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 attributable to trading frictions, liquidity, or non-synchronous trading of stocks and pose a serious challenge to rational asset pricing models.

Keywords: *short-term reversal, dynamic risks, residual returns, trading costs, market efficiency*

JEL Classification: *G11, G12, G14*

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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 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 substantially higher and substantially less volatile than those of a conventional short-term reversal strategy. We construct this strategy by sorting stocks on past month returns adjusted for the stocks' exposures to the Fama-French factors, estimated over a rolling window, and scaled using residual volatility. We document that the reversal strategy earns risk-adjusted returns that are twice as large as those of a conventional reversal strategy. Our results also show that its profitability has been relatively stable over time, including the more recent decades, and that profitability remains significant after incorporating reasonable levels of transaction costs. 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 (see, e.g., Ball *et al.*, 1995; Conrad *et al.*, 1997; and Avramov *et al.*, 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 8 percent per annum net of trading costs.

The large residual reversal profits we document are remarkably robust over time and the cross-section of stocks. When we consider reversal profits over our sample period from January 1929 to December 2008, we find that the residual reversal strategy outperforms the conventional reversal strategy during every single decade in our sample. 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 stocks. 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 ten industries of French (2011).

Our results shed new light on several alternative explanations that have been put forward in the academic literature to rationalize the reversal effect. Our finding that net reversal profits persist over the most recent decades in our sample, during which market liquidity 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 (see, e.g., Jegadeesh and Titman, 1995b). Also, 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 (see, e.g., Lo and MacKinlay, 1990; and Boudoukh *et al.*, 1994) since this explanation implies that reversal profits are concentrated among small-cap stocks. Our results are not inconsistent, however, with the behavioral explanation that market prices tend to overreact to information in the short run (see, e.g., 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 *et al.* (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 (see, e.g., Lesmond *et al.*, 2004; Korajczyk and Sadka, 2004; Avramov *et al.*, 2006; and Chordia *et al.*, 2009) and the contemporaneous work of Da *et al.* (2010) and Hameed *et al.* (2010), 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 examine the comparative strength of both reversal strategies. Section 6 analyses the profitability of both reversal strategies within industries. A robustness test in Section 7 investigates the relation between reversal strategies' dynamic factor exposures and their profitability using a non-parametric approach and Section 8 examines reversal profits and calendar month effects. We conclude in Section 9.

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; $\varepsilon_{i,t}$ 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 $E\left[f_t^i f_t^j\right] = 0$ for $i \neq j$ and $E\left[\left(f_t^k\right)^2\right] = \sigma_{f^k}^2$. In addition, we assume that $Cov\left[f_t^i, f_{t-1}^j\right] = 0$ for $i \neq j$ and $Cov\left[\varepsilon_{i,t}, \varepsilon_{j,t-1}\right] = 0$ for $i \neq j$.

Because of its analytic 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

$$(2) \qquad w_{i,t} = -\frac{1}{N_t}(r_{i,t-1} - \bar{r}_{t-1}),$$

where N_t denotes the number of stocks in the universe at time *t* and $\bar{r}_{t-1} = \frac{1}{N_t}\sum_{i=1}^{N_t} r_{i,t-1}$. The expected exposure of the reversal strategy to the *j*-th factor conditional on the return of the *j*-th factor at time *t*-1 now equals

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

where $\sigma_{\beta^j}^2 = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\beta_i^j - \bar{\beta}^j\right)^2$. Hence, the right-hand side of Equation (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

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

$$= -\sigma_\mu^2 - \Phi - \Lambda_{t-1} - \Psi,$$

where

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

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

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

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

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 in time *t*-1. It is equal to the dynamic factor exposures component, which follows from Equation (3), times the conditionally expected factor returns in 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:

$$(9) \qquad Var[\pi_t] = \frac{1}{N_t^2} Var\left[\sum_{i=1}^{N_t} w_{i,t} r_{i,t}\right]$$

$$= \frac{1}{N_t^2} \sum_{i=1}^{N_t} \left((\mu_i - \overline{\mu}) + \sum_{k=1}^{K} \left(\beta_i^k - \overline{\beta}^k\right) f_{t-1}^k + \left(\varepsilon_{i,t-1} - \overline{\varepsilon}_{t-1}\right) \right)^2 Var[r_{i,t}]$$

Equation (9) implies that if the lagged factor returns are more extreme and factor exposures are of greater magnitude, 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

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

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

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

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

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

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

(13) $$Var[\eta_t] = \frac{1}{N_t^2} Var\left[\sum_{i=1}^{N_t} \gamma_{i,t} r_{i,t}\right]$$

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

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. A final notable difference with the conventional reversal strategy is that the profits of a residual reversal strategy are associated with lower variability as a result of not having factor exposures. Based on our analytical exercise, we expect that a residual reversal strategy outperforms a conventional reversal strategy, especially if factor returns persist. In the subsequent sections we empirically test this conjecture.

3. Empirical analysis

3.1 Data

Our stock return data are obtained from the monthly CRSP Stock database. We select common U.S. stocks listed on the NYSE, AMEX and Nasdaq markets that (i) have a stock price above $1 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 (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 January 1926 to December 2008.

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) (heneceforth, Fama-French) factors. We use the Fama-French factors in our analysis since these factors are widely recognized factors that explain a large portion of the variability in U.S. stock returns. Reversal portfolios are constructed by sorting stocks into decile portfolios at the end of each month based on their returns during that month. The winner portfolio consists of the 10 percent of stocks with the highest returns over the past month and the loser portfolio consists of the 10 percent of stocks with the lowest returns. All portfolios are equally weighted.

