ANOTHER LOOK AT TRADING COSTS AND SHORT-TERM REVERSAL PROFITS

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ABSTRACT

Several studies report that abnormal returns associated with short-term reversal investment strategies diminish once transaction costs are taken into account. We show that the impact of transaction costs on the strategies' profitability can largely be attributed to excessively trading in small cap stocks. Limiting the stock universe to large cap stocks significantly reduces trading costs. Applying a more sophisticated portfolio construction algorithm to lower turnover reduces trading costs even further. Our finding that reversal strategies can generate 30 to 50 basis points per week net of transaction costs poses a serious challenge to standard rational asset pricing models. Our findings also have important implications for the understanding and practical implementation of reversal strategies.

JEL Classification: G11, G12, G14

***Keywords**: market efficiency, anomalies, short-term reversal, portfolio construction, market impact, transaction costs, liquidity*

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Several studies report that abnormal returns associated with short-term reversal investment strategies diminish once transaction costs are taken into account. We show that the impact of transaction costs on the strategies' profitability can largely be attributed to excessively trading in small cap stocks. Limiting the stock universe to large cap stocks significantly reduces trading costs. Applying a more sophisticated portfolio construction algorithm to lower turnover reduces trading costs even further. Our finding that reversal strategies can generate 30 to 50 basis points per week net of transaction costs poses a serious challenge to standard rational asset pricing models. Our findings also have important implications for the understanding and practical implementation of reversal strategies.

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1. INTRODUCTION

A growing body of literature argues that the short-term reversal anomaly documented by Rosenberg, Reid, and Lanstein (1985), Jegadeesh (1990) and Lehman (1990) can be attributed to trading frictions in securities markets that weaken the arbitrage mechanism. Kaul and Nimalendran (1990), Conrad, Kaul and Nimalendran (1991) and Ball, Kothari, and Wasley (1995) report that most of short-term reversal profits fall within bid-ask bounds. And more recently, Avramov, Chordia and Goyal (2006) evaluate the profitability of reversal investment strategies net of transaction costs using the model of Keim and Madhavan (1997). They find that reversal strategies require frequent trading in disproportionately high cost securities such that trading costs prevent profitable strategy execution. Based on these results one might conclude that the abnormal returns associated with reversal investment strategies that are documented in earlier studies create an illusion of profitable investment strategies when, in fact, none exist. The seemingly lack of profitability of reversal investment strategies is consistent with market efficiency.

In this study we show that this argument is not necessarily true. We argue that the reported impact of transaction costs on reversal strategies' profitability can largely be attributed to excessively trading in small cap stocks. When stocks are ranked on past returns, stocks with the highest volatility have the greatest probability to end up in the extreme quantiles. These stocks are typically the smallest stocks. Therefore a portfolio that is long-short in the extreme quantiles is typically invested in the smallest stocks. However, these stocks are also the most expensive stocks to trade. Even though the gross returns of reversal strategies are larger among small cap than large cap stocks, the higher returns earned on small cap stocks is fully diminished by their disproportionally higher trading costs.

At the same time, the turnover of standard reversal investment strategies is excessively high. Reversal portfolios are typically constructed by taking a long position in loser stocks and short position in winner stocks based on past returns. Then, at a pre-specified interval the portfolios are rebalanced and stocks that are no longer losers are sold immediately and replaced by newly bottom-ranked stocks. Vice versa, stocks that are no longer winners are bought back and replaced by newly top-ranked stocks. While this approach is standard in the stream of literature on empirical asset pricing to investigate stock market anomalies, it is suboptimal when the profitability of an investment strategy is evaluated and transaction costs are incorporated since the costs involved with rebalancing the portfolio are often larger than the resulting increases in gross returns.

