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Short-term residual reversal

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Abstract

Conventional short-term reversal strategies exhibit dynamic exposures to the Fama and French (1993) factors. We develop a novel reversal strategy based on residual stock returns that does not exhibit these exposures and consequently earns risk-adjusted returns that are twice as large as those of a conventional reversal strategy. Residual reversal strategies generate statistically and economically significant profits net of trading costs, even when we restrict our sample to large-cap stocks over the post-1990 period. Our results are inconsistent with the notion that reversal effects are the result of trading frictions or non-synchronous trading of stocks and pose a serious challenge to rational asset pricing models.
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1. Introduction

A conventional short-term reversal strategy as documented by Lehmann (1990) and Jegadeesh (1990), i.e., a strategy that buys (sells) stocks with low (high) total returns over the past month, exhibits dynamic exposures to the Fama and French (1993) factors. As these implicit factor bets are inversely related to factor return realizations over the formation month, the reversal strategy is negatively exposed to the short-term momentum

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effect in factor returns of Moskowitz and Grinblatt (1999) and Chen and De Bondt (2004). As a result, the dynamic factor exposures of a reversal strategy are likely to negatively affect its profitability, while, at the same time, contributing significantly to the risks involved.

We introduce a short-term reversal strategy based on residual stock returns that does not exhibit such dynamic factor exposures and find that this strategy earns returns that are higher and substantially less volatile than those of a conventional short-term reversal strategy. More specifically, stock residual returns are computed by adjusting total returns for the stocks' exposures to the Fama-French factors and scaling the residual returns by their volatility. We document that this reversal strategy earns risk-adjusted returns that are twice as large as those of a conventional reversal strategy. Our results also show that the strategy's profitability has been relatively stable over our sample period from January 1929 to December 2010, including the more recent decades, and that profitability remains economically and statistically significant after taking trading costs into account. In addition, we show that residual stock returns have predictive power for future returns above and beyond that of total stock returns.

Several authors have argued that the profits of conventional short-term reversal strategies largely disappear once trading costs are taken into account (e.g., Ball, Kothari and Wasley, 1995; Conrad, Gultekin and Kaul, 1997; Avramov, Chordia and Goyal, 2006). Consistent with this stream of literature, we find that, indeed, the returns of a conventional reversal strategy net of trading costs are indistinguishable from zero or even negative. However, when we investigate the impact of trading costs on the profitability of residual reversal strategies, we find that the profits of the strategy exceed any reasonable level of trading costs by a wide margin. Even though reversal strategies generate high portfolio turnover, we find that residual reversal strategies yield significantly positive returns of more than 7% per annum net of trading costs.

The large residual reversal profits we document are remarkably robust over time and the cross-section of stocks. We find that the residual reversal strategy outperforms a conventional reversal strategy during every single decade in our sample in terms of risk-adjusted return. Most notably, the residual reversal strategy earns large positive returns during the two most recent decades, following the public dissemination of the reversal effect, while the conventional reversal strategy earns returns close to zero over the same period. In fact, over the post-1990 period, the residual reversal strategy yields large positive returns after trading costs even when we restrict the investment universe to the 500 or only 100 largest U.S. stocks. Also during the five most recent years in our sample, which include the "quant meltdown" of August 2007 and its aftermath, we observe that the residual reversal strategy consistently outperforms a conventional reversal strategy. Moreover, when we evaluate reversal profits within different industries, we find that the strategy based on residual returns outperforms the conventional strategy within each of the 10 industries of French (2011).

Our results shed new light on several alternative explanations that have been put forward in the academic literature to understand the reversal effect. Our finding that net reversal profits persist over the most recent decades in our sample, during which trading volumes dramatically increased, does not support the explanation that reversals are induced by inventory imbalances by market makers and that reversal profits are a compensation for bearing inventory risks (e.g., Jegadeesh and Titman, 1995b). In addition, the finding that reversal profits are observed among the 500 or even 100 largest stocks is inconsistent with the notion that non-synchronous trading contributes to reversal profits (e.g., Lo and MacKinlay, 1990; Boudoukh, Richardson and Whitelaw, 1994) since this explanation implies that reversal profits should be concentrated among small-cap stocks. Our results do not appear to be inconsistent, however, with the explanation that some investors tend to overreact to information and that stock price reversals originate from transitory changes in demand for immediacy by these impatient traders (see, e.g., Lehmann, 1990; Jegadeesh and Titman, 1995a). Apart from contributing to a better understanding of the origins of the reversal effect, our findings also have important implications for the practical implementation of reversal strategies, indicating that in order to generate sufficiently large returns to cover trading costs, it is of crucial importance to control for dynamic factor exposures.

Our work is related to the research of Grundy and Martin (2001), who show that intermediate-term momentum strategies exhibit dynamic factor exposures, and the work of Gutierrez and Pirinsky (2007) and Blitz, Huij and Martens (2011), who find that intermediate-term momentum strategies based on residual instead of total stock returns yield significantly higher risk-adjusted returns. Our work is also related to the strand of literature that re-examines market anomalies after incorporating trading costs (e.g., Lesmond, Schill and Zhou, 2004; Korajczyk and Sadka, 2004; Avramov, Chordia and Goyal, 2006; Goyal, Sadka, Sadka, and Shivakumar, 2009) and the contemporaneous work of Hameed, Mian, and Huang (2010) and Da, Liu and Schaumburg (2011), who show that reversal profits are higher within industries than across industries.

The remainder of this paper is organized as follows. In Section 2 we analytically show that conventional reversal strategies exhibit dynamic exposures to common factors that affect their risks and profitability and we develop the residual reversal strategy. In Section 3 we empirically investigate the impact of these factor exposures on the risks and profits of both reversal strategies. In Section 4 we gauge the economic significance of reversal profits by evaluating their profitability net of trading costs. In Section 5 we conduct several follow-up analyses, including an examination of the comparative strength of both reversal strategies, the profitability of both reversal strategies within industries, the relation between reversal strategies' dynamic factor exposures and their profitability using a non-parametric approach, calendar month effects, and the robustness of our results to using alternative portfolio weighting schemes. In Section 6 we discuss the implications of our empirical findings for alternative explanations that have been put forward in the academic literature to understand the reversal effect. Finally, we conclude in Section 7.

2. Analytical analysis

In this section we analytically show that conventional reversal strategies implicitly exhibit dynamic exposures to common factors that affect their risks and profitability. Additionally, we develop a reversal strategy based on residual stock returns that does not exhibit these dynamic factor exposures.

Let us assume that stock returns are described by the following K-factor model:

$$r_{i,t} = \mu_i + \sum_{k=1}^{K} \beta_i^k f_t^k + \varepsilon_{i,t}, \tag{1}$$

where $\mu_i = \sum_{k=1}^{K} \beta_i^k \mu^k$ is the unconditional expected return of stock i; $\mu^k > 0$ is the unconditionally expected return on factor k; $f_t^k = r_t^k - \mu^k$ is the return on factor k above its expectation at time t; $\varepsilon_{i,t}$ is the residual return at time t; and β_i^k is the exposure of stock i to factor k. Without loss of generality, we assume the K factors are orthogonal, so $E[f_t^i f_t^j]=0$ for $i\neq j$ and $E[(f_t^k)^2]=\sigma_{f^k}^2$. In addition, we assume that $Cov[f_t^i, f_{t-1}^j]=0$ for $i\neq j$ and $Cov[\varepsilon_{i,t},\varepsilon_{j,t-1}]=0$ for $i\neq j$.

Because of its analytical tractability, we follow Lehmann (1990), Lo and MacKinlay (1990), and Jegadeesh and Titman (1995a) and consider a (zero-investment) conventional reversal strategy that assigns a portfolio weight to stock i at time t of

$$w_{i,t} = -\frac{1}{N_t}\left(r_{i,t-1}-\overline{r}_{t-1}\right), \tag{2}$$

where N_t denotes the number of stocks in the universe at time t and $\overline{r}_{t-1}=\left(1/N_t\right)\sum_{i=1}^{N_t} r_{i,t-1}$. The expected exposure of the reversal strategy to the jth factor conditional on the return of the jth factor at time $t-1$ now equals

$$E\left(\sum_{i=1}^{N_t} w_{i,t}\beta_i^j | f_{t-1}^j\right) = -\sigma_{\beta^j}^2\mu^j - \sigma_{\beta^j}^2 f_{t-1}^j, \tag{3}$$

where $\sigma_{\beta^j}^2=(1/N_t)\sum_{i=1}^{N_t}(\beta_i^j-\overline{\beta}^j)^2$. Hence, the right-hand side of Eq. (3) shows that the conventional reversal strategy's common factor exposures consist of a systematic and a dynamic component. The first component indicates that the conventional reversal strategy is systematically negatively exposed to factors that have a positive expected return, while the second component implies that the reversal strategy has dynamic factor exposures depending on the demeaned factor returns over the formation period. For example, when the market return is positive over the formation period, high-beta stocks typically earn higher average returns than low-beta stocks, causing the conventional reversal strategy to assign a relatively low weight to high-beta stocks and a high weight to low-beta stocks. As a consequence, the net market beta of the reversal strategy is negative over the subsequent investment period.

