stock at the end of the quarter. *OC Index*^{EW} is the sum of the percentile ranks of six overconfidence and self-attribution bias proxies. *OC Index*^{PCW} is the weighted sum of the six overconfidence and self-attribution bias proxies, where weights are obtained using principal component analysis. *OC*1 (*OC*3) is a tercile containing stocks with the lowest (highest) value of the stock-level overconfidence measure. *PR*1 (*PR*3) is a tercile containing past loser (winner) stocks. The table reports Fama-French (1993) three-factor model coefficients estimated over 24 months from $t + 13$ to $t + 36$, for each of the nine portfolios, for the momentum returns in each of the three overconfidence portfolios, and for the difference in momentum returns between high and low OCI portfolios. Reported alpha estimates are in percentages. Reported t-statistics (in parentheses) are based on Newey-West (1987) standard errors robust to heteroskedasticity and autocorrelation up to 21 lags.

		OCI^{EW}				OCI^{PCW}			
		Alpha	**mktrf**	**smb**	**hml**	**Alpha**	**mktrf**	**smb**	**hml**
*OC*1	*PR*1	0.41***	1.05***	0.64***	0.61***	0.38***	1.06***	0.62***	0.67***
		(5.31)	(38.89)	(9.11)	(11.39)	(4.47)	(35.77)	(8.40)	(11.40)
	*PR*2	0.45***	0.94***	0.39***	0.55***	0.41***	0.96***	0.39***	0.60***
		(6.03)	(43.55)	(5.95)	(11.45)	(5.23)	(39.64)	(5.58)	(12.17)
	*PR*3	0.43***	1.03***	0.55***	0.38***	0.39***	1.03***	0.53***	0.45***
		(5.55)	(49.83)	(7.29)	(7.11)	(5.07)	(48.45)	(7.08)	(8.16)
	*PR*3–*PR*1	0.02	−0.02	−0.09**	−0.23***	0.01	−0.03	−0.09***	−0.22***
		(0.34)	(−1.11)	(3.08)	(−6.85)	(0.21)	(−1.34)	(−3.54)	(−6.40)
*OC*2	*PR*1	0.41***	1.14***	0.68***	0.46***	0.44***	1.13***	0.66***	0.46***
		(4.80)	(41.31)	(9.48)	(8.12)	(4.89)	(42.64)	(9.14)	(7.99)
	*PR*2	0.40***	1.02***	0.40***	0.45***	0.41***	1.01***	0.40***	0.46***
		(5.40)	(50.66)	(6.10)	(8.37)	(5.42)	(52.14)	(6.33)	(8.78)
	*PR*3	0.36***	1.11***	0.49***	0.24**	0.36***	1.10***	0.49***	0.29***
		(3.95)	(40.56)	(5.48)	(3.83)	(3.74)	(39.53)	(5.33)	(4.57)
	*PR*3–*PR*1	−0.04	−0.03	−0.19***	−0.23***	−0.08	−0.03	−0.18***	−0.17***
		(−0.58)	(−1.32)	(−5.05)	(−6.13)	(−1.02)	(−1.20)	(−4.40)	(−4.62)
*OC*3	*PR*1	0.52***	1.19***	0.88***	0.20***	0.55***	1.19***	0.91***	0.18***
		(4.61)	(33.35)	(11.24)	(3.27)	(4.55)	(30.76)	(12.35)	(2.83)
	*PR*2	0.43***	1.07***	0.59***	0.23***	0.47***	1.06***	0.64***	0.21***
		(5.17)	(41.47)	(8.59)	(4.33)	(5.40)	(37.88)	(10.71)	(4.18)
	PR3	0.27***	1.19***	0.69***	−0.04	0.29***	1.19***	0.71***	−0.07
		(2.57)	(32.11)	(8.02)	(−0.60)	(2.65)	(30.67)	(9.05)	(−1.14)
	*PR*3–*PR*1	−0.25**	0.00	−0.19***	−0.24***	−0.26***	−0.01	−0.20***	−0.25***
		(−3.03)	(0.00)	(−5.46)	(−5.77)	(−3.15)	(−0.05)	(−5.71)	(−5.31)
*OC*3–*OC*1	*PR*3–*PR*1	−0.27***	0.03	−0.10***	−0.01	−0.28***	0.03	−0.11***	−0.03
		(−4.89)	(1.54)	(−5.18)	(−0.38)	(−4.30)	(1.60)	(−4.90)	(−0.89)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Table VII. Momentum Profits Across Overconfidence Portfolios: Controlling for Firm Characteristics

Each quarter, we sort all CRSP common stocks with a share price no less than \$5 and larger than the smallest NYSE size decile into independent terciles based on their past 6-month return, their stock-level overconfidence measure, and one of the firm characteristics. The stock-level overconfidence measure is either OCI^{EW} or OCI^{PCW}. OCI^{EW} (OCI^{PCW}) is the weighted average *OC Index*^{EW} (*OC Index*^{PCW}) of fund managers holding the stock, where weight is the number of shares held in the stock at the end of the quarter. *OC Index*^{EW} is the sum of the percentile ranks of six overconfidence and self-attribution bias proxies. *OC Index*^{PCW} is the weighted sum of the six overconfidence and self-attribution bias proxies, where weights are obtained using principal component analysis. *SIZE* is the market capitalization in billions of dollars. BM is the book-to-market ratio. *RESNA* is the residual analyst coverage defined as a residual from a regression of log(1+ #of analysts) on firm size. *TURN* is the prior 6-month average ratio of volume to shares outstanding in excess of the average turnover of the exchange on which the stock trades. *OC*1 (*OC*3) is a tercile containing stocks with the lowest (highest) value of the stock-level overconfidence measure. The table reports Fama-French (1993) three-factor alphas for overall momentum profits and for the difference in momentum profits between *OC*3 and *OC*1 across firm characteristics terciles. Alphas are expressed as percentages. *t*-statistics (in parentheses) are based on Newey-West (1987) standard errors robust to heteroskedasticity and autocorrelation up to three lags.