We show that taking these two issues into account when constructing stock portfolios to engage in reversal trading has a tremendous impact on the returns that reversal strategies deliver net of transaction costs. In our study we use trading cost estimates resulting from the Keim and Madhavan (1997) model and estimates that were provided to us by Nomura Securities, one of world's largest stock brokers. Consistent with Avramov, Chordia and Goyal (2006) we find that the profits of a standard reversal strategy are smaller than the likely transactions costs. A reversal investment strategy that is long in the 10 percent of the 1,500 largest U.S. stocks with the lowest one-week returns and short in the 10 percent with the highest returns earns a gross return of 92.9 basis points per week at a daily rebalancing period over the period

January 1990 to December 2009. However, once transaction costs are taken into account the profitability of this reversal strategy completely diminishes and even becomes negative.

The impact of trading costs on the short-term reversal profits becomes substantially lower once we exclude small cap stocks that are the most expensive to trade and focus on the 500 largest U.S. stocks. When we at the same time apply a slightly more sophisticated portfolio construction algorithm and do not directly sell (buy back) stocks that are no longer losers (winners) and wait until these stocks are ranked among the top (bottom) 50 percent of stocks based on past returns, the turnover and transaction costs of the strategy more than halve. While the gross return of this “smart” reversal strategy is close to that of the standard strategy, its return net of transaction costs is substantially larger with more than 30 basis points per week. This number is highly significant from both a statistical and an economic point of view. In fact, when we evaluate the performance of the reversal strategy using exclusively large cap stocks focussing on the 100 largest U.S. stocks, we even find net returns of more than 50 basis points per week.

In addition, we look at various other aspects of the reversal strategy to evaluate if the strategy can be applied in practice. Amongst others, we document that the reversal effect can be exploited by a sizable strategy employing a capital of USD 150 million; and that the strategy also earned large positive net returns over the post-decimalization era of U.S. stock markets.

Our results based on U.S. stock data appear to carry over to the European equity market. When we investigate the impact of excluding small cap stocks and limiting the turnover for reversal investment strategies using European stock data, we find very similar results: while standard reversal strategies based on the 1,000 or 600 largest European stocks yield gross returns over 80 basis points per week, their returns net of trading costs are highly negative. Once we exclusively focus on the 100 largest stocks and apply the “smart” portfolio construction, we document significantly positive net reversal profits up to 20 basis points per week.

We deem that our study contributes to the existing literature in at least two important ways. First of all, this study adds to the vast amount of literature on short-term reversal or contrarian strategies [see, e.g., Fama (1965), Jegadeesh (1990), Lehmann (1990), Lo and MacKinlay (1990), Jegadeesh and Titman (1995a,b), Chan (2003), Subrahmanyam (2005), and Gutierrez and Kelley (2008)]. Our work is also related and contributes to a recent strand in the literature that reexamines market anomalies after incorporating transaction costs [see, e.g., Lesmond, Schill, and Zhou (2004), Korajczyk and Sadka (2004), Avramov Chordia and Goyal (2006) and Chordia, Goyal, Sadka, Sadka, and Shivakumar, (2009)]. Our finding that reversal investment strategies yield significant returns net of transaction costs presents a serious challenge to standard rational asset pricing models. Our findings also have important implications for the practical implementation of reversal investment strategies. The key lesson is that investors striving to earn superior returns by engaging in reversal trading are more likely to realize their objectives by using portfolio construction rules that limit turnover and by trading in liquid stocks with relatively low transaction costs.

Our results also have important implications for several explanations that have been put forward in the literature to explain the reversal anomaly. In particular, our finding that net reversal profits are large and positive among large cap stocks over the most recent decade in our sample, during which market liquidity dramatically increased, rules out the explanation that reversals are induced by inventory imbalances by market makers and that the contrarian profits are a compensation for bearing inventory risks [see, e.g., Jegadeesh and Titman (1995b)]. Also, our finding that reversal profits are not convincingly larger for the 1,500 largest U.S. stocks than for the 500 and even 100 largest stocks is inconsistent with the notion that nonsynchronous trading contributes to contrarian profits [see, e.g., Lo andMacKinlay (1990) and Boudoukh, Richardson, and Whitelaw (1994)] as this explanation predicts a size-related lead-lag-effect in stock returns and higher reversal profits among small cap stocks.