The expected profits π_t of the conventional reversal strategy at time t, conditional on the K factor returns at time $t-1$, can now be written as

$$E[\pi_t | f_{t-1}^k, k=1,2,...,K] = E\left(\sum_{i=1}^{N_t} w_{i,t} r_{i,t} | f_{t-1}^k, k=1,2,...,K\right) = -\sigma_\mu^2 - \Phi - \Lambda_{t-1} - \Psi, \tag{4}$$

where

$$\sigma_\mu^2 = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\mu_i-\overline{\mu}\right)^2, \tag{5}$$

$$\Phi = \sum_{k=1}^{K}\sigma_{\beta^k}^2\mu^k\ Cov[f_t^k, f_{t-1}^k], \tag{6}$$

$$\Lambda_{t-1} = \sum_{k=1}^{K}\sigma_{\beta^k}^2 f_{t-1}^k\left(\mu^k + E[f_t^k | f_{t-1}^k]\right), \tag{7}$$

and

$$\Psi = \frac{1}{N_t}\sum_{i=1}^{N_t} Cov[\varepsilon_{i,t}, \varepsilon_{i,t-1}]. \tag{8}$$

Hence, the profits of a conventional reversal strategy can be decomposed into four different components. The first component, σ_μ^2, is the cross-sectional variance of expected stock returns. This component has a negative impact on reversal profits, which results from the conventional reversal strategy being systematically negatively exposed to factors with positive expected returns. The second component, Φ, is the sum of the cross-sectional variances in factor exposures times the persistence in factor returns. This component captures that the systematic exposures towards positive factors are exacerbated when persistence in factor returns is stronger. The third component, Λ_{t-1}, captures the short-term dynamics in total reversal profits due to the strategy's dynamic factor exposures conditional on the factor realizations at time $t-1$. It is equal to the dynamic factor exposures component, which follows from Eq. (3), times the conditionally expected factor returns at time t. Since the factor exposures of a conventional reversal strategy are inversely related to the unexpected factor returns over the past month, this component can have either a positive or a negative impact on reversal profits, depending on the extent to which factor returns persist. If factor returns exhibit positive autocorrelation, the impact of this component on the total reversal profits is negative. The final component, Ψ, results from autocorrelation in the residual stocks returns and is positive if residual stock returns exhibit negative serial correlation.

Our analytical exercise above not only demonstrates that conventional reversal strategies exhibit factor exposures that have a negative impact on their profitability, but can also be used to show that these exposures affect the variability in the strategy's profits:

$$\begin{aligned} Var[\pi_t] &= Var\left(\sum_{i=1}^{N_t} w_{i,t} r_{i,t}\right) \\ &= \frac{1}{N_t^2}\sum_{i=1}^{N_t}\left(\left(\mu_i - \overline{\mu}\right) + \sum_{k=1}^{K}\left(\beta_i^k - \overline{\beta}^k\right) f_{t-1}^k + \left(\varepsilon_{i,t-1} - \overline{\varepsilon}_{t-1}\right)\right)^2 Var[r_{i,t}]. \end{aligned} \tag{9}$$

Eq. (9) implies that if the lagged factor returns are more extreme and the magnitude of factor exposures is larger, the variance in expected reversal profits is also higher.

As an alternative to the conventional reversal strategy, we develop a reversal strategy that is based on residual returns instead of total returns. For tractability, we consider a strategy that assigns a portfolio weight to stock i at time t of

$$\gamma_{i,t} = -\frac{1}{N_t}\left(\varepsilon_{i,t-1} - \overline{\varepsilon}_{t-1}\right). \tag{10}$$

In the empirical analyses, we consider an implementable version of this strategy based on the same logic. The exposure of this strategy to the jth factor at time t equals zero by construction, since

$$E\left(\sum_{i=1}^{N_t} \gamma_{i,t} \beta_i^j | f_{t-1}^j\right) = -E\left(\frac{1}{N_t}\sum_{i=1}^{N_t}\left(\varepsilon_{i,t-1} - \overline{\varepsilon}_{t-1}\right)\beta_i^j\right) = 0. \tag{11}$$

The expected profits η_t of this strategy at time t can now be written as

$$E[\eta_t] = E\left(\sum_{i=1}^{N_t} \gamma_{i,t} r_{i,t}\right) = -\Psi, \tag{12}$$

while the variability for the residual reversal strategy's profits is given by

$$Var[\eta_t] = Var\left(\sum_{i=1}^{N_t} \gamma_{i,t} r_{i,t}\right) = \frac{1}{N_t^2}\sum_{i=1}^{N_t} \left(\varepsilon_{i,t-1} - \overline{\varepsilon}_{t-1}\right)^2 Var[r_{i,t}]. \tag{13}$$

Hence, by construction the residual reversal strategy does not have systematic and dynamic exposures to the K factors. Contrary to the conventional reversal strategy, the residual reversal strategy's profits are not reduced by having systematic negative exposures to factors with positive expected returns. Moreover, the strategy's profits do not depend on persistence in factor returns.

Given the stylized fact that factor returns exhibit some persistence (e.g., Fisher, 1966; Moskowitz and Grinblatt, 1999; Chen and De Bondt, 2004), we can deduce that the returns of a conventional reversal strategy are negatively affected by the strategy's negative exposure to the short-term momentum effect in factor returns and that, consequently, the expected return is larger for our residual reversal strategy. A second notable difference with the conventional reversal strategy is that the profits of a residual reversal strategy can be expected to exhibit a lower variability as a result of not having factor exposures. We therefore expect a residual reversal strategy to outperform a conventional reversal strategy in terms of both risk and return. In the subsequent sections we empirically test this conjecture.

3. Main empirical analyses

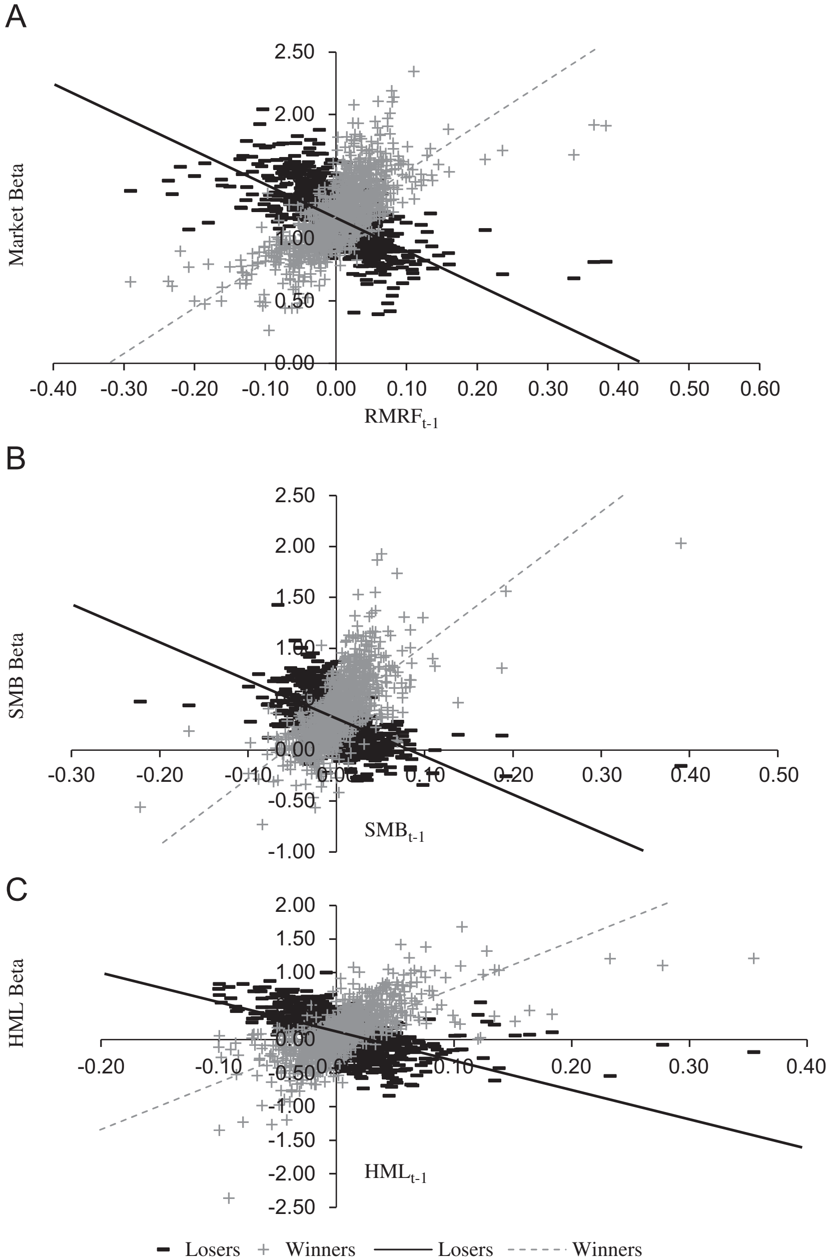
In this section we present our main empirical results. We first describe our data. Next we examine the characteristics and performance of a conventional short-term reversal strategy, after which we conduct a similar analysis for our residual reversal strategy. Finally, we discuss the robustness of our findings over time.

3.1. Data

Our stock return data are obtained from the monthly CRSP US Stock Database. We select common U.S. stocks listed on the NYSE, AMEX, and NASDAQ markets that (i) have a stock price above \$5 and (ii) have a market capitalization above the NYSE median at the end of the formation month. We exclude closed-end funds, Real Estate Investment Trusts

Fig. 1. Formation period loadings of the conventional reversal strategy.
This figure plots the estimated factor exposures of total return winner portfolios and loser portfolios against the returns of the Fama and French (1993) factors in month $t-1$. Panel A shows the market betas of the winner and loser portfolios against the excess return on the market portfolio during the formation month. Panels B and C show the *SMB* factor exposures and *HML* factor exposures against the formation period returns on the *SMB* and *HML* factors, respectively. The solid line represents the linearly fitted relation between the factor exposure of the loser portfolio and the factor return. The dashed line represents this relation for the winner portfolio. The sample period is from January 1929 to December 2010. The sample includes all common U.S. stocks listed on the NYSE, AMEX and NASDAQ markets that have, at the end of the formation month, a market capitalization above the NYSE median, a price above \$5, and return data for all preceding 36 months. Panel A: Market Factor, Panel B: SMB Factor and Panel C: HML Factor.

(REITs), unit trusts, American Depository Receipts (ADRs), and foreign stocks from our analysis. Common factor data are downloaded from French (2011). To be included in our sample at a given point in time we require a stock to have a complete return history over the preceding 36 months. Our sample covers the period from January 1926 to December 2010.



3.2. Factor exposures of conventional reversal strategies

In our first empirical analysis we investigate the extent to which conventional reversal strategies based on total stock returns exhibit dynamic exposures to the Fama and French (1993) (henceforth, Fama-French) factors. We use these factors in our analysis since they are widely accepted factors for explaining a large portion of the variability in U.S. stock returns. Reversal portfolios are constructed by sorting stocks at the end of each month into winner and loser portfolios based on their returns during that month. The winner portfolio consists of all the stocks with returns over the past month above the cross-sectional average and the loser portfolio consists of stocks with returns below the cross-sectional average, with weights inversely proportional to each stock's past 1-month return in excess of the return on the equally-weighted index as in Eq. (2). We also employ alternative portfolio weighting schemes, including equal- and value-weighting. As we discuss in detail in Section 5.5, the outcomes are virtually identical for all these weighting schemes.