Next, we estimate the winner and loser portfolios' exposures to the Fama-French factors at the end of each month by taking the average 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

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

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 Figure 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. The solid line in the figure represents the linearly fitted relation between the beta of the loser portfolio and the market return, and the dashed line represents this relation for the winner portfolio. 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.

[INSERT FIGURE 1 ABOUT HERE]

Likewise, Panels B and Panel C of Figure 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 clearly observe that the conventional reversal strategy also exhibits 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 results of our first empirical analysis 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):

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

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. Since we exclude stocks with a market capitalization below the NYSE median from our analyses, it is not surprising to see that the conventional reversal strategy does not exhibit significant exposures to the *SMB* factor. The results of this analysis not only indicate that the dynamics of the conventional reversal strategy's factor exposures are statistically significant, but also that these exposures explain a significant portion of the strategy's risks. More specifically, the adjusted R-squared of 26 percent for the relatively simple conditional regression model we estimate indicates that roughly one-fourth of the variability in the conventional reversal strategy's returns can be attributed to dynamic factor exposures.

[INSERT TABLE 1 ABOUT HERE]

Our analytical analysis in the previous section showed that persistence in factor returns hurts the profitability of a conventional reversal strategy. At the same time, several authors report persistence in common factor returns (see, e.g., Fisher, 1966; Moskowitz and Grinblatt, 1999; and Chen and De Bondt, 2004). Consistent with these studies we also observe short-term momentum in common factor returns over our sample period. More specifically, over the January 1929 to December 2008 period, the market, size and value factors show positive persistence in 55, 54 and 57 percent 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 is larger than its raw return. The conventional reversal strategy based on total stock returns earns a return of 97 basis points per month, while the strategy's alpha is 121 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 24 basis points per month (121 minus 97). In sum, the results of this empirical analysis clearly 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 deciles 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

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

estimate Equation (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, opposed to noise. This facilitates a better interpretation of the residual as firm-specific information (see Gutierrez and Pirinsky, 2007).[2] The winner (loser) portfolio of the residual reversal strategy consists of the 10 percent of stocks with the highest (lowest) residual returns.

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 Figure 2. The residual reversal strategy clearly succeeds in avoiding dynamic factor exposures. While Figure 1 shows an "X"-shaped relation between the factor exposures and lagged factor returns for the conventional reversal strategy's winner and loser portfolios, such a relation is not observable for the residual reversal strategy's winner and loser portfolios.

[INSERT FIGURE 2 ABOUT HERE]

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 134 basis points per month, which is 37 basis points more than the conventional reversal strategy. Moreover, the alpha of the conventional reversal strategy is 9 basis points per month lower. The coefficient estimates for the three interaction variables are all insignificantly different from zero, indicating that the residual reversal strategy exhibits no dynamic factor exposures. Compared to the conventional reversal strategy, the residual reversal strategy's profits

[2] Our conclusions are not materially effected by the standardization of the residual returns.

are also substantially less volatile. As a result, its Sharpe ratio of 1.28 is more than twice as large as the 0.62 Sharpe ratio of the conventional reversal strategy. Finally, the R-squared value of the conditional regression model in Equation (15) for the residual reversal strategy is close to zero. Hence, we conclude that 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.

3.4 Robustness over time

Our results in the previous subsection are based on the full January 1929 to December 2008 period. We now investigate both reversal strategies' profits over time and in different subperiods. Figure 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 located above the graph corresponding to the conventional reversal strategy (grey) at each point in time. 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.

[INSERT FIGURE 3 ABOUT HERE]

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 of our sample. 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 which 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. The reversal return over these decades of 1.00 percent per month (*t*-statistic of 3.55) is also not much different from the long-run average return of the strategy. The residual reversal effect therefore does not seem to have weakened over time.

[INSERT TABLE 2 ABOUT HERE]

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 stock returns over our full sample period and the period January 1990 to December 2008.[3] For the pre-1990 period we find a return of -0.17 percent per month (with a t-statistic of -0.71), whereas for the period from 1990 onwards we find a return of -0.89 (with a t-statistic of -1.70). It thus appears that the negative impact of a conventional reversal strategy's dynamic factor exposures has increased more than five-fold over the two most recent decades. As the residual component of stock returns still exhibits a large reversal effect over this period, we conclude that 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 not only outperforms the conventional reversal strategy during each decade in our sample in terms of raw returns, but also

[3] More specifically, we construct systematic reversal portfolios by sorting stocks into deciles 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 Equation (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 10 percent of stocks with the highest (lowest) systematic returns, i.e., $\hat{\beta}_i^M RMRF_t + \hat{\beta}_i^{SMB} SMB_t + \hat{\beta}_i^{HML} HML_t$. 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 for the sake of brevity. The results are available upon request.

in terms of risk-adjusted returns. To summarize, our subperiod results show that the residual reversal strategy exhibits a strong performance relative to the conventional reversal strategy, not only in the long run, but also during each of the eight decades in our sample period.