	Full Sample			OCI^{EW} OC3–OC1			OCI^{PCW} OC3–OC1		
Characteristic	**Low**	**Med**	**High**	**Low**	**Med**	**High**	**Low**	**Med**	**High**
SIZE	0.70***	0.45***	0.38**	0.30*	0.64***	0.49**	0.44***	0.73***	0.45**
	(4.22)	(2.75)	(1.98)	(1.89)	(4.14)	(2.32)	(3.08)	(4.49)	(2.12)
BM	0.55***	0.26	0.20	0.42***	0.12	0.29**	0.58***	0.28*	0.26
	(3.06)	(1.31)	(1.22)	(2.80)	(0.83)	(1.97)	(3.72)	(1.66)	(1.61)
RESNA	0.62***	0.47***	0.41**	0.51***	0.32**	0.50***	0.49***	0.34**	0.61***
	(3.27)	(2.67)	(2.23)	(3.02)	(2.05)	(3.20)	(2.94)	(2.14)	(3.83)
TURN	0.20	0.45***	0.81***	0.25*	0.17	0.45***	0.23	0.20	0.55***
	(1.36)	(2.76)	(3.84)	(1.83)	(1.23)	(2.85)	(1.63)	(1.40)	(3.05)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

provide the impact of OCI^{EW} on momentum after controlling for the characteristics. We find that the difference in momentum profits between high- and low-OCI^{EW} portfolios is economically and statistically significant for all size terciles, for high and low BM terciles, for all residual analyst coverage terciles, and for high and low turnover terciles. Similarly, in the last three columns, we find that the impact of OCI^{PCW} on momentum profits is significant for all size terciles, for medium and low BM terciles, for all residual analyst coverage terciles, and for high turnover terciles. Our results are very similar if we use conditional sorts, sorting by firm characteristics first and then by OCI and prior returns. Due to space constraints, we do not tabulate the analysis of the impact of overconfidence on momentum controlling for idiosyncratic volatility (Arena, Haggard, and Yan, 2008). We find that the difference in momentum profits across OCI groups is economically and statistically significant for high and medium idiosyncratic volatility firms. Overall, our results suggest that the impact of overconfidence on momentum is distinct from and robust to stock characteristics known to influence momentum.

D. Regression Analysis

In this section, we explore the relation between overconfidence based on self-attribution bias and return continuation in a multiple regression setting. The purpose of this analysis is to disentangle the impact of OCI on future returns and continuation in future returns from the impact of other variables known to predict future returns. We use the Fama-MacBeth (1973) method to estimate the following predictive cross-sectional regressions each quarter-end month:

$$\begin{aligned} RET_{i;t+1,t+6} = {} & a_t + b_{1;t}RET_{i;t-5,t} + b_{2;t}OC_{i;t} + b_{3;t}(RET_{i;t-5,t} \times OC_{i;t}) + b_{4;t}SIZE_{i;t-6} \\ & + b_{5;t}RESNA_{i;t-6} + b_{6;t}BM_{i;t-6} + b_{7;t}TURN_{i;t} + b_{8;t}IVOL_{i;t-1} \\ & + b_{9;t}PRESSURE_{i;t} + b_{10;t}(RET_{i;t-5,t} \times SIZE_{i;t-6}) \\ & + b_{11;t}(RET_{i;t-5,t} \times RESNA_{i;t-6}) + b_{12;t}(RET_{i;t-5,t} \times BM_{i;t-6}) \\ & + b_{13;t}(RET_{i;t-5,t} \times TURN_{i;t}) + b_{14;t}(RET_{i;t-5,t} \times IVOL_{i;t-1}) \\ & + b_{15;t}(RET_{i;t-5,t} \times PRESSURE_{i;t}) + e_{i;t}, \end{aligned} \tag{1}$$

where $RET_{i;t+1,t+6}$ is the cumulative stock return over month $t + 1$ through $t + 6$. $RET_{i;t\text{-}5,t}$ is the cumulative stock return over month $t - 5$ through t. The coefficient b_2 is a measure of the autocorrelation in the 6-month returns. $OC_{i;t}$ is the quintile rank of the stock-level overconfidence measure at time t and can be either OCI^{EW} or OCI^{PCW}.[14] The model specification also includes an interaction term between the quintile rank of OCI and the prior return to capture the cross-sectional variation in return continuation attributable to overconfidence. If overconfidence impacts momentum, we expect the estimate of b_3 to be positive and statistically significant. $SIZE_{i;t\text{-}6}$, $BM_{i;t\text{-}6}$, $RESNA_{i;t\text{-}6}$, and $TURN_{i;t}$ are as described in Section III.C. $IVOL_{i;t-1}$ is the firm's idiosyncratic volatility constructed following Wurgler and Zhuravskaya (2002). $PRESSURE_{i;t}$ is a stock-level measure of flow induced price pressure. We define it as the weighted average of the percentage flow into the funds that hold the stock.[15] We include $IVOL_{i;t-1}$ to address the possibility raised by Bandarchuck and Hilscher (2013) that OC impacts momentum simply because it captures firms with more extreme returns. We include $PRESSURE_{i;t}$ to control for flow-based explanations of return predictability (Coval and Stafford, 2007; Frazzini and Lamont, 2008; Lou, 2012).