Our second main contribution is that we not only employ the transaction costs estimates from the Keim and Madhavan (1997) model that are typically used in this stream of literature, but that we also use estimates that were provided to us by Nomura Securities. Despite the fact that most researchers now seem to acknowledge the importance of taking transaction costs into account when evaluating the profitability of investment strategies, only very little is documented in the academic literature on how these costs should be modelled. Perhaps the most authoritative research in this field is the work of Keim and Madhavan (1997) who modelled market impact as well as commission costs for trades for NYSE-AMEX stocks during 1991 to 1993. However, since markets have undergone important changes over time (e.g., quotation in decimals, increases in trading volumes, more competition among brokers, technological improvements) one may wonder whether the parameter estimates of Keim and Madhavan can be used to estimate transaction costs accurately also over more recent periods. Another concern with the Keim and Madhavan model relates to the functional form that is imposed on the relation between market capitalization and transaction costs. This functional form may cause estimates for both the largest and the smallest stocks in the cross-section to be biased downwards. Later in the paper we provide some detailed examples which indicate that trading costs estimates resulting from the Keim and Madhavan model should be interpreted with caution in some cases. For example, the model systematically yields negative cost estimates for a large group of stocks over the most recent period. We believe that our study makes a significant contribution to the literature on evaluating the profitability of investment strategies by providing a comprehensive overview of transaction costs estimates for S&P1500 and S&P500 stocks during the period 1990 to 2009 obtained from Nomura Securities. Moreover, the trading cost schemes we publish in this study are set up in such a way that other researchers can employ them in their studies as the schemes merely require readily-available volume data for their usage.

An additional attractive feature of the trading cost model we obtained from Nomura Securities is that it has also been calibrated using European trade data. This enables us to investigate trading costs and reversal profits in European equity markets. To our best knowledge, this study is the first to provide a comprehensive overview of trading costs and to investigate trading cost impact on the profitability of short-term reversal investment strategies in European equity markets.

In what follows, Section 2 describes our data and transaction cost estimates. Section 3 the way we construct our reversal portfolios and our main empirical results. Section 4 discusses the results for European equity markets. Section 5 documents the results of several robustness checks. Finally Section 6 summarizes and concludes.

2. DATA

This section describes the stock data and transaction cost estimates that are used throughout our study.

2.1 U.S. stock data

We use return data for the 1,500 largest stocks that were constituents of the Citigroup US Broad Market Index (BMI) during the period January 1990 and December 2009. This sample roughly corresponds to the 75 percent largest stocks in the CRSP universe over the same time period. We intentionally leave out micro cap stocks from our sample that are sometimes included in other studies to ensure that our findings are not driven by market micro-structure concerns. Daily stock returns including dividends, market capitalizations and price volumes are obtained from FactSet. Table 1 presents an overview of the distributions of the stocks' market capitalization, daily trading volumes, and turnover over our sample period. Trading volumes and turnover are median values over the past three months. In addition, we compute Amihud's (2002) illiquidity measure for the stocks and present its distribution in Table 1.

[INSERT TABLE 1 ABOUT HERE]

Panel A in Table 1 shows the distributions of the stocks' market capitalization. We observe a large increase in market capitalization over time. While the median market capitalization was USD 300 million in 1990, this figure increased to USD 1.4 billion in 2009. On average, the 5 percent smallest stocks in our sample have a market capitalization of USD 400 million, while the largest stocks have a market capitalization of USD 17.1 billion. For comparison, the 25th percentile of market capitalization of NYSE stocks is USD 390 million over the period January 1990 to December 2009.

Panel B in Table 1 shows the distributions of the stocks' trading volumes. Consistent with French (2008) we document a tremendous increase in trading volumes over time. While the median trading volume was USD 0.8 million per day in 1990, this figure increased to 18.7 million in 2009; an increase of more than 2400 percent. The median trading volume over our sample period is 9.4 million USD per day. For the 5 percent of most heavily traded stocks we even find a median trading volume of USD 120.8 million per day. For comparison, in the study of Avramov, Chordia and Goyal (2006) the most liquid group of stocks (i.e., stocks with below median illiquidity and turnover; see Table 6 of their study) has an average daily trading volume of USD 10.6 million, while the least liquid stocks have an average daily trading volume of USD 0.15 million.