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 *et al.* (2004) and Korajczyk and Sadka (2004) argue that momentum profits are difficult to capture because momentum strategies require frequent rebalancing, while Chordia *et al.* (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 (see, e.g., Ball *et al.*, 1995; Conrad *et al.*, 1997; and Avramov *et al.*, 2006). In particular, Avramov *et al.* (2006) find that stocks with the smallest capitalization and highest illiquidity exhibit the largest reversals. These stocks are also very 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 *et al.* (2006) and most of the related literature, we estimate trading costs using the model of Keim and Madhavan (1997) and 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 over the period of January 1990 to December 2008. 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

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

and

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

respectively, where $C_{i,t}^{Buy}$ $\left(C_{i,t}^{Sell}\right)$ 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; $size_{i,t}$ 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 impose that the trading costs of a single order are 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 1929-2008 sample period. In fact, the return on the conventional reversal strategy is only 18 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 *et al.*

(2006). The residual reversal strategy, however, earns an average gross return of 100 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 70 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 cost prevent profitable execution of a residual reversal strategy. Examining the distribution of trading cost for the cross-section of stocks over time, we find that the 80th percentile corresponds to roughly 60 basis points per roundtrip 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 percent most illiquid stocks in our sample.

[INSERT TABLE 3 ABOUT HERE]

We further evaluate the profitability of reversal strategies by excluding small cap stocks from our sample. Panels B and C of Table 3 show the results for the largest 500 and 100 stocks in our sample, respectively.[4] For both subsamples the net profits of the conventional reversal strategy are not significantly larger than zero. In contrast, with net returns of 67 and 83 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 48 and 50 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 Stock

[4] 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 in our sample.

database and skip the first trading day of each month.[5] The returns over the reversal strategies with a one-day skip are presented in the third column of Table 3. Even after taking trading costs as well as an implementation lag into account when evaluating reversal profits, we find that the residual reversal strategies for the 500 and 100 largest stocks in our sample generate large net profits of 47 and 62 basis points per month, respectively. We can therefore safely conclude that it is very unlikely that real-life frictions such as trading costs and implementation lags prevent the profitable execution of residual reversal strategies.

An important note we would like to make is that our approach to examine the economic significance of reversal profits is likely to be 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. 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 naïve top-minus-bottom decile reversal strategies that are rebalanced at a monthly frequency. In a recent study, De Groot *et al.* (2012) show that applying a more sophisticated portfolio construction algorithm can help to significantly reduce the turnover of reversal strategies without

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

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.

A final observation is that the higher net return of the residual reversal strategy compared to the conventional reversal strategy not only comes from its higher gross expected return, but also from incurring lower trading costs. For example, while the gross return difference between the conventional and residual reversal strategies is 82 basis points per month (= 100 - 18 basis points; see Table 3), the difference in net returns is 96 basis points per month (= 70 + 26 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. Therefore a portfolio that is long-short in the extreme quantiles is typically concentrated in the smallest stocks. However, these stocks are also the most expensive to trade, so this feature of the conventional reversal strategy may be 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. To investigate whether this conjecture is true we consider the decile portfolios' characteristics for both reversal strategies in Table 4.

[INSERT TABLE 4 ABOUT HERE]

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, we observe 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 35 basis points, versus 22 basis points for the residual reversal strategy. Similarly, the single-trip sell costs for loser stocks based on the conventional reversal strategy are 8 basis points, compared to only 4 basis points for the residual reversal strategy.

5. Double-sorted rank portfolios and cross-sectional Fama-MacBeth regressions

In our next analysis we construct double-sorted rank portfolios and perform cross-sectional Fama-MacBeth (1973) regressions to investigate what portion of the predictive power of stocks' total returns can be attributed to the residual component of the return. 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. In this way, we end up with a total of 25 portfolios that all contain an equal number of stocks. For each of these portfolios, we show the portfolios' average returns over the investment month in Panel A of Table 5. Within each total return quintile, the returns are monotonically decreasing over the residual return quintiles. 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.

[INSERT TABLE 5 ABOUT HERE]

Next, we perform a similar double-sorting procedure, but now first sorting stocks into quintiles based on their residual returns and next subdividing the stocks into quintiles based on their total returns. The resulting portfolio returns are shown in Panel B of Table 5. Interestingly, we do not observe any return pattern at all across the portfolios sorted on total stock returns. Hence, after controlling for residual returns, total returns do not appear to have predictive power for future stock returns. This finding is in line with the results of Jegadeesh and Titman (1995a), who report that over- or underreaction to firm-specific information always contributes to the profitability of reversal strategies, while over- or underreaction to the systematic factors can either reduce or increase these profits.

Finally, 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 size and value effects. More specifically, we estimate the following equation every month:

$$\text{(18)} \qquad r_{i,t} = a_t + b_{1,t} r_{i,t-1} + b_{2,t} \hat{\varepsilon}_{i,t-1} + b_{3,t} \ln(size_{i,t-1}) + b_{4,t} btm_{i,t-1} + b_{5,t} TRL_{i,t-1} + b_{6,t} TRW_{i,t-1} + b_{7,t} RRL_{i,t-1} + b_{8,t} RRW_{i,t-1} + u_{i,t},$$

where $\hat{\varepsilon}_{i,t-1}$ is the residual return of stock *i* in month *t*-1 estimated using Equation (14); $size_{i,t-1}$ is the market capitalization of stock *i* in month *t*-1; $btm_{i,t-1}$ denotes the book-to-market ratio of stock *i* in month *t*-1; and $TRL_{i,t\text{-}1}$, $TRW_{i,t\text{-}1}$, $RRL_{i,t\text{-}1}$ and $RRW_{i,t\text{-}1}$ are dummy variables that take the value of one if stock *i* belongs to the total-return loser decile, total-return winner decile, residual-return loser decile and residual-return winner decile, respectively, in month *t*-1 and zero otherwise. Data on firms' book values are obtained from the Compustat database. Since Compustat data are only available as from 1963, this analysis is performed over the January 1963 to December 2008 period.