We estimate Equation (1) each quarter and compute the time-series average of the coefficients following the Fama and MacBeth (1973) methodology. We correct the Fama-MacBeth (1973) standard errors using the Newey-West (1987) procedure to account for serial correlation in the error term induced by overlapping cumulative returns. Since we estimate the regressions quarterly, we adjust the standard errors for three lags. Table VIII presents the results.

Models 1 to 5 use OCI^{EW}, while Models 6 to 10 use the OCI^{PCW} measure. Overconfidence by itself does not significantly predict future stock returns. However, overconfidence has a positive and significant impact on return momentum. The coefficient on the interaction term between OCI and prior return is positive and statistically significant in all specifications suggesting that the impact of overconfidence is independent of and incremental to the impact of stock characteristics. The coefficient on the interaction term ranges from 0.61% to 0.87%. Coupled with the coefficients

[14] The economic and statistical significance of the results are similar if we use the raw OCI variable instead of the quintile ranks.

[15] To capture only the portion of flows that goes into equity positions, we construct the percentage fund flows using equity positions reported in Thompson. Specifically, Fund flow = [Equity Holdings$_t$ – Equity Holdings$_{t\text{-}1}$ $\times (1 + RET_t)$]/ Equity Holdings$_t$.

Table VIII. Cross-Sectional Regressions

Each quarter, we regress subsequent 6-month cumulative returns on the stock level overconfidence measure (*OCI*), the prior 6-month cumulative return, the interaction of overconfidence and prior return, and controls. The stock-level overconfidence measure is either OCI^{EW} or OCI^{PCW}. OCI^{EW} (OCI^{PCW}) is the weighted average $OC\ Index^{EW}$ ($OC\ Index^{PCW}$) of fund managers holding the stock, where weight is the number of shares held in the stock at the end of the quarter. $OC\ Index^{EW}$ is the sum of the percentile ranks of six overconfidence and self-attribution bias proxies. $OC\ Index^{PCW}$ is the weighted sum of the six overconfidence and self-attribution bias proxies, where weights are obtained using principal component analysis. $RET_{i;t-5,t}$ is the prior 6-month cumulative return. *SIZE* is the firm's market cap measured at $t - 7$. BM is the book-to-market ratio of the stock measured in the most recent June prior to the portfolio formation. *RESNA* is the residual analyst coverage for the stock measured at $t - 7$. *TURN* is the prior 6-month average ratio of volume to shares outstanding in excess of the average turnover of the exchange on which the stock trades. *IVOL* is the average idiosyncratic volatility of a stock over the prior 12 months. *Pressure* is the weighted average flow into mutual funds that hold the stock. Reported coefficients are time-series averages of 124 cross-sectional coefficients. Coefficients are expressed in percentages. *t*-statistics (in parentheses) are based on Newey-West (1987) standard errors robust to heteroskedasticity and autocorrelation up to three lags.

	OCI^{EW}					OCI^{PCW}				
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
OCI	−0.11		−0.10	0.09	0.09	−0.01		−0.03	0.17	0.18
	(−0.35)		(−0.34)	(0.47)	(0.58)	(−0.04)		(−0.10)	(0.78)	(1.09)
$RET_{i;t\text{-}5,t}$		2.57	0.84	2.70	2.00		2.57	0.75	2.35	1.75
		(1.64)	(0.49)	(1.39)	(0.83)		(1.64)	(0.46)	(1.24)	(0.75)
$OCI \times RET_{i;t\text{-}5,t}$			0.84***	0.66**	0.61**			0.87***	0.78***	0.75***
			(2.86)	(2.55)	(2.25)			(3.12)	(3.14)	(2.91)
SIZE				0.03	0.02				0.03	0.02
				(1.25)	(0.83)				(1.34)	(0.92)
BM				1.12**	0.86				1.14**	0.88
				(1.94)	(1.54)				(2.00)	(1.59)
RESNA				0.79***	0.73***				0.79***	0.74***
				(3.95)	(4.27)				(3.99)	(4.32)
TURN				−2.66**	−1.68**				−2.76**	−1.78**
				(−2.33)	(−2.19)				(−2.46)	(−2.31)
IVOL					−0.72					−0.73
					(−1.31)					(−1.34)
Pressure					0.48					0.37
					(0.54)					(0.42)

(Continued)

Table VIII. Cross-Sectional Regressions (*Continued*)

	OCI^{EW}					OCI^{PCW}				
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
$RET_{i;t\text{-}5,t} \times SIZE$				−0.14	−0.19				−0.15	−0.19
				(−0.96)	(−1.43)				(−0.98)	(−1.44)
$RET_{i;t\text{-}5,t} \times \mathrm{BM}$				1.13	−1.14				−1.02	−1.06
				(−1.17)	(−1.35)				(−1.06)	(−1.26)
$RET_{i;t\text{-}5,t} \times RESNA$				−0.46	−0.70*				−0.45	−0.68*
				(−1.09)	(−1.83)				(−1.07)	(−1.79)
$\mathrm{RET}_{\mathrm{i;t\text{-}5,t}} \times TURN$				0.09	−0.32				−0.07	−0.50
				(0.06)	(−0.21)				(−0.05)	(−0.33)
$RET_{i;t\text{-}5,t} \times IVOL$					0.53					0.49
					(0.98)					(0.92)
$RET_{i;t\text{-}5,t} \times Pressure$					−2.77					−3.24
					(−0.83)					(−0.92)
Adj. R^2	0.01	0.01	0.02	0.07	0.08	0.01	0.01	0.02	0.07	0.08

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

for OCI, which are between −0.10% and 0.18%, these estimates indicate that return continuation over subsequent 6-months is between 2.80% and 3.80% stronger for stocks held by the most overconfident investors than for stocks held by the least overconfident investors. Overall, the regression results support the hypothesis that the relation between past and subsequent returns is stronger for stocks held by more overconfident investors. Moreover, it does not appear that OCI impacts momentum only because it captures stocks with more extreme past returns as measured by idiosyncratic volatility.