Next, we estimate the winner and loser portfolios' exposures to the Fama-French factors at the end of each month by taking the weighted factor exposures of all stocks in the winner and loser portfolios. Exposures to the Fama-French factors are estimated over the preceding 36 months [$t-36$, $t-1$] from

$$r_{i,t} = \alpha_i + \beta_i^M \; RMRF_t + \beta_i^{SMB} \; SMB_t + \beta_i^{HML} \; HML_t + \varepsilon_{i,t}, \tag{14}$$

where $r_{i,t}$ is the return of stock i in month t in excess of the one-month U.S. Treasury bill rate; $RMRF_t$, SMB_t, and HML_t are the three Fama-French factors representing the market factor, the size factor, and the value factor, respectively; α_i, β_i^M, β_i^{SMB}, and β_i^{HML} are parameters to be estimated; and $\varepsilon_{i,t}$ is the residual return of stock i in month t.

In Fig. 1 we plot the estimated factor exposures of the winner and loser portfolios against the returns of the Fama-French factors in month $t-1$. Panel A shows the market betas against the excess return on the market portfolio during the formation month. Consistent with the predictions of our analytical model in the previous section, we observe a negative relation between the market beta of the loser portfolio and lagged market returns, and a positive relation for the winner portfolio. Hence, a conventional reversal strategy that is long in loser stocks and short in winner stocks exhibits dynamic exposures to the market factor depending on the sign and magnitude of the return on the market factor during the formation month $t-1$.

Likewise, Panels B and C of Fig. 1 plot the *SMB* and *HML* factor exposures of the winner and the loser portfolios against the formation period returns on the *SMB* and *HML* factors, respectively. We observe that the conventional reversal strategy also exhibits

Fig. 2. Formation period loadings of the residual reversal strategy.
This figure plots the estimated factor exposures of residual return winner portfolios and loser portfolios against the returns of the Fama and French (1993) factors in month $t-1$. Panel A shows the market betas of the winner and loser portfolios against the excess return on the market portfolio during the formation month. Panels B and C show the *SMB* factor exposures and *HML* factor exposures against the formation period returns on the *SMB* and *HML* factors, respectively. The solid line represents the linearly fitted relation between the factor exposure of the loser portfolio and the factor return. The dashed line represents this relation for the winner portfolio. The sample period is from January 1929 to December 2010. The sample includes all common U.S. stocks listed on the NYSE, AMEX, and NASDAQ markets that have, at the end of the formation month, a market capitalization above the NYSE median, a price above \$5, and return data for all preceding 36 months. Panel A: Market Factor, Panel B: SMB Factor and Panel C: HML Factor.

dynamic exposures to these two common factors. In months during which the return on the *SMB* factor was positive, the winner portfolio typically consists of small-capitalization stocks while the loser portfolio typically consists of large-capitalization stocks. In months during which the return on the *HML* factor was positive, the winner portfolio typically consists of value stocks while the loser portfolio typically consists of growth stocks. The

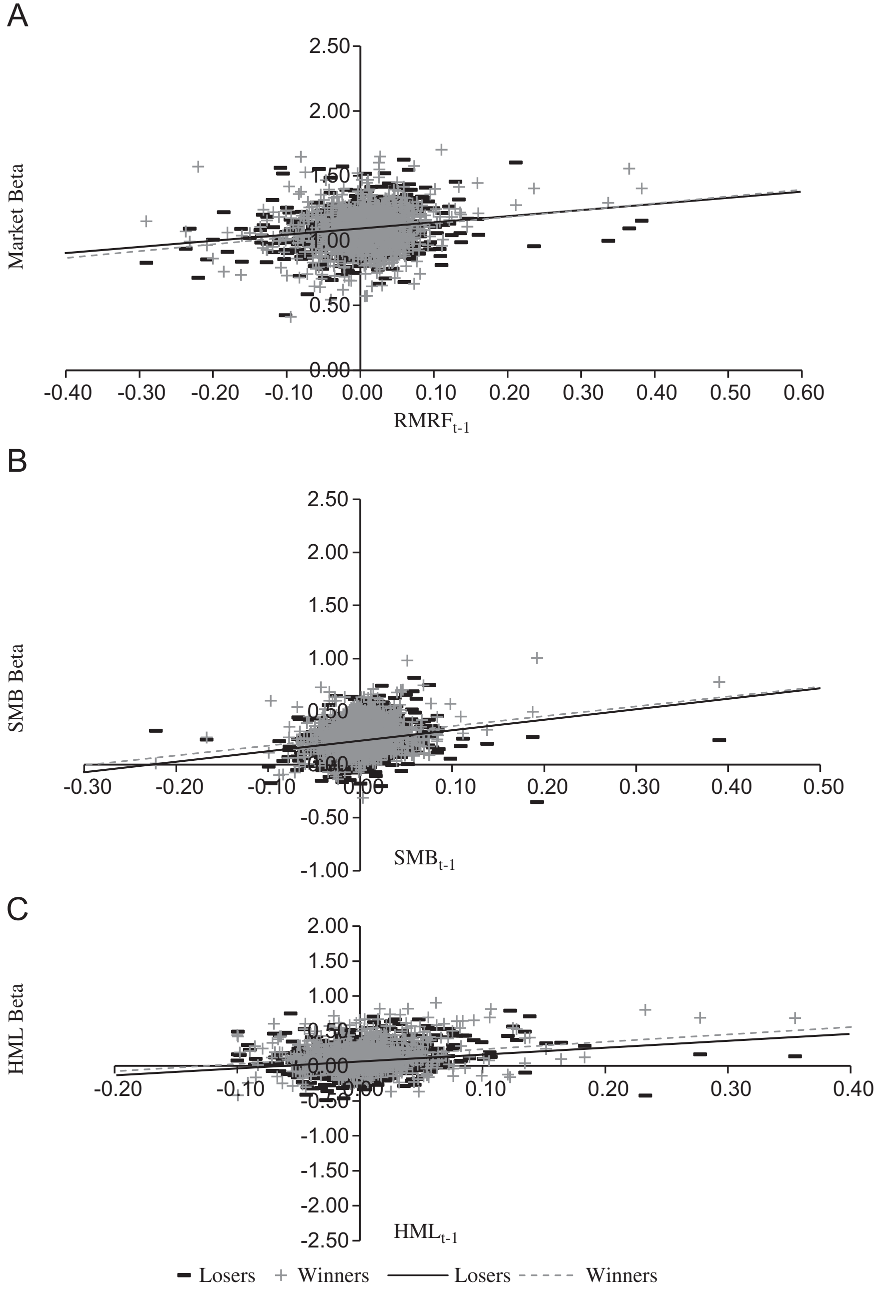


Table 1
Reversal returns and dynamic factor exposures.

This table presents average monthly reversal strategy returns, standard deviations and annualized Sharpe ratios, as well as coefficient estimates belonging to the conditional factor model explained in Eq. (15). In Panel A, the results are reported for the conventional reversal strategy and Panel B reports the results for the residual reversal strategy. The sample period is from January 1929 to December 2010. The sample includes all common U.S. stocks listed on the NYSE, AMEX, and NASDAQ markets that have, at the end of the formation month, a market capitalization above the NYSE median, a price above \$5, and return data for all preceding 36 months. Newey-West corrected t-statistics are reported in parentheses.

Panel A: Conventional reversal strategy							
Return	Stdev	Sharpe					
0.69	4.21	0.57					
(5.13)							
Alpha	RMRF	SMB	HML	RMRF_UP	SMB_UP	HML_UP	Adj. R^2
0.87	0.40	-0.01	0.39	−0.56	−0.02	−0.69	0.27
(7.41)	(13.49)	(−0.10)	(7.82)	(−13.04)	(−0.23)	(−10.47)	
Panel B: Residual reversal strategy							
Return	Stdev	Sharpe					
0.90	2.60	1.20					
(10.85)							
Alpha	RMRF	SMB	HML	RMRF_UP	SMB_UP	HML_UP	Adj. R^2
0.90	0.12	−0.03	0.02	−0.08	0.08	−0.12	0.04
(10.89)	(5.54)	(−0.77)	(0.49)	(−2.57)	(1.65)	(−2.48)	

results demonstrate that conventional reversal strategies exhibit dynamic exposures to the Fama-French factors.

To illustrate the impact of the dynamic exposures to the Fama-French factors on the risks and profits of conventional reversal strategies, we evaluate reversal returns using a conditional factor model in the spirit of Grundy and Martin (2001):

$$r_t = \alpha + \beta^1 RMRF_t + \beta^2 SMB_t + \beta^3 HML_t + \beta^4 RMRF\_UP_t \\ + \beta^5 SMB\_UP_t + \beta^6 HML\_UP_t + \varepsilon_{i,t}, \tag{15}$$

where $RMRF\_UP_t$, SMB_UP_t, and HML_UP_t are interaction variables that indicate the excess returns on the $RMRF$, SMB, and HML factors in month t, respectively, if the returns on the factors are positive in month $t-1$, and zero otherwise. In this setup, finding significantly negative coefficients for the interaction variables is consistent with the factor exposures of reversal strategies being inversely related to the signs of the factor returns over the past month.

The results of the conditional factor model analysis for the conventional reversal strategy are presented in Panel A of Table 1. Consistent with our expectation, the coefficient estimates for $RMRF_t$ and HML_t are significantly positive, while the estimates for $RMRF\_UP_t$ and HML_UP_t are significantly negative. Only the exposures to the SMB factor are insignificant, but this is not surprising in light of the fact that we exclude stocks with a share price below \$5 or a market capitalization below the NYSE median from our sample. The results indicate that the dynamics of the conventional reversal strategy's factor exposures are statistically significant, and also that these exposures explain a significant portion of the strategy's risks. More specifically, the adjusted R^2 of 27% for our relatively simple conditional regression model indicates that over one-fourth of the variability in the conventional reversal strategy's returns can be attributed to dynamic factor exposures.