[INSERT TABLE 6 ABOUT HERE]

The time-series averages of the monthly coefficient estimates are presented in Table 6. For the regression specifications that exclude stocks' lagged residual returns (or dummy variables indicating if a stock belongs to the top or bottom decile of stocks ranked on lagged residual returns) we observe statistically significant loadings on the lagged total return variables, indicating that past month stock returns have predictive power for future stock returns. However, once lagged residual stock returns are included in the regression specifications practically all predictive power disappears. Only for $TRW_{i,t\text{-}1}$ we still observe a significant coefficient estimate. 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.

6. 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 Da *et al.* (2010) and Hameed *et al.* (2010), 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 rank stocks on their total and residual returns over the past month within each of the ten industries of French (2011). The results for both reversal strategies are shown in Table 7, which reports the average monthly returns for both reversal strategies within each industry.

[INSERT TABLE 7 ABOUT HERE]

The full-sample results in Panel A of Table 7 show that residualization not only improves the performance of a conventional reversal strategy, but also the performance of a within-industry reversal strategy. The average return increases from 1.37 to 1.63 percent per month and the Sharpe ratio almost doubles, from 1.11 to 1.99. In fact, we observe that the residualization approach improves the Sharpe ratio within each of the ten different industries. In Panel B of Table 7 we examine the results over the post-1990 period. Comparing these results to those in Table 2 we observe that applying a conventional reversal strategy within industries does little to improve its weak performance over this period, with average returns increasing only marginally from 0.18 to 0.26 percent 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. For the within-industry application raw returns are slightly lower (0.87 percent per month versus 1.00 percent per month), but risk-adjusted returns are slightly higher (Sharpe ratio of 1.03 versus 0.81).

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 each other. 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).

7. 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 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.

[INSERT TABLE 8 ABOUT HERE]

The results of the analysis presented in Table 8 clearly 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 -44 basis point per month. In contrast, when all Fama-French factors revert the conventional reversal strategy earns a highly positive return of 4.58 percent 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 1.12 and 2.13 percent 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.

8. Calendar month effects

In a final analysis, we investigate the performances of the conventional and residual reversal strategies per calendar month. Several authors document strong seasonal patterns in reversal returns (see, 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 Ferris *et al.* (2001) 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. To investigate this issue in more detail, we examine the average monthly returns during each calendar month for the conventional reversal versus the residual reversal strategy. The results of this analysis are presented in Table 9.

[INSERT TABLE 9 ABOUT HERE]

Consistent with the prior literature we observe 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 plus two in only four out of twelve months. By contrast, residual reversal returns have *t*-statistics larger than plus two in ten out of twelve months. Interestingly, when we consider the results of the same analysis for the post-1990 period, it even appears to be the case that the conventional reversal strategy only earns positive returns in January months; the return during non-January months is -0.05 percent. The residual reversal strategy, on the other hand, not only earns positive returns in January months, but also shows large positive returns of 0.84 percent on average in non-January months. We thus conclude that residual reversal strategies are also more robust than conventional reversal strategies during the calendar year.

9. Summary and concluding comments

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 not only increase the risk of a reversal strategy, but also 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 have important implications for different explanations that have been put forward in the academic literature for understanding the reversal anomaly. 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. An explanation that has been put forward in the literature which is not inconsistent with our findings is the behavioral argument that market prices tend to overreact to information in the short run (see, e.g., Jegadeesh and Titman, 1995a). We acknowledge, however, that our study only provides indirect evidence in support of this behavioral hypothesis, by arguing against the competing explanations that have been put forward in the literature.

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 returns sufficiently large enough to cover trading costs it is of crucial importance to control factor exposures.

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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 Equation (15) of the paper. 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 2008 and 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 $1 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
0.97	5.43	0.62
(5.69)		

Alpha	RMRF	SMB	HML	RMRF_UP	SMB_UP	HML_UP	Adj. R^2
1.21	0.45	0.03	0.55	-0.58	-0.03	-1.06	0.26
(7.72)	(5.71)	(0.11)	(4.65)	(-3.38)	(-0.10)	(-7.46)	

Panel B: Residual reversal strategy

Return	Stdev	Sharpe
1.34	3.63	1.28
(11.21)		

Alpha	RMRF	SMB	HML	RMRF_UP	SMB_UP	HML_UP	Adj. R^2
1.30	0.14	-0.02	0.03	-0.03	0.04	-0.09	0.03
(11.50)	(2.21)	(-0.17)	(0.27)	(-0.35)	(0.23)	(-0.63)	

Table 2: **Reversal returns per decade**

This table presents average monthly returns and annualized Sharpe ratios per decade, the pre-1990 period and the post-1990 period for the conventional reversal strategy and the residual reversal strategy. 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 $1 and return data for all preceding 36 months. Newey-West corrected *t*-statistics are reported in parentheses.