In addition, regression Specifications (5) and (10) suggest that only residual analyst coverage continues to impact return continuation after controlling for the impact of OCI and other characteristics. The coefficients on the remaining interaction terms are insignificant suggesting that size, BM ratio, turnover, idiosyncratic volatility, and flow induced price pressure do not have incremental power in explaining return continuation after accounting for the impact of OCI and residual analyst coverage.

IV. Additional Analyses and Discussions

A. Alternative Interpretations of the OC Index

Overconfidence notwithstanding, there are other candidates for what the OC Index could measure. For example, the OC Index may capture risk preferences as gender, age (tenure), and portfolio risk are all reasonably related to the investor's risk tolerance. Alternatively, one might argue that several measures used to form the OC Index can reasonably capture managerial skill. For example, Kacperczyk, Sialm, and Zheng (2005) link portfolio concentration to superior performance and investment ability. In addition, superior prior performance may reflect superior skill. If the OC Index captures risk tolerance and managers trade rationally, we would expect managers with high values of the OC Index to earn higher raw returns, on average, as compensation for bearing greater risk. Similarly, if the OC Index captures managerial skill and not overconfidence, we expect that managers with high values of the OC Index to continue outperforming managers with low values of the OC Index over subsequent periods in risk adjusted terms.

These predictions are inconsistent with two sets of our findings. First, the results in Tables III and IV indicate that both loser and middle portfolios predominantly held by managers with high values of the OC Index underperform similar portfolios held by managers with lower values of the OC Index. The performance of the winner portfolios is similar. In addition, the coefficients on OCI in the regression analysis (Table VIII) are all insignificant suggesting that stocks predominantly held by high OC Index managers do not perform better than stocks held by low OC Index managers.

To provide a more formal test of the above prediction, we examine the subsequent performance of mutual funds conditional on their managers' OC Index values. We use monthly fund returns net of expenses from CRSP MFDB and sort managers into quintile portfolios based on their OC Index. In this unreported analysis, we find no evidence that mutual funds managed by managers with high values of the OC Index outperform mutual funds managed by managers with low values of the OC Index over the following 12 to 36 months in either raw or risk adjusted terms.[16] These

[16] Ex ante, the impact of overconfidence on mutual fund managers' performance is unclear. Odean (1998) and Barber and Odean (2001, 2002) find that overconfidence increases trading costs and hurts performance. In contrast, DeLong et al. (1991), Kyle and Wang (1997), and Hirshleifer and Lou (2001) demonstrate that because risk-averse overconfident investors trade more aggressively on their valid private information than rational investors do, they should earn higher expected profits. Our findings suggest that, on average, the two effects cancel each other.

findings indicate that it is unlikely that the OC Index captures risk preferences or managerial skill.

B. Alternative Explanations of OCI–Momentum Relation

We interpret our findings of a strong positive relation between OCI and momentum profits as evidence consistent with the Daniel et al. (1998) proposition that momentum is caused by investor overconfidence and self-attribution bias. However, it is possible that the presence of overconfident investors does not lead to stronger momentum, but rather the stocks with strong momentum returns attract overconfident investors.

We argue that this reverse causality story is inconsistent with several features of our results. First, as discussed in Section III.C, prior literature indicates that momentum is particularly strong for small stocks, growth stocks, high turnover stocks, and stocks with low analyst coverage. If overconfident fund managers are indeed attracted to these stocks, then we would expect those stocks to be disproportionately represented in overconfident managers' portfolios. Since we use a manager's holdings to convert the overconfidence measure from the manager to the stock level, we would further expect stocks with high OCI values to have smaller size, higher growth, lower analyst coverage, and higher turnover. The correlation coefficients between OCI and these characteristics, presented in Table II, are not consistent with this prediction. Although the correlation coefficients are statistically significant, the magnitudes of the coefficients are generally small. For example, the highest magnitude of the correlation coefficient between OCI and firm size is only 0.07. Moreover, the correlation coefficients between OCI and residual analyst coverage have the wrong signs.

Additionally, if overconfident managers' preference for stocks with strong momentum drives the OCI-momentum relation, then there should be no difference in momentum profits between high and low OCI stocks for stocks that exhibit weaker momentum. In contrast, our results in Table VII indicate that the difference in momentum profits between high and low OCI stocks is significant for large firms, value firms, and high analyst coverage firms and it is marginal for low turnover firms. Finally, Table VIII indicates that OCI has a significant impact on the continuation of stock returns even after controlling for various stock characteristics that are related to the strength of the momentum effect. These results suggest that it is unlikely that reverse causality is driving our findings.

Another alternative interpretation of our findings is that fund styles, rather than a manager's overconfidence, drive the documented relation between OCI and the momentum effect. Specifically, the inclusion of a manager's portfolio characteristics in the construction of the OC Index raises a possibility that the OC Index captures funds that employ momentum strategies.