Our analytical analysis in the previous section showed that persistence in factor returns hurts the profitability of a conventional reversal strategy. As several authors report persistence in common factor returns (e.g., Fisher, 1966; Moskowitz and Grinblatt, 1999; Chen and De Bondt, 2004), this concern is justified. Consistent with these studies, we indeed observe short-term momentum in common factor returns over our sample period. More specifically, over the January 1929 to December 2010 period, the market, size and value factors show positive persistence in 55%, 54%, and 56% of the months, respectively.[1] Hence, we expect that the dynamic factor exposures of conventional reversal strategies negatively affect the strategies' profits. Consistent with this notion, we find that the alpha of the conventional reversal strategy following from the conditional model in Eq. (15) is larger than its raw return. The conventional reversal strategy based on total stock returns earns an average return of 69 basis points per month, while the strategy's alpha is 87 basis points per month. The strategy's negative exposure to short-term persistence in the Fama-French factors therefore appears to come at the cost of 18 basis points per month (87–69). All in all, the results show that the conventional reversal strategy's dynamic factor exposures significantly contribute to the strategy's risk and negatively affect its profitability.

3.3. Factor exposures of reversal strategies based on residual returns

As an alternative to a conventional reversal strategy based on total stock returns, we propose to construct reversal portfolios based on residual stock returns resulting from performing rolling regressions using the Fama and French (1993) model. More specifically, we construct residual reversal portfolios by sorting stocks into either a winner or a loser portfolio at the end of each month based on their estimated residual returns during that month. For each stock i and each formation month $t-1$, we estimate Eq. (14) using stock returns over the preceding 36 months $[t-36, t-1]$. Next, the estimated residual returns are standardized by dividing them by their standard deviations over the preceding 36 months. Standardization of the residual returns yields an improved measure of the extent to which a given firm-specific return shock is actually news, as opposed to noise. This facilitates a better interpretation of the residual as firm-specific information (Gutierrez and Pirinsky, 2007). Following the portfolio construction for the conventional reversal strategy, the winner (loser) portfolio of the residual reversal strategy consists of the stocks with an above (below) average standardized residual return.

Both portfolios are designed to be orthogonal to the Fama-French factors. To investigate the extent to which the factors are actually factor-neutral, we plot the factor exposures of the winner and loser portfolios of the residual reversal strategy against the factor returns during the formation month in Fig. 2. The residual reversal strategy clearly succeeds in avoiding dynamic factor exposures. While Fig. 1 shows an "X"-shaped relation between the factor exposures and lagged factor returns for the conventional reversal

[1] We measure persistence by the empirical probability of having two consecutive factor-return observations with the same sign.

strategy's winner and loser portfolios, such a relation is not observable for the residual reversal strategy's winner and loser portfolios.

Panel B of Table 1 shows the conditional regression results for the residual reversal strategy. As expected, the residual reversal strategy outperforms the conventional reversal strategy in terms of both raw returns and risk-adjusted returns. The residual reversal strategy on average earns 90 basis points per month, which is 21 basis points more than the conventional reversal strategy. Moreover, the coefficient estimates of the conditional regression model in Eq. (15) are much closer to zero compared to the coefficient estimates for the conventional reversal strategy. At the same time, the R^2 value of the conditional regression model for the residual reversal strategy is close to zero. As a result, the alpha of the residual reversal strategy is virtually identical to the strategy's return. This observation is consistent with the predictions that follow from the analytical analysis discussed in the previous section. We also note that the alphas of the conventional and residual reversal strategies are almost identical, at 87 and 90 basis points per month, respectively. Assuming the conditional regression model from Eq. (15) is able to pick up the (dynamics in) factor exposures correctly, this is again consistent with the predictions that follow from the analytical analysis. To see this, compare Eqs. (4) and (12) and notice that the differences between the expected profits of the two reversal strategies only arise as a result of their differences between the factor exposures, for which we correct using the conditional regression model. Finally, note that compared to the conventional reversal strategy, the residual reversal strategy's profits are also substantially less volatile. As a result, its Sharpe ratio of 1.20 is more than twice as large as the 0.57 Sharpe ratio of the conventional reversal strategy. Hence, ranking stocks on their residual returns is an effective approach for neutralizing the dynamic factor exposures that are present in conventional reversal strategies based on total returns.

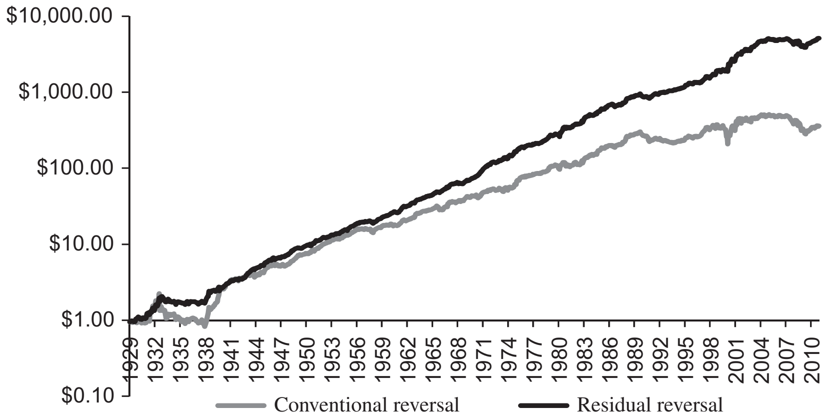


Fig. 3. Cumulative reversal returns.
This figure plots the cumulative returns from January 1929 to December 2010 for a hypothetical $1 invested in the conventional reversal strategy (gray) and the residual reversal strategy (black). The sample includes all common U.S. stocks listed on the NYSE, AMEX, and NASDAQ markets that have, at the end of the formation month, a market capitalization above the NYSE median, a price above $5, and return data for all preceding 36 months.

3.4. Robustness over time

Our results in the previous subsection are based on the full January 1929 to December 2010 period. We now investigate both reversal strategies' profits over time and in different subperiods. Fig. 3 displays the cumulative returns for a hypothetical $1 invested in each of the two reversal strategies in January 1929. We observe that the graph corresponding to the residual reversal strategy (black) is steeper than the graph corresponding to the conventional reversal strategy (gray). Moreover, whereas the return on the conventional reversal strategy appears to flatten off over the most recent 20 years of our sample, the cumulative return of the residual reversal strategy portfolio continues to increase during the same period.

We further examine the performance of both reversal strategies over time by calculating average returns and Sharpe ratios for each decade in our sample. As reported in Table 2, the conventional reversal strategy earns significant profits in five of the eight decades. Notably, the strategy is not profitable during the two most recent decades. This finding is consistent with results of Stivers and Sun (2011), who also document that the short-term reversal effect has substantially weakened over the post-1990 period, following the publication of several papers that describe the effect. In contrast, the residual reversal strategy earns significantly positive returns in each of the eight decades in our sample, including the 1990s and 2000s. Its return over these decades of 0.74% per month (t-statistic of 3.89) is also not much different from its long-run average return. Even when we consider the five most recent years of our sample period from 2006 to 2010, which includes the

Table 2
Reversal returns for different sample periods.

This table presents average monthly returns and annualized Sharpe ratios per decade, the pre-1990 period, the post-1990 period and the last five years for the conventional reversal strategy and the residual reversal strategy. The test statistics and p-values of the Memmel (2003) corrected Jobson and Korkie (1981) test for equal Sharpe ratios are reported in the final two columns. The sample includes all common U.S. stocks listed on the NYSE, AMEX, and NASDAQ markets that have, at the end of the formation month, a market capitalization above the NYSE median, a price above $5, and return data for all preceding 36 months. The reported t-statistics are Newey-West corrected.

	Conventional reversal			Residual reversal			Jobson-Korkie test	
Time period	Return	t-Stat	Sharpe	Return	t-Stat	Sharpe	z-Score	p-value
1929–1939	1.01	1.53	0.46	0.82	2.25	0.68	2.94	0.01
1940–1949	0.95	3.90	1.23	1.09	7.32	2.31	7.80	0.00
1950–1959	0.74	4.54	1.43	0.81	5.89	1.86	3.11	0.00
1960–1969	0.75	3.82	1.21	0.95	7.29	2.30	7.14	0.00
1970–1979	0.78	3.21	1.01	1.11	6.71	2.12	9.03	0.00
1980–1989	0.85	2.97	0.94	1.00	4.26	1.35	5.89	0.00
1990–1999	0.00	0.02	0.00	0.69	3.97	1.26	11.15	0.00
2000–2010	0.42	0.80	0.24	0.79	2.39	0.72	8.04	0.00
1929–1989	0.85	5.84	0.75	0.96	10.68	1.37	15.50	0.00
1990–2010	0.22	0.72	0.16	0.74	3.89	0.85	13.35	0.00
2006	0.07	0.13	0.13	0.31	0.90	0.90	3.21	0.00
2007	−2.01	−3.62	−3.62	−1.32	−2.94	−2.94	1.38	0.15
2008	−1.19	−0.60	−0.60	−0.38	−0.24	−0.24	2.14	0.04
2009	0.10	0.09	0.09	0.98	1.25	1.25	3.05	0.00
2010	0.94	1.21	1.21	1.15	3.87	3.87	2.90	0.01

"quant meltdown" in 2007, the residual reversal strategy outperforms the conventional reversal strategy in every year.

We argue that the weakening of the returns of a conventional reversal strategy can largely be attributed to the impact of the strategy's dynamic factor exposures being particularly negative over the two most recent decades of our sample. To gauge the magnitude of this negative impact, we evaluate the performance of a reversal strategy based on systematic returns, i.e., non-residual stock returns over the full sample period and the period from January 1990 to December 2010.[2] For the pre-1990 period, we find a return of −0.05% (*t*-statistic of −0.43) per month, whereas for the period from 1990 onwards, we find a return of −0.68% (*t*-statistic of −2.58) per month. It thus appears that the negative return impact of a conventional reversal strategy's dynamic factor exposures has increased to a significant level over the two most recent decades in the sample. As the residual component of stock returns still exhibits a large reversal effect over this period, the weak performance of conventional reversal strategies over the past two decades is largely attributable to the detrimental impact of the strategies' dynamic factor exposures over this particular period.