	Conventional reversal strategy			Residual reversal strategy		
Time period	Return	*t*-Stat	Sharpe	Return	*t*-Stat	Sharpe
1929-1939	1.41	(1.81)	0.50	1.50	(3.02)	0.92
1940-1949	1.42	(4.43)	1.38	1.59	(7.34)	2.26
1950-1959	0.89	(4.37)	1.30	1.09	(6.20)	1.72
1960-1969	0.98	(4.10)	1.29	1.30	(6.80)	2.16
1970-1979	1.35	(4.33)	1.32	1.61	(7.11)	2.12
1980-1989	1.17	(3.19)	0.96	1.55	(5.12)	1.50
1990-1999	-0.08	(-0.22)	-0.07	0.90	(3.85)	1.13
2000-2008	0.49	(0.73)	0.21	1.15	(2.19)	0.71
1929-1990	1.21	(6.40)	0.82	1.44	(11.53)	1.48
1990-2008	0.18	(0.42)	0.10	1.00	(3.55)	0.81

Table 3: **Reversal returns and trading costs**

This table presents average gross and net monthly returns for 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 Equations (16) and (17) of the paper. 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 2008 and 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 $1 and return data for all preceding 36 months. Newey-West corrected *t*-statistics are reported in parentheses.

Panel A: Above NYSE median	Gross return	Net return	Net return skip day	Break-even	Turnover
Conventional reversal	0.18	-0.26	-0.48	10	174%
	(0.42)	(-0.62)	(-1.13)		
Residual reversal	1.00	0.70	0.36	56	181%
	(3.55)	(2.42)	(1.24)		

Panel B: 500 Large caps	Gross return	Net return	Net return skip day	Break-even	Turnover
Conventional reversal	0.30	0.15	0.04	18	160%
	(0.89)	(0.45)	(0.13)		
Residual reversal	0.79	0.67	0.47	48	165%
	(3.29)	(2.77)	(1.94)		

Panel C: 100 Large caps	Gross return	Net return	Net return skip day	Break-even	Turnover
Conventional reversal	0.31	0.29	0.22	19	161%
	(0.88)	(0.81)	(0.62)		
Residual reversal	0.83	0.81	0.62	50	165%
	(3.11)	(3.03)	(2.32)		

Table 4: **Portfolio characteristics**

This table presents characteristics of the 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 Equation (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 & 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 2008 and 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 $1 and return data for all preceding 36 months.

Panel A: Conventional reversal	Losers	2	3	4	5	6	7	8	9	Winners
Volatility (%)	7.37	5.63	4.77	4.58	4.19	4.20	4.14	4.19	4.45	6.16
$ß^{M}$	1.17	1.04	0.97	0.95	0.95	0.94	0.96	0.99	1.05	1.19
$ß^{SMB}$	0.30	0.18	0.13	0.12	0.12	0.13	0.13	0.17	0.25	0.44
$ß^{HML}$	0.10	0.21	0.25	0.26	0.28	0.27	0.26	0.25	0.20	0.05
Size	4.52	5.22	5.34	5.42	5.46	5.54	5.46	5.46	5.27	4.42
Price ($)	28.89	33.57	35.41	36.71	37.01	37.85	38.36	38.30	38.14	36.40
Buy (%)	0.35	0.21	0.17	0.15	0.15	0.14	0.14	0.15	0.17	0.25
Sell (%)	0.08	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.05

Panel B: Residual reversal	Losers	2	3	4	5	6	7	8	9	Winners
Volatility (%)	5.69	5.34	5.05	4.83	4.84	4.56	4.39	4.31	4.37	4.64
$ß^{M}$	1.02	1.02	1.02	1.02	1.02	1.01	1.01	1.01	1.00	0.99
$ß^{SMB}$	0.17	0.18	0.19	0.19	0.21	0.19	0.20	0.19	0.19	0.20
$ß^{HML}$	0.21	0.20	0.21	0.22	0.24	0.23	0.24	0.23	0.26	0.28
Size	5.27	5.17	5.17	5.06	5.16	5.14	5.16	5.26	5.25	5.27
Price ($)	33.59	34.75	35.32	35.39	35.72	35.98	36.08	36.42	36.98	37.51
Buy (%)	0.22	0.20	0.20	0.20	0.19	0.19	0.18	0.18	0.17	0.17
Sell (%)	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Table 5: **Double-sorted reversal returns**

This table presents average monthly returns on double-sorted rank portfolios based on total returns and residual returns. In Panel A, stocks are first sorted into quintile portfolios based on their total returns and then each total-return quintile is subdivided into quintiles based on the stocks' residual returns. Panel B reports the results using a similar double-sorting procedure, but now stocks are first sorted into quintiles based on their residual returns, and next we subdivide the stocks into quintiles based on their total returns. The sample period is from January 1929 to December 2008 and 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 $1 and return data for all preceding 36 months. Newey-West corrected *t*-statistics are reported in parentheses.

Panel A: Controlling for total returns

		Residual return						
		Losers	2	3	4	Winners	L-W	*t*-Stat
Total return	Losers	1.63	1.36	1.33	1.20	0.97	0.66	(4.86)
	2	1.45	1.24	1.09	1.04	0.83	0.62	(4.36)
	3	1.31	1.12	1.00	1.02	0.66	0.66	(4.55)
	4	1.29	1.06	0.91	0.79	0.41	0.87	(5.98)
	Winners	1.03	0.82	0.64	0.34	-0.06	1.10	(7.28)
	Average	1.34	1.12	0.99	0.88	0.56	0.78	(7.23)

Panel B: Controlling for residual returns

		Total return						
		Losers	2	3	4	Winners	L-W	*t*-Stat
Residual return	Losers	1.41	1.43	1.37	1.52	1.38	0.03	(0.17)
	2	1.14	1.07	1.14	1.25	1.34	-0.20	(-1.03)
	3	0.95	0.89	1.06	1.12	1.15	-0.20	(-1.12)
	4	0.78	0.89	0.83	0.96	0.93	-0.14	(-0.72)
	Winners	0.44	0.51	0.43	0.28	0.22	0.23	(1.33)
	Average	0.95	0.96	0.97	1.02	1.00	-0.06	(-0.38)