To examine this alternative explanation, we focus on manager turnover events as fund style does not change with a change in fund manager. If fund style drives the relation between OCI and momentum, then we would expect that the holdings of new and old managers exhibit similar momentum effects. Conversely, if a manager's overconfidence drives the OCI-momentum relation, then we would expect the holdings of the more overconfident manager to exhibit a stronger momentum effect.

We use manager names to identify turnover events. In the case of management teams, we require that at least half of the managers change from the previous quarter to classify the fund-quarter observation as a turnover event. For each turnover event, we obtain the OC Index and portfolio holdings for the previous manager in the quarter prior to the turnover event and we obtain the OC Index and portfolio holdings for the new manager in the quarter 12 quarters (36 months) after the turnover event. We allow a 36-month gap between the turnover and the measurement of the new manager's OC Index as prior performance and portfolio risk require 36 months of data to calculate. In addition, we obtain cumulative returns for each of the holdings of the previous and the new manager. To examine whether stocks have lower momentum when an overconfident manager is replaced by a less overconfident one, we estimate the following panel regression:

$$RET_{i;t+1,t+6} = a_0 + b_0 RET_{i;t-5,t} + b_1 OC\_HLD_{i;t} + b_2 RET_{i;t-5,t} \times OC\_HLD_{i;t} + e_i. \qquad (2)$$

$RET_{i;t+1,t+6}$ is a cumulative return in the subsequent 6 months. $RET_{i;t-5,t}$ is the prior 6-month cumulative return. *OC_HLD* is an indicator variable that takes a value of one if the return observation is for the portfolio holding of the more overconfident manager and zero otherwise. For example, if the previous manager is more overconfident than the new manager, then *OC_HLD* will be equal to one for the return observations of holdings belonging to the previous manager and will equal zero for the return observations of holdings belonging to the new manager. To account for managers holding more of the stocks that they are most overconfident about, we use a weighted least squares regression with dollar holdings as weights. We adjust standard errors for heteroskedasticity and serial correlation up to six lags using the Newey-West (1987) adjustment. We report the results of this analysis in Table IX.

The main variable of interest is the interaction term, $RET_{i;t-5,t} \times OC\_HLD$. If a manager's overconfidence drives the relation between OCI and momentum, we expect coefficient b_2 to be positive and significant. Consistent with this expectation, we find that the coefficient b_2 is positive and statistically significant in all specifications. When examining the full sample of turnovers, the coefficient on the interaction term suggests that holdings of more overconfident managers exhibit between 3.22% and 5.52% stronger return continuation. The results are even stronger when we focus on a subsample of turnovers where a more overconfident manager is replaced by a less overconfident manager. In this subsample, holdings of more overconfident managers exhibit between 8.25% and 10.32% stronger return continuation. These results are economically significant given that the average return autocorrelation is −1.40%.

As an additional test of the impact of fund style on the momentum effect, we replicate our analyses using only a manager's tenure to measure overconfidence. Tenure is a manager's attribute that captures the strength of the self-attribution bias, but should not be related to the fund style. The unreported results based on this alternative measure continue to indicate that overconfidence affects the momentum effect. Overall, our additional analyses suggest that the relation between OCI and momentum is driven by a manager's personal attributes rather than fund style.

C. Aggregate OCI, Market States, and Momentum Profits

In this section, we examine how aggregate OCI compares to the market-level measure of overconfidence proposed by Cooper et al. (2004), market states. If OCI indeed captures overconfidence, then we would expect to find a positive correlation between the two measures of aggregate overconfidence. In addition, we examine whether momentum profits vary with the aggregate OCI in the time series.

We define aggregate OCI (AGGOCI) in two ways: 1) as a market capitalization-weighted OCI across all stocks and 2) as equal-weighted OCI across all stocks. Following Cooper et al. (2004), we calculate cumulative market return in the prior 36 months and define *UPMKT* as an indicator variable that is equal to one if the prior 36-month market return is positive and zero otherwise. To examine the relation between AGGOCI and the overconfidence measure of Cooper et al. (2004), we report the correlation coefficients in Panel A of Table X. The results indicate that aggregate overconfidence is significantly positively correlated with past market returns with correlation

Table IX. Momentum Effect in Portfolio Holdings around Manager Turnover

We identify manager turnover events in the sample where the new manager remains with the fund for more than 36 months. For each turnover event, we calculate *OC Index*^{EW} and *OC Index*^{PCW} for the previous manager using the quarter immediately prior to the turnover and, for the new manager, using data from the quarter 12 quarters (36 months) after the turnover. *OC Index*^{EW} is the sum of the percentile ranks of six overconfidence and self-attribution bias proxies. *OC Index*^{PCW} is the weighted sum of the six overconfidence and self-attribution bias proxies, where weights are obtained using principal component analysis. We allow a 36-month gap for the new manager as some of the index components require 36 months of data. We obtain all stock holdings for the previous and the new manager and calculate the subsequent 6-month cumulative return for each holding ($RET_{i;t+1,t+6}$). The table presents results of the following panel regression:

$RET_{i;t+1,t+6} = \alpha_0 + \beta_0 \times RET_{i;t-5,t} + \beta_1 \times OC\_HLD_{i,t} + \beta_2 \times RET_{i;t-5,t} \times OC\_HLD_{i,t}$. $RET_{i;t\text{-}5,t}$

is the prior 6-month cumulative return. *OC_HLD* is an indicator variable that takes a value of one if the return observations are for the holdings of the more overconfident manager (holdings of the previous manager if the previous manager is more overconfident than the new manager and vice versa) and zero otherwise. The regression is the weighted least square with weights equal to the manager's dollar holdings in the stock. The first two columns report the results for the full sample and the last two columns report the results for the subset of turnovers where the previous manager is more overconfident than the new manager. The coefficients are multiplied by 100 for expositional purposes. *t*-statistics in parentheses are based on Newey-West (1987) standard errors robust to heteroskedasticity and autocorrelation up to six lags.