When we consider the stocks' illiquidity in Panel C of Table 1, it appears that illiquidity decreased dramatically over time. While the median illiquidity measure was 0.02 in 1990 this figure decreased to 0.001 in 2009. Avramov, Chordia and Goyal (2006) report this figure to be 0.05 for the most liquid group of stocks in their sample. For the least liquid group of stocks the authors even report average illiquidity of 10.8. This figure basically implies that the price impact resulting from trading one million USD in these stocks is roughly 10 percent. We do not observe such large numbers for illiquidity in our sample. The largest value we observe is 0.386 for the 95th percentile of stocks in 1991. We therefore conclude that illiquidity plays a less important role in our study than in that of Avramov, Chordia and Goyal (2006) whose sample period goes back to the 1960s.

Finally, in Panel D of Table 1 the distribution of the stocks' turnover is displayed. The fact that volumes increased to a larger extent than market capitalization caused turnover to increase over time as well. Still, the turnover figures are very low with a median value of 0.6 percent in our sample. For comparison, in the study of Avramov, Chordia and Goyal (2006) the least liquid group of stocks have an average turnover of 0.47 percent.

All in all, compared to the sample studied by Avramov, Chordia and Goyal (2006) our sample seems to be much more liquid. We believe that the largest portion of this difference can be attributed to the fact that we investigate a more recent period of time during which markets were much more liquid. In addition, our sample does not include micro cap stocks.

2.2 Transaction cost estimates

Consistent with most of the literature we use the transaction costs estimates of Keim and Madhavan (1997) to estimate net returns of reversal investment strategies for our first analyses. Keim and Madhavan estimate the trading costs for 21 institutions from January 1991 through March 1993 using 62,333 trades. Their trading cost estimates include commissions paid as well as an estimate of the price impact of the trades. Keim and Madhavan regress total trading costs on several characteristics of the trade and the traded stock.

As Avramov, Chordia and Goyal (2006) do in their study, we employ the regression results of Keim and Madhavan to estimate the transaction costs involved with reversal investment strategies. Using the results in Table 5 of Keim and Madhavan (1997) we obtain our estimates of buyer and seller trading costs:

(1) $$\hat{C}^{Buy}{}_i = 0.767 + 0.336 D^{NASDAQ} + 0.092 \frac{1}{mcap_i} Trsize_i - 0.084 \log mcap_i + 13.807 \left(\frac{1}{P_i} \right)$$

(2) $$\hat{C}^{Sell}{}_i = 0.505 + 0.058 D^{NASDAQ} + 0.214 \frac{1}{mcap_i} Trsize_i - 0.059 \log mcap_i + 6.537 \left(\frac{1}{P_i} \right)$$

where $\hat{C}^{Buy}{}_i$ and $\hat{C}^{Sell}{}_i$ are the estimated total trading costs for stock *i* in percent for either a buyer-initiated or seller-initiated order, respectively. D^{NASDAQ} is equal to one if stock *i* is a NASDAQ-traded stock and zero if stock *i* is traded on NYSE or AMEX, $mcap_i$ is the market value of outstanding stock *i*, $Trsize_i$ is the trade size of stock *i*, and P_i is the price per share of stock *i*. For our long portfolios we use $\hat{C}^{Buy}{}_i$ to open the positions in the component stocks and $\hat{C}^{Sell}{}_i$ to close the positions, vice versa for the short portfolios.

An important caveat that should be taken into account when using the Keim and Madhavan (1997) model to estimate trading costs is that the coefficients are based on the period January 1991 through March 1993. Since markets have undergone important changes over time one may wonder if the parameter estimates resulting from the Keim and Madhavan model are suitable to estimate transaction costs accurately over more recent periods. For example, after two centuries pricing in fractions, the NYSE and AMEX converted all of its stocks to decimal pricing in 2001 which led to a large decrease in bid-ask spreads on both exchanges. Also, increasing trading volumes over time; more competition among stock brokers; and technological improvements may have had an important impact on bid-ask spreads, market impact costs and commissions.