Table 6: **Cross-sectional Fama-MacBeth (1973) regressions**

This table presents time-series averages of monthly coefficient estimates (multiplied by 100) that follow from cross-sectional Fama and MacBeth (1973) type of regressions. The dependent variable is the monthly excess stock return. Independent variables are the one-month lagged stock return, the one-month lagged residual stock return (estimated using Equation 14 of the paper), the one-month lagged log market capitalization of the stock, the one-month lagged book-to-market ratio and four dummy variables that take the value of one if the stock belongs to the total-return loser decile, total-return winner decile, residual-return loser decile and/or residual-return winner decile in the previous month and zero otherwise. The sample period is from January 1963 to December 2008 and 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 $1 and return data for all preceding 36 months. Newey-West corrected *t*-statistics are reported in parentheses.

	Excluding previous month (residual) return			Including previous month (residual) return		
	Total	Residual	Both	Total	Residual	Both
Intercept	0.48	0.45	0.46	0.52	0.43	0.42
	(1.83)	(1.60)	(1.76)	(2.02)	(1.56)	(1.80)
$r_{i,t-1}$				-3.87		1.11
				(-7.83)		(0.74)
$\hat{\varepsilon}_{i,t-1}$					-3.90	-5.41
					(-8.89)	(-3.89)
ln(Size)	-0.06	-0.06	-0.07	-0.06	-0.06	-0.05
	(-1.67)	(-1.59)	(-1.77)	(-1.55)	(-1.51)	(-1.50)
Book-to-Market	0.31	0.34	0.33	0.31	0.35	0.34
	(2.75)	(2.82)	(2.98)	(2.82)	(2.97)	(3.42)
Total Return Loser Dummy	0.53		0.15	-0.12		-0.15
	(4.10)		(1.03)	(-1.37)		(-1.51)
Total Return Winner Dummy	-0.72		-0.32	0.00		0.07
	(-5.28)		(-2.14)	(-0.04)		(0.59)
Residual Return Loser Dummy		0.78	0.70		0.24	0.27
		(10.21)	(9.11)		(3.66)	(3.50)
Residual Return Winner Dummy		-0.88	-0.67		-0.30	-0.28
		(-10.09)	(-8.74)		(-5.16)	(-4.21)
Adjusted R^2	0.03	0.03	0.04	0.04	0.03	0.05

Table 7: **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. In Panel A, the sample period is from January 1929 to December 2008 and Panel B presents results for the sample period starting from January 1990 to December 2008. 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 $1 and return data for all preceding 36 months. Newey-West corrected *t*-statistics are reported in parentheses.

Panel A: January 1929 to December 2008

	Conventional reversal			Residual reversal		
Industries	Return	*t*-Stat	Sharpe	Return	*t*-Stat	Sharpe
Consumer non durables	1.27	(6.69)	0.75	1.67	(10.00)	1.12
Consumer durables	0.85	(2.88)	0.32	1.33	(5.25)	0.59
Manufacturing	1.71	(9.75)	1.09	1.88	(13.07)	1.46
Energy	1.71	(6.93)	0.77	1.50	(7.01)	0.78
HiTec	0.34	(1.21)	0.14	0.93	(3.91)	0.44
Telecom	0.97	(2.03)	0.30	1.12	(2.55)	0.39
Shops	1.60	(7.10)	0.79	2.06	(10.59)	1.18
Health	1.42	(4.59)	0.58	2.13	(7.69)	0.99
Utilities	2.04	(7.04)	0.79	1.94	(9.04)	1.01
Other	1.18	(5.79)	0.65	1.29	(7.43)	0.83
Within industries	1.37	(9.90)	1.11	1.63	(17.76)	1.99

Panel B: January 1990 to December 2008

	Conventional reversal			Residual reversal		
Industries	Return	*t*-Stat	Sharpe	Return	*t*-Stat	Sharpe
Consumer non durables	0.96	(2.46)	0.56	1.52	(4.45)	1.02
Consumer durables	0.92	(1.49)	0.34	0.86	(1.61)	0.37
Manufacturing	0.65	(1.48)	0.34	1.20	(3.76)	0.86
Energy	-0.54	(-1.10)	-0.25	-0.49	(-1.10)	-0.25
HiTec	-0.89	(-1.54)	-0.35	0.23	(0.50)	0.11
Telecom	0.73	(0.88)	0.20	1.28	(1.73)	0.40
Shops	0.40	(0.96)	0.22	1.18	(3.51)	0.80
Health	0.40	(0.62)	0.14	1.04	(2.03)	0.46
Utilities	0.12	(0.25)	0.06	0.28	(0.83)	0.19
Other	0.87	(2.54)	0.58	1.21	(5.56)	1.28
Within industries	0.26	(0.96)	0.22	0.87	(4.48)	1.03

Table 8: **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 2008 and 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 $1 and return data for all preceding 36 months. *t*-Statistics are reported in parentheses.

	Conventional reversal		Residual reversal		
	Return	*t*-Stat	Return	*t*-Stat	Probability
All 3 factors persist	-0.44	(-1.18)	1.54	(5.49)	0.20
1 factor reverts	-0.06	(-0.19)	1.12	(6.40)	0.37
2 factors revert	1.62	(6.27)	1.16	(5.83)	0.30
All 3 factors revert	4.58	(8.20)	2.13	(5.14)	0.12

Table 9: **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 2008 in Panel A. Panel B presents average January returns and non-January returns for the sample period starting from January 1990 to December 2008. 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 $1 and return data for all preceding 36 months. *t*-Statistics are reported in parentheses.