	Full Sample		**Previous Manager More Overconfident**	
	***OC Index*^{EW}**	***OC Index*^{PCW}**	***OC Index*^{EW}**	***OC Index*^{PCW}**
Intercept	4.85***	4.20***	5.79***	5.66***
	(12.12)	(10.38)	(9.71)	(9.68)
$RET_{i;t\text{-}5,t}$	1.95	−0.89	−0.32	−0.84**
	(1.54)	(−0.72)	(−0.19)	(−0.51)
$OC\_HLD_{i,t}$	−6.04***	−4.70***	−11.53***	−9.89***
	(−9.83)	(−7.59)	(−12.07)	(−10.44)
$RET_{i;t\text{-}5,t} \times OC\_HLD_{i,t}$	3.22*	5.52***	8.25***	10.32***
	(1.80)	(3.04)	(3.37)	(4.07)
Adj. R^2	0.01	0.01	0.04	0.04

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

coefficients between 41% and 52%. These results reinforce the notion that OCI captures investor overconfidence.

Next, we examine whether momentum profits vary with our measure of aggregate overconfidence. Specifically, we follow Avramov, Cheng, and Hameed (2015) and estimate the following time-series regression:

$$WML_t = a_0 + b_1 AGGOCI_{t-1} + b_2 UPMKT_{t-1} + b_3 MktIlliq_{t-1} + c' FF_t + e_t, \tag{3}$$

where *WML* is momentum profit defined as a difference in returns of the top and bottom terciles of stocks sorted on the prior 6-month return. *MktIlliq* is aggregate illiquidity defined following Avramov et al. (2015) as a value-weighted average of individual stocks' monthly Amihud illiquidity measure using only NYSE/AMEX stocks. We include *MktIlliq* in our regressions as

Table X. Aggregate OCI, Market States, and Momentum Profits

AGGOCI is the average stock-level overconfidence across all stocks in the quarter. The stock-level overconfidence measure is either OCI^{EW} or OCI^{PCW}. OCI^{EW} (OCI^{PCW}) is the weighted average *OC Index*^{EW} (*OC Index*^{PCW}) of fund managers holding the stock, where weight is the number of shares held in the stock at the end of the quarter. *MktRet*36 is the market return over the previous 36 months. *UPMKT* is an indicator variable that is equal to one if the *MktRet*36 is positive and zero otherwise. *MktIlliq* is the value-weighted average of individual stocks' monthly Amihud illiquidity using only NYSE/AMEX stocks. Each quarter, we sort all CRSP common stocks with a share price no less than $5 and larger than the smallest NYSE size decile into terciles based on their past 6-month return and calculate momentum return (*WML*) as the difference between past winners and past losers. Panel A reports correlation coefficients between AGGOCI and *MktRet*36. Panel B presents the results for a regression of momentum profits (*WML*) on AGGOCI, the *UPMKT* indicator, Market Illiquidity, and the Fama-French (1993) three factors. The column entitled *VW* (*EW*) indicates that AGGOCI is the value- (equal-) weighted average of stock-level overconfidence. *t*-statistics (in parentheses) are based on Newey-West (1987) standard errors robust to heteroskedasticity and autocorrelation up to three lags.

Panel A. Correlation Coefficients with Past Market Return

	VW AGGOCI^{EW}	*VW* AGGOCI^{PCW}	*EW* AGGOCI^{EW}	*EW* AGGOCI^{PCW}
MktRet36	0.52***	0.41***	0.47***	0.45***

Panel B. Regression of Momentum Profits on Aggregate OC Index and Market State

		AGGOCI^{EW}				AGGOCI^{PCW}			
		VW		*EW*		*VW*		*EW*	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Alpha	0.49***	−0.15	−0.50	0.01	−0.48	0.16	−0.80	−0.01	−0.94*
	(2.96)	(−0.52)	(−1.02)	(0.03)	(−1.08)	(0.61)	(−1.41)	(−0.04)	(−1.72)
AGGOCI		0.33***	0.40**	0.25**	0.32**	0.15	0.11	0.30***	0.27**
		(2.57)	(2.06)	(2.12)	(1.96)	(1.25)	(0.97)	(2.43)	(2.05)
UPMKT			0.91*		0.91*		1.34**		1.33**
			(1.74)		(1.82)		(2.24)		(2.40)
MktIlliq			−0.27*		−0.21		−0.06		−0.08
			(−1.69)		(−1.50)		(−0.66)		(−0.83)
mktrf	−0.15***	−0.14**	−0.14***	−0.16***	−0.15***	−0.16**	−0.15**	−0.18***	−0.17***
	(−2.49)	(−2.38)	(−2.43)	(−2.59)	(−2.60)	(−2.68)	(−2.71)	(−2.92)	(−2.95)
smb	0.21	0.20	0.21	0.23	0.24*	0.16	0.18	0.28**	0.29**
	(1.52)	(1.41)	(1.48)	(1.61)	(1.69)	(1.23)	(1.33)	(2.17)	(2.25)
hml	−0.07	−0.12	−0.12	−0.07	−0.06	−0.15	−0.15	−0.12	−0.12
	(−0.42)	(−0.76)	(−0.77)	(−0.41)	(−0.40)	(−0.97)	(−0.95)	(−0.76)	(−0.76)
Adj. R^2	0.04	0.05	0.06	0.04	0.05	0.04	0.05	0.05	0.06

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Avramov et al. (2015) show that momentum profits are markedly larger in liquid market states. Vector FF includes the Fama and French (1993) three factors (mktrf, smb, and hml). Panel B of Table X reports the results.