Table 2 also shows that the residual reversal strategy outperforms the conventional reversal strategy in all but one decade in our sample in terms of raw returns, and in each decade in terms of risk-adjusted returns. The Jobson and Korkie (1981) test statistics show that the difference in Sharpe ratios is statistically significant in each decade. To summarize, our subperiod results show that the residual reversal strategy exhibits a strong performance relative to the conventional reversal strategy in each of the eight decades in our sample period, as well as over the long run.

4. Reversal profits and trading costs

Consistent with most of the literature, we find that reversal strategies yield large positive returns. The results obtained hitherto, however, ignore the impact of trading costs, such as bid-ask spreads, commissions, and price impact costs. A recent strand of literature re-examines stock market anomalies after incorporating trading costs. For example, Lesmond, Schill and Zhou (2004) and Korajczyk and Sadka (2004) argue that momentum profits are difficult to capture because momentum strategies require frequent rebalancing, while Chordia, Goyal, Sadka, Sadka, and Shivakumar, (2009) study the profitability of an investment strategy based on the post-earnings announcement drift and find that trading costs of the strategy are likely to be larger than the hypothetical profits. Directly related to our study, several studies find that a large portion of the profitability of a conventional reversal strategy disappears once trading costs are taken into account (e.g., Ball, Kothari and Wasley, 1995; Conrad, Gultekin and Kaul, 1997; Avramov, Chordia and Goyal, 2006). In particular, Avramov, Chordia and Goyal (2006) find that stocks with the smallest capitalization and highest illiquidity exhibit the largest reversals. These stocks are also very

[2]We construct a long-short systematic reversal portfolio by giving weights to stocks at the end of each month based on their estimated systematic returns during that month. For each stock i and each formation month $t-1$, we estimate Eq. (14) using stock returns over the preceding 36 months $[t-36, t-1]$. The winner (loser) portfolio of the systematic reversal strategy consists of the stocks with above (below) average systematic returns, i.e., $\hat{\beta}_i^M RMRF_{t-1} + \hat{\beta}_i^{SMB} SMB_{t-1} + \hat{\beta}_i^{HML} HML_{t-1}$, in spirit similar to Eq. (2). The performance of a reversal strategy that is long in the loser portfolio and short in the winner portfolio is not presented in tabular form. The results are available upon request.

expensive to trade, however. After taking trading costs into account, the authors find that a conventional reversal strategy does not yield positive net returns.

Consistent with Avramov, Chordia and Goyal (2006) and most of the related literature, we construct equally-weighted decile and quintile reversal portfolios of stocks and estimate trading costs using the model of Keim and Madhavan (1997) to investigate if reversal profits remain significant once trading costs are taken into account. Keim and Madhavan provide estimates of trading costs for 21 institutions from 1991 to 1993. These trading cost estimates include commissions paid, as well as an estimate of the price impact (including the impact of crossing the bid-ask spread) of the trades. Since trading costs are likely to be substantially larger before this period and because we have no reliable estimates before the 1990s, we perform this part of our analysis for the period from of January 1990 to December 2010. Based on the Keim and Madhavan (1997) estimates, we model trading costs such that the costs of buy-initiated orders and sell-initiated orders are equal to

$$C_{i,t}^{Buy} = 0.767 + 0.336 D_i^{Nasdaq} - 0.084 \ln\left(MC_{i,t}\right) + \frac{13.807}{P_{i,t}} \tag{16}$$

and

$$C_{i,t}^{Sell} = 0.505 + 0.058 D_i^{Nasdaq} - 0.059 \ln\left(MC_{i,t}\right) + \frac{6.537}{P_{i,t}}, \tag{17}$$

respectively, where $C_{i,t}^{Buy}$ ($C_{i,t}^{Sell}$) is the trading cost at time t in case order i is a buy-initiated (sell-initiated) order; D_i^{Nasdaq} is a dummy variable that takes the value one for stocks traded on the NASDAQ markets and is zero otherwise; $MC_{i,t}$ is the market capitalization in month t of the stock traded; and $P_{i,t}$ is the price per share of the stock traded at time t. Furthermore, we restrict the trading costs of a single order to be nonnegative.

The profits of both reversal strategies over this recent period are shown in Table 3, Panel A. As discussed in the previous section, the average gross returns of both reversal strategies are lower over this period compared to those over the full 1929–2010 sample period. In fact, the return on the conventional reversal strategy is only 25 basis points per month and statistically indistinguishable from zero over the post-1990 period. Not surprisingly therefore, the net returns of the conventional reversal strategy even become negative after estimated trading costs are taken into account. These findings are consistent with the results reported by Avramov, Chordia and Goyal (2006). The residual reversal strategy, however, earns an average gross return of 102 basis points per month over the same period. Even after trading costs are taken into account, the strategy remains highly profitable, with a net return of 66 basis points per month. We estimate that the break-even level is reached for trading costs of 56 basis points for a round-trip transaction. With such a high break-even level, it seems very unlikely that trading costs prevent profitable execution of a residual reversal strategy. Examining the distribution of trading costs for the cross-section of stocks over time, we find that the 80th percentile corresponds to roughly 60 basis points per round-trip transaction. In other words, trading costs would only subsume the profits of the residual reversal strategy if the strategy would systematically trade in the 20% most illiquid stocks in our sample. The results also show that the net returns, in excess of the CRSP total return index, of the individual long (Losers) and short (Winners) portfolios of the residual reversal strategy are both significantly positive and roughly equally large. This finding indicates that the residual reversal profits are not concentrated in short positions.

Table 3
Reversal returns and trading costs.

This table presents average gross and net monthly returns in excess of the CRSP total return index for the long portfolios (Losers), the short portfolios (Winners) and the long plus short portfolios of the conventional reversal strategy and the residual reversal strategy. Furthermore, the table presents average round-trip trading costs that would have resulted in break-even strategy returns, as well as the average monthly strategies' turnover. Panel A reports the results for our universe of stocks that have a market capitalization that is above the NYSE median. Panel B and C report the results for the largest 500 and 100 stocks in our sample, respectively. Net returns are calculated by subtracting the estimated trading costs that are based on the Keim and Madhavan (1997) model and are explained in detail in Eqs. (16) and (17). We also report the net returns of the reversal strategies using a skip day approach in which the returns of the first trading day of the new month are not taken into account. The sample period is from January 1990 to December 2010. The sample includes all common U.S. stocks listed on the NYSE, AMEX, and NASDAQ markets that have, at the end of the formation month, a price above \$5, and return data for all preceding 36 months. Newey-West corrected t-statistics are reported in parentheses.

Panel A: Above NYSE median	Gross returns			Net returns			Net returns with skipday			Break-even	Turnover
	Losers	Winners	L+W	Losers	Winners	L+W	Losers	Winners	L+W		
Conventional reversal	0.08	0.17	0.25	−0.19	−0.05	−0.24	−0.19	−0.19	−0.39	14	173
	(0.32)	(0.71)	(0.65)	(−0.74)	(−0.22)	(−0.63)	(−0.74)	(−0.85)	(−1.03)		
Residual reversal	0.49	0.53	1.02	0.30	0.36	0.66	0.23	0.17	0.40	56	182
	(2.89)	(3.09)	(3.88)	(1.80)	(2.09)	(2.53)	(1.36)	(1.04)	(1.57)		
Panel B: 500 Large caps											
Conventional reversal	0.10	0.16	0.26	0.00	0.08	0.09	0.02	−0.01	0.02	16	158
	(0.49)	(0.97)	(0.82)	(0.02)	(0.49)	(0.27)	(0.11)	(−0.04)	(0.05)		
Residual reversal	0.35	0.39	0.74	0.28	0.32	0.60	0.24	0.20	0.44	46	163
	(2.53)	(2.91)	(3.27)	(1.98)	(2.38)	(2.62)	(1.73)	(1.58)	(1.99)		
Panel C: 100 Large caps											
Conventional reversal	0.06	0.07	0.13	0.03	0.05	0.08	0.02	−0.01	0.02	8	160
	(0.26)	(0.34)	(0.35)	(0.14)	(0.23)	(0.22)	(0.10)	(−0.03)	(0.05)		
Residual reversal	0.34	0.42	0.76	0.32	0.40	0.73	0.24	0.30	0.54	47	163
	(2.13)	(3.01)	(3.10)	(2.01)	(2.89)	(2.95)	(1.52)	(2.20)	(2.21)		

We further evaluate the profitability of reversal strategies by excluding small capitalization stocks from our sample. Panels B and C of Table 3 show the results for, respectively, the largest 500 and largest 100 stocks in our sample.[3] For both subsamples, the net profits of the conventional reversal strategy are not significantly larger than zero. In contrast, with net returns of 60 and 73 basis points per month, the residual reversal strategy generates statistically and economically significant profits for both subsamples. The estimated break-even levels of trading costs are 46 and 47 basis points per round-trip transaction.

Besides taking into account trading costs, we also want to incorporate the effect of a potential implementation lag that might occur with a real-time application of a reversal strategy. To this end we additionally compute stock returns using return data from the daily CRSP US Stock Database, skipping the first trading day of each month.[4] The returns of the reversal strategies with a 1-day skip are presented in the third column of Table 3. Even after taking trading costs and an implementation lag into account, we find that the residual reversal strategies for the 500 and 100 largest stocks in our sample generate large net profits of 44 and 54 basis points per month, respectively. Therefore, it is very unlikely that real-life frictions such as trading costs and implementation lags prevent the profitable execution of residual reversal strategies.

Our approach to examine the economic significance of reversal profits is likely conservative. First, as Keim and Madhavan (1997) show in their study, trading style may have a significant impact on trading costs. For example, technical traders that follow momentum-like strategies and have a great demand for immediacy typically experience large bid-ask costs, since the market demand for the stocks they aim to buy is substantially larger than the supply, and vice versa for sell transactions. In their study, Keim and Madhavan (1997) also find that technical traders generally experience higher trading costs than traders following strategies that demand less immediacy, such as value traders or index managers, and adjust trading cost estimates for these styles. Lehmann (1990) argues that short-term reversal traders are liquidity providers, and likely benefit from buying (shorting) prior period losers (winners) near the bid (ask). The Keim and Madhavan (1997) model, however, does not make an adjustment for liquidity-providing trading styles, such as reversal strategies. Because reversal strategies provide liquidity, trading costs are likely to be somewhat lower than the estimates we use in this analysis.