To cope with this issue, we asked one of world's largest stock brokers, Nomura Securities, if they could provide us with transaction cost estimates for stocks that are constituents of the S&P1500 index over our sample period 1990 through 2009. The model developed by Nomura estimates transaction costs by decomposing them into three components. The first component is the instantaneous impact due to crossing the bid-ask spread. For instance, if one always bought on ask and sold on bid, the instantaneous impact should be approximately half ask-bid spread. However, this impact is often less than that due to the possibility to passively execute fraction of the trade size. The second component in the Nomura model is the permanent impact which is the change in market equilibrium price due to executing a trade. It accumulates over time thus affecting all subsequent orders. Finally, the third component is the temporary impact which refers to a temporary movement of price away from equilibrium price because of short-term imbalances in supply and demand. This component depends heavily on trading strategy and duration, and affects the subsequent orders and decay to zero after the trade. The model does not take opportunity costs into account that result from unfilled trades. As estimates for broker commissions a 5 basis points rate per trade is used during the 1990s and a 3 basis points rate over the most recent 10 years of our sample period. The decrease in commissions reflects the trading landscape becoming more competitive in the last decade.

The variables that are assumed to determine trading costs in the model developed by Nomura are spread, trade size, volume and volatility:

$$(3)\quad \hat{C}_i = a + b_1 spread_i + b_2 \frac{1}{volume_i^{\,2}} Trsize_i + b_3 volatility_i + \varepsilon_i$$

where $spread_i$ is the average bid-ask spread of stock *i* over the trade period, $volume_i$ is the total executed volume for stock *i* over the trade horizon, $Trsize_i$ is the trade size of stock *i* over the trade horizon, and $volatility_i$ the intra-day volatility of stock *i* over the trade horizon. The Nomura trading cost model is calibrated in every quarter over the period 1995 to 2009. For each calibration, actual order flows in the previous 12 months for approximately 500,000 executed trades per time are used from the trading platform formerly owned by Lehman Brothers. The calibration is done per region and exchange to take differing transaction costs across exchange into account.

We asked the researchers of Nomura to provide us with aggregated data in the form of average trading costs for decile portfolios of S&P1500 stocks sorted on their trading volumes in each quarter during the period January 1990 to December 2009 using this model. Trading cost estimates for an individual stock can now be derived using the stock’s volume rank at a particular point in time. An attractive feature of this approach is that it only requires readily-available volume data, and not proprietary intraday data. The trading cost schemes we publish in this study also enable other researchers to employ the Nomura trading cost estimates in their studies.

Because the S&P1500 Index started in 1995, we asked the researchers of Nomura to backfill their series of transaction cost estimates using the 1,500 largest stocks that are constituents of the Russell Index over the period January 1990 to December 1994. We also asked them to assume that the trades are closed within one day and the trade size is one million USD per stock by the end of 2009. The trade size is deflated back in time with 10 percent per annum. The assumption of such a large trade size ensures that any effects we document can be exploited by a sizable strategy. For example, a strategy that is long-short in the losers and winners of the largest 1,500 U.S. stocks and trades one million USD per stock employs a capital of USD 150 million by the end of 2009. We use the same trade sizes when using the Keim and Madhavan (1997) model to estimate transaction costs.

Consistent with the approach of Keim and Madhavan (1997), the model of Nomura also adjusts for the relevant exchange by estimating the model coefficients per region and exchange. An important difference with the Keim and Madhaven approach, however, is that all coefficients of the Nomura model might be different for NYSE-, AMEX-, or NASDAQ-traded stocks. With the Keim and Madhaven approach only the intercept is different for stocks trading at different exchanges.

Also, the researchers at Nomura told us that they do not observe different costs for buy or sell transactions. So unlike the Keim and Madhavan (1997) model, the Nomura model does not differentiate between buy and sell transactions.