We find that AGGOCI has a positive effect on momentum profits. The coefficients for AGGOCI are always positive and are statistically significant in six out of eight specifications. We also find that momentum profits are higher in the *UPMKT* states, consistent with Cooper et al. (2004) and lower when aggregate illiquidity is high (although not always statistically significantly so), consistent with Avramov et al. (2015).

D. Robustness Tests

1. Subsample Periods

Panel A of Table IX reports the momentum profits across overconfidence groups for two equal length subperiods, January 1984 to June 1999 and July 1999 to December 2014. Momentum profits are stronger in the first half of the sample period, consistent with the disappearance of momentum post 2001 (Chordia et al., 2014). The difference in momentum profits between high and low overconfidence portfolios is similar (OCI^{PCW}) or stronger (OCI^{EW}) in the first half of the sample period.

2. Seasonality

Panel B of Table XI presents the seasonality results. Consistent with Jegadeesh and Titman (2001), we find that momentum profits are concentrated in February to December and do not exist in January. The difference in momentum profits between high and low overconfidence portfolios is economically and statistically significant for period from February to December. In January, the difference is smaller and statistically insignificant.

3. Up and Down Markets

Panel C of Table XI reports the results for the analysis of momentum profits across market states. Following Cooper et al. (2004), we define a month as an UP (DOWN) state month if the cumulative market return in the prior 36-months is positive (negative). We find strong momentum profits and pronounced difference in momentum profits between high and low overconfidence portfolios in UP states. We do not detect momentum profits in the DOWN states, consistent with Cooper et al. (2004). If market states proxy for aggregate overreaction, as Cooper et al. (2004) argue, then our findings provide additional support for the overconfidence interpretation. In particular, in DOWN states, overconfidence is generally low due to the self-attribution bias. As such, neither momentum profits nor difference in momentum profits are significant. In UP states, however, self-attribution bias leads to high overconfidence and potentially large differences in overconfidence among managers leading to a significant difference in momentum profits between high and low overconfidence groups.

V. Conclusions

Our paper examines the impact of investor overconfidence on momentum and reversal in stock returns. In particular, we examine the Daniel et al. (1998) proposition that overconfidence with biased self-attribution generates positive autocorrelations in asset returns in the short term and negative autocorrelations in returns in the long term. We develop a novel measure of overconfidence due to the self-attribution bias based on characteristics and trading patterns of US equity mutual fund managers. The measure allows us to rank managers ex ante based on their overconfidence.

We find that stocks predominantly held by the most overconfident managers exhibit higher momentum profits than stocks held by the least overconfident managers. This result is not compensation for the risks captured by the Fama-French (1993) three-factor model and it is robust to

Table XI. Robustness Tests

Each quarter, we sort all CRSP common stocks with a share price no less than \$5 and larger than the smallest NYSE size decile into independent terciles based on their past 6-month return and their stock-level overconfidence measure. The stock-level overconfidence measure is either OCI^{EW} or OCI^{PCW}. OCI^{EW} (OCI^{PCW}) is the weighted average *OC Index*^{EW} (*OC Index*^{PCW}) of fund managers holding the stock, where weight is the number of shares held in the stock at the end of the quarter. *OC*1 (*OC*3) is a tercile containing stocks with the lowest (highest) value of the stock-level overconfidence measure. *PR*1 (*PR*3) is a tercile containing past loser (winner) stocks. We report the average monthly momentum profits for each overconfidence group and the difference in momentum profits between *OC*3 and *OC*1. Panel A presents the results for two subperiods that split the sample in half. Panel B reports the results for subsamples containing January only and non-January months only. Panel C examines momentum returns in up and down markets. *t*-statistics (in parentheses) are based on Newey-West (1987) standard errors robust to heteroskedasticity and autocorrelation.

		OCI^{EW}				OCI^{PCW}			
		OC1	OC2	OC3	OC3–OC1	OC1	OC2	OC3	OC3–OC1
Panel A. Subsample Periods									
1:84-6:99	PR3–PR1	0.30*	0.55***	0.82***	0.52***	0.32*	0.45***	0.86***	0.54***
		(1.88)	(3.25)	(4.61)	(4.16)	(1.94)	(2.72)	(4.82)	(4.33)
7:99-12:14	PR3–PR1	0.02	0.03	0.36	0.35*	−0.03	0.04	0.38	0.41*
		(0.07)	(0.11)	(1.07)	(1.67)	(−0.12)	(0.13)	(1.07)	(1.89)
Panel B. January and non-January Months									
January	PR3–PR1	−1.42**	−1.48**	−1.06	0.35	−1.48**	−1.48*	−1.10	0.38
		(−2.19)	(−2.00)	(−1.30)	(1.00)	(−2.37)	(−1.91)	(−1.34)	(1.11)
Non-January	PR3–PR1	0.31*	0.46***	0.76***	0.45***	0.29*	0.40**	0.79***	0.50***
		(1.79)	(2.44)	(3.41)	(3.44)	(1.66)	(2.26)	(3.49)	(3.63)
Panel C.UP and DOWN Markets									
UP	PR3–PR1	0.24	0.46***	0.80***	0.56***	0.22	0.40**	0.83***	0.61***
		(1.46)	(2.88)	(4.12)	(4.68)	(1.38)	(2.54)	(4.19)	(4.62)
DOWN	PR3–PR1	−0.31	−0.69	−0.68	−0.37	−0.35	−0.70	−0.59	−0.24
		(−0.46)	(−0.93)	(−0.93)	(−1.22)	(−0.49)	(−1.05)	(−0.77)	(−0.75)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