Second, in this study we investigate naive top-minus-bottom decile reversal strategies that are rebalanced at a monthly frequency. In a recent study, De Groot, Huij and Zhou (2012) show that applying a more sophisticated portfolio construction algorithm can help to significantly reduce the turnover of reversal strategies without lowering their expected returns. In their application, the authors find that more sophisticated buy/sell rules can approximately halve the negative impact of trading costs on reversal profits. By not taking into account the liquidity-providing nature of reversal trading, and by ignoring the potential efficiency gains that may be obtained with more sophisticated portfolio construction rules, our results are likely to underestimate the full profit potential of residual reversal investment strategies.

[3] In order to have a sufficient large number of stocks in the portfolios, we sort stocks into quintiles instead of deciles when we evaluate the profitability of reversal strategies for the largest 500 and 100 stocks.

[4] By skipping the first day after portfolio formation, the results should also be less affected by potential bid-ask bounce effects.

A final observation is that the higher net return of the residual reversal strategy compared to the conventional reversal strategy comes from its higher gross expected return, as well as from incurring lower trading costs. For example, while the gross return difference between the conventional and residual reversal strategies is 77 basis points per month (102–25 basis points; see Table 3), the difference in net returns is 90 basis points per month (66+24 basis points). The reason for the lower trading costs of the residual reversal strategy is that, unlike the conventional reversal strategy, it does not trade excessively in volatile, small stocks. When stocks are ranked on raw past returns, stocks with the highest volatility have the greatest probability to end up in the extreme quantiles. These stocks are typically the stocks with the smallest market capitalizations. As a result, a portfolio that is long and short in these extreme quantiles is typically biased towards the smaller capitalization stocks. However, these stocks are also the most expensive to trade, so this feature of the conventional reversal strategy is harmful to its after-cost profitability. Because the residual reversal strategy is constructed in such a way that it is neutral to the SMB factor, we expect this effect to be less pronounced for the residual reversal strategy.

Table 4
Portfolio characteristics.

This table presents characteristics of equally-weighted decile portfolios sorted on previous month total returns (Panel A) and previous month residual returns (Panel B). The monthly return volatility and the Fama and French (1993) three-factor betas from Eq. (14) are the time-series averages of the medians in a portfolio and are estimated using the 36 months prior to formation date. Size denotes the time-series average of the median size decile, using NYSE, breakpoints in a portfolio at the end of the formation period; price denotes the time-series average of the median stock price at the end of the formation period. The Keim and Madhavan (1997) transaction costs of 'buy' and 'sell' induced orders are the time-series averages of the average costs in a portfolio. The sample period is from January 1990 to December 2010. The sample includes all common U.S. stocks listed on the NYSE, AMEX, and NASDAQ markets that have, at the end of the formation month, a price above $5, and return data for all preceding 36 months.

Panel A: Conventional reversal	Losers	2	3	4	5	6	7	8	9	Winners
Volatility (%)	11.08	8.86	8.11	7.87	7.75	7.82	8.01	8.43	9.28	11.95
β^{M}	1.16	1.03	0.97	0.94	0.94	0.94	0.96	1.00	1.06	1.19
β^{SMB}	0.31	0.19	0.15	0.13	0.14	0.15	0.15	0.20	0.27	0.47
β^{HML}	0.09	0.19	0.22	0.23	0.24	0.24	0.22	0.21	0.17	0.05
Size	4.57	5.23	5.36	5.49	5.48	5.49	5.45	5.39	5.30	4.41
Price ($)	28.73	33.22	35.04	36.18	36.60	37.07	37.71	37.76	37.63	35.60
Buy (%)	0.28	0.18	0.15	0.14	0.13	0.13	0.13	0.13	0.15	0.22
Sell (%)	0.05	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.04

Panel B: Residual reversal	Losers	2	3	4	5	6	7	8	9	Winners
Volatility (%)	8.66	8.87	8.83	8.81	8.88	8.79	8.72	8.72	8.59	8.75
β^{M}	1.01	1.03	1.01	1.02	1.02	1.01	1.00	1.00	0.99	1.00
β^{SMB}	0.18	0.21	0.21	0.22	0.22	0.20	0.21	0.21	0.20	0.22
β^{HML}	0.19	0.17	0.17	0.20	0.20	0.20	0.21	0.20	0.23	0.25
Size	5.31	5.16	5.14	5.07	5.17	5.11	5.17	5.28	5.28	5.19
Price ($)	33.39	34.33	34.91	35.07	35.39	35.69	35.67	36.22	36.87	37.03
Buy (%)	0.18	0.17	0.17	0.17	0.17	0.16	0.16	0.16	0.15	0.16
Sell (%)	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02

To investigate whether this conjecture is true, we consider the decile portfolios' characteristics for both reversal strategies in Table 4.

Consistent with the intuition that stocks with the highest volatility have the greatest probability to end up in the extreme quantiles when stocks are ranked on raw past returns, Table 4 shows that the top and bottom deciles for a conventional reversal strategy exhibit a substantially higher volatility than the mid-ranked portfolios. Furthermore, the portfolios' exposures to the *SMB* factor are substantially larger and their ranks on market capitalization are lower. When we consider the characteristics of the top and bottom decile portfolios for the residual reversal strategy, we do not observe that the extreme deciles contain more volatile, small-cap stocks. As a consequence, the trading costs involved with the residual reversal strategy are significantly lower than the costs associated with the conventional reversal strategy. For example, the single-trip buy trading costs for loser stocks based on the conventional reversal strategy are 28 basis points, vs. 18 basis points for the residual reversal strategy. Similarly, the single-trip sell costs for loser stocks based on the conventional reversal strategy are 4 basis points, compared to only 2 basis points for the residual reversal strategy.

5. Follow-up empirical analyses

In this section we conduct several follow-up analyses. We first examine the comparative strength of both reversal strategies. Next, we investigate the profitability of both reversal strategies within industries. We then examine the relation between reversal strategies' dynamic factor exposures and their profitability using a non-parametric approach. This is followed by an analysis of calendar month effects. Finally, we examine the robustness of our results to using alternative portfolio weighting schemes.

5.1. Cross-sectional Fama-MacBeth regressions and double-sorted rank portfolios

We perform cross-sectional regressions in the spirit of Fama and MacBeth (1973) to investigate what portion of the predictive power of total stock returns can be attributed to the residual component of the return. These regressions are performed at the individual stock level, allowing us to control for other effects. More specifically, we estimate the following two equations every month:

$$r_{i,t} = a_t + b_{1,t} z^{r}_{i,t-1} + b_{2,t} z^{\hat{\varepsilon}}_{i,t-1} + \delta_t X_{i,t-1} + u_{i,t}, \tag{18}$$

and

$$r_{i,t} = a_t + b_{1,t} z\_L^{r}_{i,t-1} + b_{2,t} z\_W^{r}_{i,t-1} + b_{3,t} z\_L^{\hat{\varepsilon}}_{i,t-1} + b_{4,t} z\_W^{\hat{\varepsilon}}_{i,t-1} + \delta_t X_{i,t-1} + u_{i,t}, \tag{19}$$

where $z^{r}_{i,t-1}$ is a standardized score of stock i's return in month $t-1$; $z^{\hat{\varepsilon}}_{i,t-1}$ is a standardized score of stock i's standardized residual return in month $t-1$ estimated using Eq. (14); $X_{i,t-1}$ is a vector of control variables; $z\_L^{r}_{i,t-1}$ and $z\_W^{r}_{i,t-1}$ ($z\_L^{\hat{\varepsilon}}_{i,t-1}$ and $z\_W^{\hat{\varepsilon}}_{i,t-1}$) are interaction variables that indicate the score $z^{r}_{i,t-1}$ ($z^{\hat{\varepsilon}}_{i,t-1}$) if stock i is a loser stock or winner stock based on its return (residual return) in month $t-1$, respectively, and zero otherwise.[5] Following Fama and French (2008), we include several variables to control for other effects that might explain the stock returns. These variables are the natural log of market

[5]Standardization occurs in the cross-section and scores are truncated between -3 and 3.

Table 5
Cross-sectional Fama-MacBeth (1973) regressions.
This table presents time-series averages of monthly coefficient estimates (multiplied by 100) that follow from the cross-sectional Fama and MacBeth (1973) type of regressions of Eqs. (18) and (19). The dependent variable is the monthly excess stock return. The sample period is from July 1963 to December 2010. The sample includes all common U.S. stocks listed on the NYSE, AMEX, and NASDAQ markets that have, at the end of the formation month, a positive book-to-market ratio, a market capitalization above the NYSE median, a price above $5, and return data for all preceding months. Newey-West corrected t-statistics are reported in parentheses.