An additional interesting difference with the approach of Keim and Madhavan (1997) is that the researchers of Nomura assume an inverse quadratic relation between trading volume and transaction costs. Because there is a strong positive correlation between trading volume and market capitalization, the relation between trading volume and transaction costs also implies an inverse quadratic relation between stocks' market capitalization and transaction costs. With the approach of Keim and Madhavan, however, a logarithmic relation is imposed between stocks' market capitalization and transaction costs. An attractive feature of the quadratic relation over the logarithmic relation is that it captures the stylized fact that transaction costs asymptotically converge to a certain minimum. As we will see later, an important consequence of imposing a quadratic relation is that transaction cost estimates cannot become negative for the largest stocks.

And finally, a notable difference we observe between the Keim and Madhaven (1997) model and the Nomura model is that the Keim and Madhaven model incorporates stock price. We believe that this difference can be explained by the fact that Keim and Madhaven also include a significant number of small cap penny stocks in their analysis for which the inclusion of their prices might be relevant (especially during the pre-decimalization era in U.S. stock markets).

Another important aspect that came to light in the conversations with the researchers from Nomura is that trading style may have a significant impact on transaction 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 transaction costs than traders whose strategies demand less immediacy like value traders or index managers. The researchers of Nomura told us that the transaction costs that are associated with a reversal investment strategy are likely to be somewhat lower than the estimates they provided since a reversal strategy by nature buys (sells) stocks for which the market supply (demand) is larger than the demand (supply). However, they could not provide us with an exact number to correct for this feature of reversal investment strategies. Keim and Madhavan also do not consider differential costs for liquidity providers like reversal traders in their study. To be conservative we therefore assume that there is no liquidity-provision premium involved with reversal trading.

Table 2 presents an overview of the transaction estimates we received from Nomura for S&P1500 stocks. For comparison, the table also lists the estimates for our sample of the 1,500 largest U.S. stocks resulting from the Keim and Madhavan model.

[INSERT TABLE 2 ABOUT HERE]

The table presents the average single-trip costs of buy and sell transactions in basis points for each year in our sample for decile portfolios of stocks sorted on their three-month median dollar trading volume. The shaded areas in the table mark the periods over which the employed transaction cost models are calibrated.

Panel A of Table 2 reports the average cost estimates for buy and sell transactions resulting from the Keim and Madhavan (1997) model. The cost estimates for our sample of stocks during the period 1991 to 1993 seem to be close to the estimates reported by Keim and Madhavan on aggregate. For example, for trades in NYSE and AMEX stocks with sizes below 0.16 percent of total market capitalization, Keim and Madhavan report average buy trade costs ranging from 23 to 39 basis points (see Table 3 of their paper). For comparison, the median trade size in our sample varies between 0.04 and 0.05 percent of total market capitalization over 1991 to 1993 and we find average single-trip transaction costs ranging between 22 to 39 basis points for volume deciles 5 and 6 in Panel A of Table 2 of our paper. However, there are also a few notable observations. First of all, we find negative cost estimates for the most liquid stocks with the largest trading volumes. The number of stocks with negative transaction cost estimates also increases over time. In fact, the Keim and Madhavan model yields negative cost estimates for almost half of the stocks in our sample during 2007.

Panel B of Table 2 reports the transaction cost estimates that were provided to us by Nomura for S&P1500 stocks. Interestingly, Nomura's cost estimates appear not only to be higher for the most liquid stocks with the highest trading volumes, but also for the least liquid stocks with the lowest trading volumes. For these stocks the cost estimates of Nomura can be up to six times higher than those resulting from the Keim and Madhavan (1997) model. At the same time the median transaction cost estimates are higher for the Keim and Madhavan model.

[INSERT FIGURE 1 ABOUT HERE]

We offer the following explanations for the differences between transaction cost estimates resulting from the Keim and Madhavan model and the Nomura model. First of all, the differences may be caused by the fact that the model of Nomura imposes a quadratic relation between trading volume and transaction costs. For example, as illustrated in Figure 1, if transaction costs indeed asymptotically converge to a certain minimum when trading volumes increase and the relation is fitted using a logarithmic function as in the Keim and Madhavan model, both cost estimates for stocks with relatively high and low trading volumes are biased downwards. In fact, cost estimates for stocks with relatively high trading volumes may become negative. At the same time, cost estimates for the average stock might be biased upwards. Also, the Keim and Madhavan model uses a constant negative coefficient for market capitalization. Because the average market capitalization increased in our sample, cost estimates become lower over time. It should be stressed here that we did not apply scaling techniques on the coefficient estimates in the Keim and Madhavan model as is typically done in this stream of literature to inflate trading costs back in time [see, e.g., Gutierrez and Kelley (2008) and Avramov Chordia and Goyal (2006)]. If we would have applied these scaling techniques, the resulting cost estimates would be even lower.