Panel A: January 1929 to December 2008

	Conventional reversal		Residual reversal	
Month	Return	*t*-Stat	Return	*t*-Stat
January	3.35	(5.56)	2.75	(6.62)
February	0.79	(1.41)	1.41	(3.55)
March	1.49	(2.20)	1.86	(3.35)
April	0.21	(0.44)	0.49	(1.77)
May	0.43	(1.05)	1.13	(3.98)
June	1.61	(2.36)	1.33	(3.27)
July	1.84	(3.47)	1.87	(3.56)
August	0.25	(0.28)	1.16	(3.62)
September	0.59	(1.13)	0.88	(2.29)
October	0.84	(1.37)	1.32	(2.77)
November	-0.43	(-0.77)	0.58	(1.75)
December	0.60	(1.07)	1.32	(3.70)

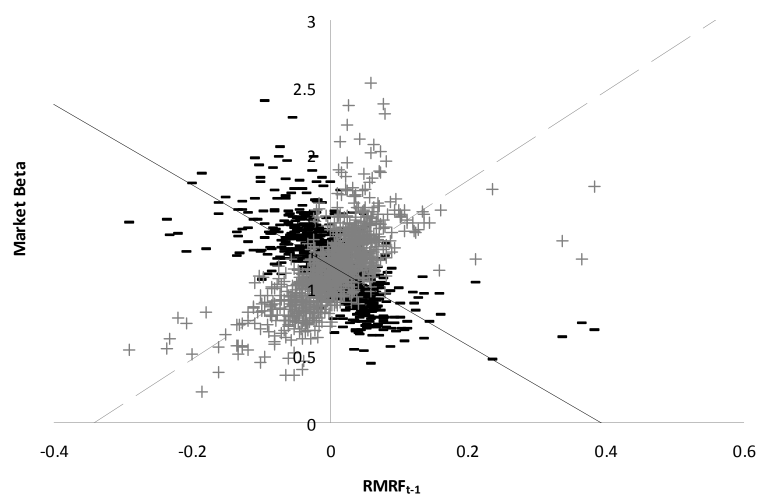
Panel B: January 1990 to December 2008

	Conventional reversal		Residual reversal	
Month	Return	*t*-Stat	Return	*t*-Stat
January	2.82	(1.92)	2.95	(3.55)
Non-Januaries	-0.05	(-0.12)	0.84	(2.80)

Figure 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 and Panel 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 in the figure represents the linearly fitted relation between the factor exposure of the loser portfolio and the factor return and the dashed line represents this relation for the winner portfolio. The sample period is from January 1929 to December 2008 and 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 $1 and return data for all preceding 36 months.

Panel A: Market Factor



Panel B: SMB Factor

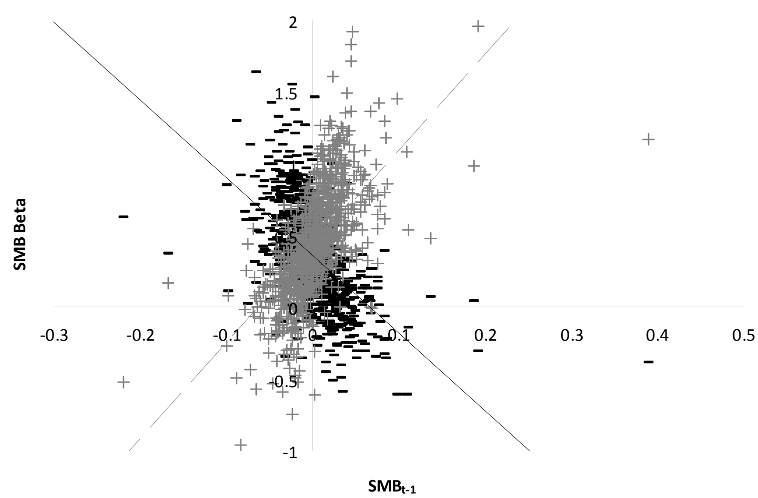


Figure 1 (continued): **Formation period loadings of the conventional reversal strategy**

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 and Panel 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 in the figure represents the linearly fitted relation between the factor exposure of the loser portfolio and the factor return and the dashed line represents this relation for the winner portfolio. The sample period is from January 1929 to December 2008 and 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 $1 and return data for all preceding 36 months.