	Total	Residual	Both	Total	Residual	Both
Constant	11.64	11.77	11.35	11.31	11.74	11.05
	(10.84)	(10.67)	(11.04)	(10.82)	(10.70)	(10.95)
z^r	−0.28		0.11			
	(−4.73)		(1.03)			
z^ε		−0.35	−0.44			
		(−7.88)	(−5.68)			
z_L^r				−0.51		−0.24
				(−6.70)		(−1.92)
z_W^r				−0.13		0.29
				(−1.84)		(2.34)
z_L^ε					−0.37	−0.19
					(−6.02)	(−2.06)
z_W^ε					−0.33	−0.58
					(−6.50)	(−5.83)
ln(*MC*)	−0.75	−0.76	−0.73	−0.73	−0.76	−0.70
	(−11.30)	(−11.05)	(−11.50)	(−11.27)	(−11.15)	(−11.41)
ln(*B*/*M*)	0.03	0.04	0.07	0.05	0.04	0.08
	(0.33)	(0.46)	(0.74)	(0.48)	(0.45)	(0.87)
R_{12m1}	0.68	0.61	0.53	0.68	0.62	0.53
	(2.58)	(2.31)	(2.11)	(2.62)	(2.37)	(2.15)
NS	−0.83	−0.91	−0.88	−0.88	−0.90	−0.92
	(−2.58)	(−2.77)	(−2.83)	(−2.75)	(−2.75)	(−3.00)
Ac/*B*	0.08	0.04	0.13	0.08	0.04	0.13
	(0.26)	(0.14)	(0.42)	(0.27)	(0.13)	(0.42)
dA/*A*	−0.24	−0.26	−0.31	−0.28	−0.27	−0.34
	(−1.37)	(−1.49)	(−1.84)	(−1.60)	(−1.59)	(−2.08)
Y/*B*	0.32	0.28	0.28	0.37	0.29	0.33
	(0.90)	(0.82)	(0.78)	(1.03)	(0.85)	(0.91)
Adjusted R^2	0.08	0.08	0.09	0.09	0.08	0.09

capitalization, ln(*MC*); the natural log of the ratio between last fiscal year-end's book equity divided by market equity in December, ln(*B*/*M*); past twelve-minus-one month return, R_{12m1}; net stock issuance, *NS*; accruals, *Ac*/*B*; growth in assets, *dA*/*A*; and profitability, *Y*/*B*.[6] Data on firms' book values, net stock issuance, accruals, assets, and profitability are obtained from the Compustat database. Since Compustat data are only available as from 1963, this analysis is performed over the July 1963 to December 2010 period.

The time-series averages of the monthly coefficient estimates are presented in Table 5. For the first regression specification, there are statistically significant loadings on the

[6] A detailed description of the definition of the variables can be found in Fama and French (2008).

z-scores of the lagged total returns (z^r), indicating that past month stock returns have predictive power for future stock returns. However, once z-scores of lagged residual returns (z^ε) are included, all predictive power disappears. In the second regression specification, in which a distinction is made between (residual) return loser stocks and winner stocks, there is an asymmetric total return reversal effect. The residual return reversal effect, on the other hand, is equally strong for loser stocks as for winner stocks. Including all four interaction variables results in significant reversal effects for residual return losers and winners, but no reversal effect for total return winners. This finding is in line with the results of Jegadeesh and Titman (1995a), who report that over- or under-reaction to firm-specific information always contributes to the profitability of reversal strategies, while over- or under-reaction to the systematic factors can either reduce or increase these profits.

We now construct double-sorted rank portfolios to further investigate what portion of the predictive power of stocks' total returns can be attributed to the residual component of the return. For brevity, we do not report the results of this analysis in tabular form. To construct double-sorted rank portfolios, we start by sorting stocks into quintile portfolios based on their total returns and then subdivide each total-return quintile into quintiles based on the stocks' residual returns. This process generates 25 portfolios that all contain an equal number of stocks. When we consider the portfolios' average returns over the investment month, we observe that the returns are monotonically decreasing over the residual return quintiles within each total return quintile. The residual return loser quintile outperforms the residual return winner quintile by at least 62 basis points per month. Controlling for total returns, the loser-minus-winner spread is highly significant at 78 basis points per month. These results indicate that residual stock returns have predictive power for future stock returns above and beyond that of total stock returns.

Next, we perform a similar double-sorting procedure, but now first sorting stocks into quintiles based on their residual returns and then subdividing the stocks into quintiles based on their total returns. Interestingly, when we consider these portfolios' reversal-weighted returns over the investment month, we do not observe any return pattern at all across the portfolios sorted on total stock returns; the return spread between losers and winners is close to zero in all cases. Hence, after controlling for residual returns, total returns do not appear to have predictive power for future stock returns. These results corroborate our previous finding that most of the predictive power of total stock returns can be attributed to the residual component of the return.

5.2. *Within-industry reversal profits*

In this section we explore the profitability of both reversal strategies within different industries. Our motivation to investigate this issue stems from the contemporaneous findings of Hameed, Mian, and Huang (2010) and Da, Liu and Schaumburg (2011), who report higher returns for within-industry reversal strategies. To investigate if the residualization of stock returns relative to the Fama-French factors goes above and beyond correcting for industry effects, we compare conventional and residual reversal strategies applied *within* each of the 10 industries of French (2011). Similar to our earlier analyses, the winner (loser) portfolios consist of all the stocks with returns over the past month above (below) the cross-sectional average, and the weights of stocks are set

Table 6
Reversal returns per industry.

This table presents average monthly returns and annualized Sharpe ratios for the conventional reversal strategy and the residual reversal strategy for the 10 industries as classified by French (2011) for two sample periods. The bottom rows of the panels report the average monthly returns and annualized Sharpe ratios for the conventional reversal and residual reversal strategies within the industries. The test statistics and p-values of the Memmel (2003) corrected Jobson and Korkie (1981) test for equal Sharpe ratios are reported in the final two columns. In Panel A, the sample period is from January 1929 to December 2010 and Panel B presents results for the sample period from January 1990 to December 2010. The sample includes all common U.S. stocks listed on the NYSE, AMEX, and NASDAQ markets that have, at the end of the formation month, a market capitalization above the NYSE median, a price above \$5, and return data for all preceding 36 months. The reported t-statistics are Newey-West corrected.

Panel A: January 1929 to December 2010

	Conventional reversal			Residual reversal			Jobson-Korkie test	
Industries	Return	t-Stat	Sharpe	Return	t-Stat	Sharpe	z-Score	p-Value
Consumer non durables	1.04	6.58	0.73	1.21	10.40	1.15	14.84	0.00
Consumer durables	0.51	2.49	0.28	0.89	5.36	0.59	15.24	0.00
Manufacturing	1.17	9.23	1.02	1.28	13.39	1.48	13.83	0.00
Energy	1.08	6.15	0.68	1.09	8.24	0.91	9.18	0.00
HiTec	0.59	3.15	0.35	0.83	5.63	0.62	12.83	0.00
Telecom	0.67	2.24	0.33	1.02	4.36	0.65	13.17	0.00
Shops	0.93	5.55	0.61	1.19	9.87	1.09	18.25	0.00
Health	0.86	3.50	0.44	1.34	8.18	1.04	20.26	0.00
Utilities	1.26	5.86	0.65	1.29	9.30	1.03	12.45	0.00
Other	0.60	3.37	0.37	0.97	7.70	0.85	13.77	0.00
Within industries	0.90	8.94	0.99	1.12	17.89	1.98	21.27	0.00

Panel B: January 1990 to December 2010

	Conventional reversal			Residual reversal			Jobson-Korkie test	
Industries	Return	t-Stat	Sharpe	Return	t-Stat	Sharpe	z-Score	p-Value
Consumer non durables	1.19	3.62	0.79	1.31	5.76	1.26	15.65	0.00
Consumer durables	0.21	0.48	0.11	0.67	2.01	0.44	16.53	0.00
Manufacturing	0.53	1.83	0.40	1.00	4.86	1.06	23.29	0.00
Energy	−0.15	−0.46	−0.10	0.06	0.22	0.05	7.40	0.00
HiTec	0.31	0.83	0.18	0.65	2.42	0.53	16.56	0.00
Telecom	0.60	1.20	0.26	0.98	2.75	0.60	14.35	0.00
Shops	0.58	2.09	0.46	0.87	4.17	0.91	18.64	0.00
Health	−0.10	−0.17	−0.04	1.01	3.17	0.69	26.80	0.00
Utilities	0.25	0.77	0.17	0.28	1.23	0.27	4.19	0.00
Other	0.43	1.27	0.28	1.00	5.55	1.21	23.73	0.00
Within industries	0.38	1.84	0.40	0.78	6.18	1.35	25.57	0.00

inversely proportional to the deviation of their past month return from the cross-sectional average industry return.

Table 6 reports the average monthly returns for both reversal strategies within each industry. The full-sample results in Panel A of Table 6 show that residualization improves the performance of a conventional reversal strategy, as well as the performance of a within-industry reversal strategy. The average return increases from 0.90% to 1.12% per month and the Sharpe ratio doubles, from 0.99 to 1.98. In fact, the residualization approach improves the Sharpe ratio within each of the 10 different industries. In Panel B of Table 6 we examine the results over the post-1990 period. Comparing these results to those in Table 2, applying a conventional reversal strategy within industries does little to improve its weak performance over this period, with average returns increasing only marginally from 0.22% to 0.38% per month. The residual reversal strategy, on the other hand, continues to perform strongly over the same period, regardless of whether the strategy is applied within industries or not. The within-industry application raw returns are slightly higher (0.78% per month vs. 0.74% per month) and the risk-adjusted returns are much higher (Sharpe ratio of 1.35 vs. 0.85) too.

These results imply that residualization offers distinct benefits that cannot be simply captured by neutralizing industry exposures and that, rather than being substitutes, the two approaches are complimentary. To put it differently, a reversal strategy is in general most effective when both dynamic exposures to the Fama-French factors and dynamic exposures to industries are neutralized. This is consistent with the finding of several authors that the Fama and French factors do not suffice to describe the returns on industry portfolios (see, e.g., Fama and French, 1997).

5.3. Non-parametric approach to measuring factor exposures

Most of our evidence reported so far on the impact of dynamic factor exposures on the profitability of reversal strategies relies on the outcomes of the conditional factor regressions in the spirit of Grundy and Martin (2001) we performed in the previous section. In this section we re-investigate the relation between reversal strategies' dynamic factor exposures and their profitability using a non-parametric approach that, unlike the factor regressions, does not rely on a linear factor structure. More specifically, with our non-parametric approach we regress the returns of the reversal strategies on dummy variables that indicate the number of Fama-French factors that revert (i.e., for which the sign of the

Table 7
Reversal returns conditional on factor returns.

This table presents average monthly returns for the conventional reversal strategy and the residual reversal strategy conditional on the number of common factors that persist and revert. A factor persists (reverts) if the sign of the factor return in month t is similar (opposite) to the sign of the factor return in month t-1. The final column of the table reports the empirical probabilities of the four different states. The sample period is from January 1929 to December 2010. The sample includes all common U.S. stocks listed on the NYSE, AMEX, and NASDAQ markets that have, at the end of the formation month, a market capitalization above the NYSE median, a price above $5, and return data for all preceding 36 months.