[INSERT TABLE 3 ABOUT HERE]

Once we focus on 500 largest stocks in our sample the differences between the trading cost estimates resulting from the Keim and Madhavan (1997) model and the Nomura model become even more extreme. Panel A of Table 5 reports the average cost estimates for buy and sell transactions resulting from the Keim and Madhavan model. We immediately observe that the cost estimates for our sample of large cap stocks are very low and even negative in a lot of cases. In fact, for a large number of years in our sample, transaction cost estimates are negative for basically all stocks in our sample. These observations are consistent with our previous notion that the Keim and Madhavan model might yield trading costs estimates that are systematically biased downwards for large cap stocks with high trading volumes.

Panel B of Table 5 reports the transaction cost estimates that were provided to us by Nomura. For all deciles, Nomura's cost estimates are substantially higher than the estimates resulting from the Keim and Madhavan (1997) model. Based on the Keim and Madhavan model, the average roundtrip transaction costs for the 10 percent most expensive stocks to trade are 4 basis points. This figure is substantially lower than the 6 basis points trading costs that result from the Nomura model for the 10 percent cheapest stocks. Especially for the sample of large cap stocks, we believe that the cost estimates provided by Nomura are more realistic than those resulting from the Keim and Madhavan model.

The observation that transaction cost estimates for stocks with the highest and lowest trading volumes resulting from the Keim and Madhavan (1997) model are substantially lower than the estimates resulting from the model of Nomura (and even negative in many cases) makes us believe that the trading cost estimates resulting from the Keim and Madhavan model should be interpreted with caution in some of our analyses. Of course, it should be acknowledged that the Keim and Madhavan model was originally developed to describe the in-sample relation between trading costs and stock characteristics, and not to predict stocks' trading out-of-sample costs for evaluating trading strategies. Imposing a quadratic instead of a logarithmic relation between market capitalization and transaction costs would probably not increase the in-sample explanatory power of the model. The Keim and Madhavan model is therefore probably optimally specified for the purpose it was originally developed for.

3. EMPIRICAL RESULTS

This section describes our empirical results.

3.1 The profitability of reversal strategies for the 1,500 largest stocks

In our first analysis we evaluate the profitability of a standard reversal strategy for the 1,500 largest U.S stocks. Reversal portfolios are constructed by daily sorting all available stocks into mutually exclusive decile portfolios based on their past week returns (i.e., five trading days). Consistent with most of the literature, we assign equal weights to the stocks in each decile. Our base case reversal strategy is long (short) in the 10 percent of stocks with the lowest (highest) returns over the past week. To control for the bid-ask bounces, we skip one day after each ranking before we construct portfolios. Therefore, we construct the portfolios on day t based on the stock returns from working day t-6 to t-1. Portfolios are rebalanced at a daily frequency. For the resulting decile portfolios we compute gross excess returns. Returns are in excess of the equally-weighted return of all 1,500 stocks in the cross-section.

Proceeding further, we compute the gross and net excess returns of the long portfolio, the short portfolio, and the long-short portfolio of a standard reversal investment strategy. Again, gross and net returns are in excess of the equally-weighted return of all 1,500 stocks in the cross-section. In addition, we compute the long-short portfolios' turnover per week. We compute net returns for each stock at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the Keim and Madhavan (1997) model and the transaction cost model of Nomura listed in Table 2. We impose that the minimum transaction cost estimates resulting from the Keim and Madhavan model are zero for each volume decile to be conservative. The results of this analysis are presented in Table 4.