controls for firm characteristics known to influence momentum returns. In addition, in the event of manager turnover, we find that the stock holdings of more overconfident managers experience stronger momentum than the holdings of less overconfident managers. Moreover, stocks predominantly held by the most overconfident managers experience strong and significant return reversals while stocks held by the least overconfident managers experience no return reversals at all. Finally, in the time series, momentum profits are stronger when aggregate overconfidence is higher, even after controlling for market state and market liquidity. Overall, our results are consistent with the proposition that overconfidence with biased self-attribution intensifies stock return momentum. Although we attempt to carefully address various alternative interpretations of our evidence, we cannot claim that no alternative interpretation of some or all of the evidence is possible. Despite this caveat, we believe that our findings and our empirical measure of overconfidence should be of interest to a broad range of researchers examining the cross-section of stock returns as behavioral models suggest numerous implications of investor overconfidence for financial markets, which are largely empirically untested.

Appendix

In the Daniel et al. (1998) model, overconfident investor overreaction to private information pushes prices up (down) when they receive positive (negative) signals. If the subsequent public information confirms this private signal, the investor becomes more overconfident. If it disconfirms the signal, this overconfidence does not change by much. Thus, on average, public information would increase overconfidence thereby intensifying the overreaction and pushing prices to even more extreme levels. Since it is the overconfident investor's demand that pushes prices, the Daniel et al. (1998) model suggests that, on average, overconfident investors' demand will be positively related to returns. To the extent that overconfident investors' private information is valid (on average) and that the strength of this overreaction increases with their overconfidence and in a magnitude of their signal, one would typically expect that positive relation between demand and returns will be more pronounced for stocks with more extreme returns.

In this section, we examine whether the OC Index captures fund managers' behavior consistent with this pattern of overreaction. Specifically, each quarter, we sort all funds into deciles based on the fund manager's OC Index. For each manager, we calculate the proportion of buys with positive returns and sells with negative returns among all trades executed during the subsequent reporting period. In addition, we limit our sample to stocks with the most extreme returns (i.e., top and bottom decile) and calculate the proportion of trades in the direction of the returns in this limited sample. Table A1 reports the average proportion of trades in the direction of the returns for each OC Index decile, as well as the difference in proportions between the top and bottom OC Index deciles. Managers with high values of the OC Index trade in the direction of the returns significantly more often than managers with low values of the OC Index. For example, looking at $OC\ Index^{EW}$, managers in the bottom decile trade in the direction of the returns 45.84% of the time, while managers in the top decile trade in the direction of the returns 50.63% of the time. The difference of 4.80% is highly statistically significant ($t = 5.89$). The results are similar if we consider $OC\ Index^{PCW}$. As expected, the relation between trading and returns is even more significant among extreme performers. In this subsample, managers with the highest (lowest) values of $OC\ Index^{EW}$ trade in the direction of the returns 8.69% (4.85%) of the time, whereas managers with the highest (lowest) values of $OC\ Index^{PCW}$ trade in the direction of the returns 10.15% (5.22%) of the time. The differences of 3.85% ($t = 10.00$) for $OC\ Index^{EW}$ and 4.93% ($t = 6.87$) for $OC\ Index^{PCW}$ are highly significant. They suggest that highly overconfident managers trade in the direction of the returns almost twice as frequently as less confident managers. These results are consistent with the overreaction pattern suggested by Daniel et al. (1998), and provide support for use of the OC Index as a measure of overconfidence with biased self-attribution.

Table A1. Trading Patterns across OC Index Portfolios

Each quarter, we sort mutual fund managers into deciles based on their level of the OC Index. $OC\ Index^{EW}$ is the sum of the percentile ranks of six overconfidence and self-attribution bias proxies. $OC\ Index^{PCW}$ is a weighted sum of the same six proxies, where the weights are obtained using principal component analysis. We calculate the proportion of trades in which the manager trades in the direction of the stock returns. To calculate this proportion, we only use the managers' holdings in common stock (CRSP Sharecode of 10 or 11) with a price no less than $5 and larger than the smallest NYSE size decile. The table reports the average proportion of trades that are in the direction of the returns, as well as the difference in proportions between the high and low OC index deciles. Column "All Stocks" presents results for the full sample. Column "Extreme Performers" provides the results for the top and bottom deciles of stocks sorted on 6-month cumulative returns. *t*-statistics (in parentheses) are based on Newey-West (1987) standard errors robust to heteroskedasticity and autocorrelation.

	All Stocks		Extreme Performers	
	OC_Index^{EW}	OC_Index^{PCW}	OC_Index^{EW}	OC_Index^{PCW}
OCM1	45.84	47.05	4.85	5.22
OCM2	46.33	46.47	5.25	5.19
OCM3	47.52	46.82	5.76	5.29
OCM4	47.13	47.69	5.73	5.99
OCM5	47.67	48.01	6.38	6.41
OCM6	48.31	48.47	6.58	6.52
OCM7	48.35	48.90	6.75	7.10
OCM8	49.33	49.85	7.26	7.47
OCM9	49.37	49.79	7.61	7.75
OCM10	50.63	51.11	8.69	10.15
OCM10–OCM1	4.80***	4.06***	3.85***	4.93***
	(5.89)	(3.36)	(10.00)	(6.87)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

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