	Conventional reversal		Residual reversal		
	Return	*t*-Stat	Return	*t*-Stat	Probability
All 3 factors persist	−0.61	−2.08	1.00	5.02	0.20
1 factor reverts	−0.01	−0.06	0.70	5.90	0.37
2 factors revert	1.25	6.27	0.85	6.13	0.30
All 3 factors revert	3.57	8.10	1.51	4.76	0.12

return during the formation period and investment period are different). If reversal strategies exhibit dynamic factor exposures that are inversely related to the signs of the factor returns during the formation period, reversal profits are negatively affected by persistence in common factor returns and returns are lower when fewer factors revert.

The results in Table 7 indicate that a conventional reversal strategy exhibits dynamic factor exposures that affect its profitability: reversal profits appear to increase monotonically with the number of Fama-French factors that revert. When all Fama-French factors persist, the strategy earns a negative return of −61 basis points per month. In contrast, when all Fama-French factors revert, the conventional reversal strategy earns a highly positive return of 3.57% per month. Interestingly, the residual reversal strategy does not seem to exhibit such dynamic factor exposures as the strategy earns positive returns irrespective of the number of factors that revert, ranging between 0.70% and 1.51% per month. In all cases, the residual reversal profits are highly significant. These results are consistent with our previous finding that a residual reversal strategy is less sensitive to the returns of common factors over the investment period than a conventional reversal strategy, resulting in less volatile returns.

Table 8
Reversal returns per calendar month.

This table presents average returns for the conventional reversal strategy and the residual reversal strategy per calendar month for the sample period January 1929 to December 2010 in Panel A. Panel B presents average January returns and non-January returns for the sample period starting from January 1990 to December 2010. The sample includes all common U.S. stocks listed on the NYSE, AMEX, and NASDAQ markets that have, at the end of the formation month, a market capitalization above the NYSE median, a price above $5, and return data for all preceding 36 months.

Panel A: January 1929 to December 2010

	Conventional reversal		Residual reversal	
Month	Return	*t*-Stat	Return	*t*-Stat
January	2.51	5.92	1.98	6.76
February	0.56	1.14	1.00	3.49
March	1.11	2.05	1.20	3.03
April	−0.14	−0.38	0.23	1.10
May	0.30	0.97	0.82	4.62
June	1.12	2.25	1.12	3.40
July	1.68	3.31	1.35	4.21
August	0.15	0.25	0.60	2.42
September	0.62	1.67	0.67	2.33
October	0.53	1.18	0.83	2.54
November	−0.47	−1.08	0.24	1.03
December	0.30	0.68	0.82	3.48

Panel B: January 1990 to December 2010

	Conventional reversal		Residual reversal	
Month	Return	*t*-Stat	Return	*t*-Stat
January	2.11	2.31	2.03	3.96
Non-Januaries	0.05	0.16	0.63	3.10

5.4. Calendar month effects

Proceeding further, we investigate the performances of the conventional and residual reversal strategies per calendar month. Several authors document strong seasonal patterns in reversal returns (e.g., Grinblatt and Moskowitz, 2004). In particular, average reversal returns in January are found to be highly positive. The cited reason is the tax-loss selling effect: fund managers tend to sell small-cap loser stocks by the year-end, resulting in downward price pressure in that month, which is followed by an upward price pressure in January. Because a reversal strategy is long in small-cap loser stocks, this effect causes a large positive return for the strategy in January. We refer to Roll (1983), Griffiths and White (1993), and D'Mello, Ferris, and Hwang (2003) for a detailed discussion of this effect.

Because a residual reversal strategy is less concentrated in small-cap stocks compared to a conventional reversal strategy, we expect the January effect to have a smaller impact on the performance of a residual reversal strategy. Therefore, we examine the average monthly returns during each calendar month for the conventional reversal vs. the residual reversal strategy. The results are presented in Table 8.

Consistent with the prior literature, Table 8 shows that a large portion of the reversal profits are concentrated in January months. For example, the t-statistics of the conventional reversal strategy's returns exceed $+2.0$ in only 4 out of 12 months. By contrast, residual reversal returns have t-statistics larger than $+2.0$ in 10 out of 12 months. Interestingly, for the post-1990 period, the conventional reversal strategy only earns positive returns in January. The average returns on other months are an insignificant 0.05%. The residual reversal strategy, on the other hand, earns positive returns in January, as well as large positive returns of 0.63% on average in other months. Thus, residual reversal strategies are also more robust than conventional reversal strategies during the calendar year.

5.5. Alternative weighting schemes

We performed most of our analyses on return-weighted portfolios as there does not seem to be a consensus in the literature on the use of a particular weighting scheme. Several important studies on the reversal effect employ a return-weighting scheme to construct reversal portfolios (e.g., Lehmann, 1990; Lo and MacKinlay, 1990; Jegadeesh and Titman, 1995a; Da, Liu and Schaumburg, 2011). However, there are also studies that employ equally-weighted portfolios instead (e.g., Jegadeesh, 1990; Boudoukh, Richardson and Whitelaw, 1994; Avramov, Chordia and Goyal, 2006; Hameed, Mian, and Huang, 2010; Stivers and Sun, 2011; De Groot, Huij and Zhou, 2012), while the short-term reversal factor of French (2011) is constructed using a value-weighting scheme. To investigate the robustness of our findings to the use of alternative weighting schemes, we redo all our analyses using equal-weighted and value-weighted decile portfolios. For brevity, the results of these analyses are not reported in tabular form but are available upon request from the authors. While the results of the analyses using the alternative weighting schemes are qualitatively very similar, they are generally the strongest for the equally-weighting scheme (e.g., the returns of the conventional and residual reversal strategies are 0.92% and 1.28% per month, respectively, vs. 0.69% and 0.87% per month for the return-weighting scheme; see Table 1), and somewhat less pronounced using the value-weighting scheme (e.g., the returns of the conventional and residual reversal strategies are 0.53% and 0.74% per month, respectively). For both alternative weighting schemes, the residual reversal strategy is more than 30% less volatile compared to the conventional reversal strategy. The profits of the residual reversal strategy for both alternative weighting schemes remain statistically and economically large over the most recent decades in our sample. We conclude that our results are robust to the weighting scheme used to construct reversal portfolios.

6. Explanations for short-term stock reversals

In this section we discuss alternative hypotheses that have been put forward in the academic literature for understanding the reversal anomaly and the extent to which our results are consistent with the predictions following from these explanations. The literature on short-term stock reversals provides three main explanations for the effect: (1) reversals are the result of liquidity effects (e.g., Jegadeesh and Titman, 1995b); (2) reversals originate from non-synchronous trading of small and large cap stocks (e.g., Lo and MacKinlay, 1990; Boudoukh, Richardson and Whitelaw, 1994); and (3) reversals are the result of investor overreaction to new information in the market (e.g., Lehmann, 1990; Jegadeesh and Titman, 1995a).

Our finding that net reversal profits persist over the most recent decades in our sample, during which market liquidity dramatically increased, is not supportive of the explanation that reversals are induced by inventory imbalances by market makers and that reversal profits are a compensation for bearing inventory risks. Also, our finding that reversal profits are observed among the 500 and even 100 largest stocks is inconsistent with the notion that non-synchronous trading contributes to reversal profits. Only the behavioral explanation that investors tend to overreact to information and that stock price reversals originate from transitory changes in demand for immediacy by these impatient traders, does not appear to be inconsistent with our findings. Our finding that the short-term reversal effect is concentrated in the firm-specific component of stock returns is consistent with the results of Gutierrez and Pirinsky (2007), who argue that agency issues in the money management industry (i.e., institutions keeping their portfolios near a market index for reputation and career concerns) cause mispricing to be larger in the idiosyncratic return component of momentum strategies.

However, our results do not provide direct evidence in support of such a (rationalized) behavioral explanation. A formal test for competing explanations for the short-term reversal effect is beyond the scope of this paper. An interesting avenue for future research would involve an in-depth empirical investigation of the relation between reversal profits and proxies for liquidity provision and investor sentiment [e.g., the sentiment factor of Baker and Wurgler (2006)] to directly test the liquidity hypothesis vs. the overreaction hypothesis. Another interesting research question that emerges from our results is, if reversals indeed originate from investor overreaction, why investors overreact to firm-specific information and not to macro information. A framework as employed by Gutierrez and Pirinsky (2007) that incorporates institutional holdings data might be used to investigate this research question.

7. Conclusion

Conventional short-term reversal strategies exhibit dynamic exposures to the Fama and French (1993) factors. These factor exposures are inversely related to factor returns over the formation month, causing the reversal strategy to be negatively exposed to the short-term momentum effect in factor returns. As a result, dynamic factor exposures increase the risk of a reversal strategy, as well as negatively affect its profitability.

We show that a short-term reversal strategy based on residual stock returns does not exhibit these dynamic factor exposures and earns returns that are substantially larger than those of a conventional short-term reversal strategy. Additionally, the residual reversal strategy has a significantly lower volatility. The lower volatility together with the higher returns cause the residual reversal strategy to earn risk-adjusted returns that are twice as large as those of a conventional reversal strategy. In fact, the profits of the residual reversal strategy are statistically and economically significant after trading costs. The large residual reversal profits we document are remarkably robust over time and the cross-section of stocks.

Our results shed new light on different explanations for the reversal anomaly that have been suggested in the literature. Our finding that net reversal profits persist over the most recent decades in our sample, during which market liquidity dramatically increased, is not supportive of the explanation that reversals are induced by inventory imbalances by market makers and that reversal profits are a compensation for bearing inventory risks. Moreover, our finding that reversal profits are observed among the 500 and even 100 largest stocks is inconsistent with the notion that non-synchronous trading contributes to reversal profits. Our findings do not appear to be inconsistent though with the behavioral argument that investors tend to overreact to information and that stock price reversals originate from transitory changes in demand for immediacy by these impatient traders (Lehmann, 1990; Jegadeesh and Titman, 1995a), although our study does not provide direct support for this hypothesis.

Finally, our findings indicate that in order to generate returns sufficiently large enough to cover trading costs, it is of crucial importance to control factor exposures. Hence, apart from contributing to a better understanding of the origins of the reversal effect, our findings also have important implications for the practical implementation of reversal strategies.

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