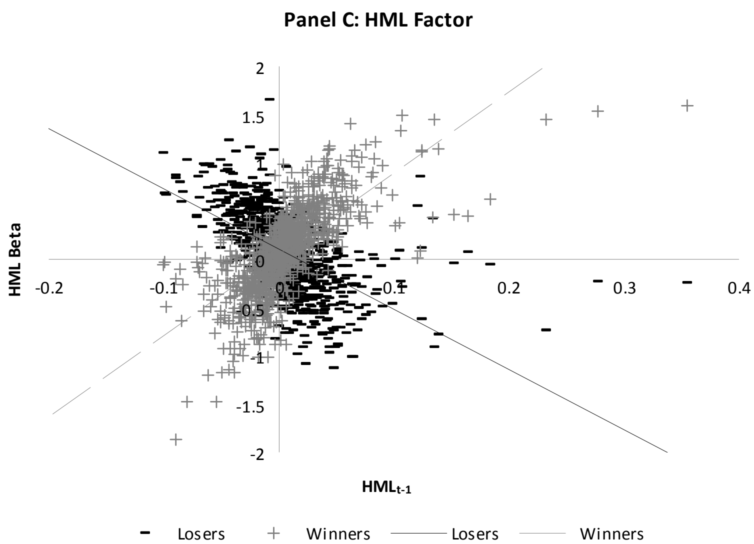
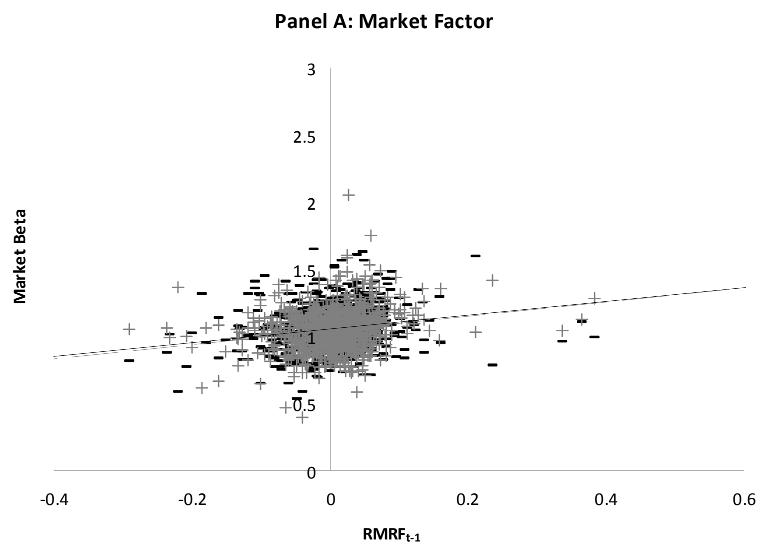


Figure 2: **Formation period loadings of the residual reversal strategy**

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 and Panel 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 in the figure represents the linearly fitted relation between the factor exposure of the loser portfolio and the factor return and the dashed line represents this relation for the winner portfolio. The sample period is from January 1929 to December 2008 and 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 $1 and return data for all preceding 36 months.



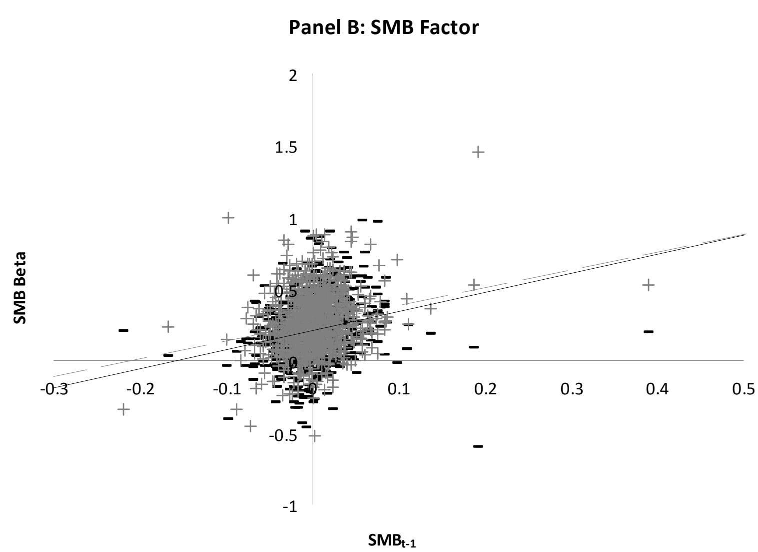


Figure 2 (continued): **Formation period loadings of the residual reversal strategy**

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 and Panel 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 in the figure represents the linearly fitted relation between the factor exposure of the loser portfolio and the factor return and the dashed line represents this relation for the winner portfolio. The sample period is from January 1929 to December 2008 and 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 $1 and return data for all preceding 36 months.

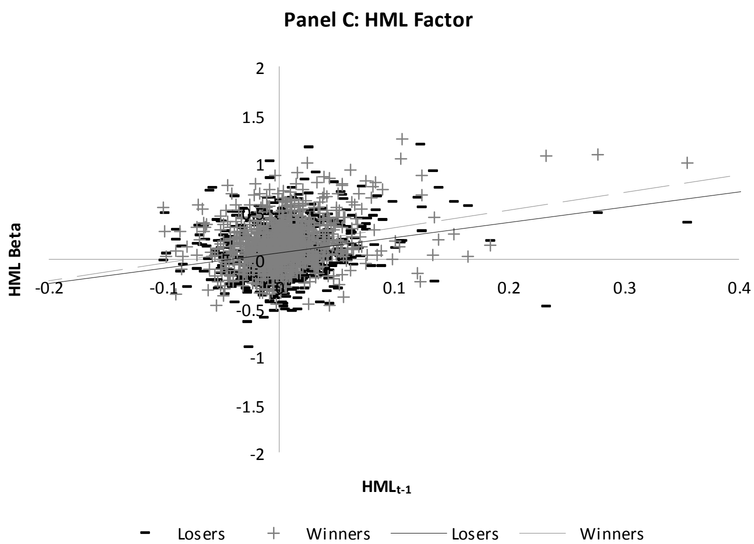


Figure 3: **Cumulative reversal returns**

This figure plots the cumulative returns from January 1929 to December 2008 for a hypothetical $1 invested in the conventional reversal strategy (grey) 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 $1 and return data for all preceding 36 months.