[INSERT TABLE 4 ABOUT HERE]

Consistent with most of the literature we find that a standard reversal strategy yields extremely large returns before transaction costs. More specifically, a reversal investment strategy that is long in the 10 percent of the 1,500 largest stocks with the lowest one-week returns and short in the 10 percent with the highest returns earns a gross return of 92.9 basis points per week at a daily rebalancing period over the period January 1990 to December 2009. The results are statistically highly significant since the *t*-statistic of the return earned by the long-short portfolio is larger than 10.

However, at the same time the reversal strategy has an extremely high portfolio turnover of 780 percent per week. We find that the average holding period of a stock is less than three days. Once transaction costs are taken into account the profitability of the reversal strategy completely diminishes. When we take the transaction cost scheme based on the Keim and Madhavan model, we document a net return of minus 52.8 basis points per week. And when we use the cost scheme based on the transaction cost model of Nomura, we even find a return of minus 88.2 basis points per week.

These results are consistent with the findings of Avramov, Chordia and Goyal (2006) who evaluate the profitability of reversal investment strategies net of transaction costs and report that reversal strategies require frequent trading in disproportionately high cost securities such that trading costs prevent profitable strategy execution.

3.2 The profitability of reversal strategies for the 500 largest stocks

One of the most notable observations in the previous sections was that there is a highly non-linear relation between market capitalization/trading volume and transaction costs such that the smallest and least liquid stocks are disproportionally expensive to trade. Especially since these stocks generally have the highest volatility and therefore have the greatest probability to end up in the extreme quantiles when stocks are ranked on past returns, a long-short reversal portfolio is typically invested in these stocks that are the most expensive to trade. While it has been documented that reversal strategies yield larger returns among small cap stocks than large cap stocks, one may wonder whether this increase in return compensates for the higher transaction costs that are associated with trading in these stocks.

To investigate the impact of including small cap stocks in our previous analysis, we conduct a second analysis where we evaluate the profitability of a reversal investment strategy for the largest 500 stocks in our sample. All the settings are the same as in our previous analysis with two exceptions: first, because the number of stocks in the cross-section is much smaller with this analysis, we construct quintile portfolios based on stocks' past-week returns instead of decile portfolios as we did with our analysis for the largest 1,500 stocks. Second, for our transaction cost estimates we use the scheme we received from Nomura with average trading cost estimates for decile portfolios of S&P500 stocks sorted on their trading volumes which are presented in Table 3.

Like in our previous analysis, we compute the gross and net returns of the long portfolio, the short portfolio and the long-short portfolio. We also compute the turnover of the long-short portfolios. Net returns are computed using the transaction cost models of Keim and Madhavan (1997) and Nomura. The results are presented in Panel A of Table 5.

[INSERT TABLE 5 ABOUT HERE]

Indeed it appears that reversal investment strategies yield higher returns among small cap stocks than large cap stocks. While the reversal strategy for the largest 1,500 stocks in the previous section earned a gross return of 92.9 basis points per week, the strategy we test in this section for the largest 500 stocks earns 71.9 basis points per week. Nonetheless, it appears that the impact of transaction costs on the profitability of the strategy is much lower for our sample of large cap stocks. Given the large number of negative cost estimates we found using the Keim and Madhavan (1997) model for the largest 500 stocks, it is not surprising to see that the net return of the reversal strategy computed using these cost estimates are very close to the strategy's gross return since we impose minimum trading costs of zero. However, also when we use the transaction cost scheme based on the model of Nomura, it appears that transaction costs have a much smaller impact on the profitability of reversal investment strategies. The net return of minus 3 basis points per week of the strategy indicates that transaction costs consume roughly 75 basis points of the strategy's gross return. For our sample of the 1,500 largest stocks this figure is roughly one-and-a-half times larger at 114 basis points.

So even though the gross returns of reversal strategies are larger among small cap than large cap stocks, we conclude that the increase in profitability is fully diminished by the higher transaction costs that are associated with trading in small cap stocks. Nonetheless, the gross return of reversal investment strategies for the 500 largest stocks is fully consumed by transaction costs.

3.3 Reducing reversal strategies' turnover by "smart" portfolio construction

Another important reason why transaction costs have such a large impact on the profitability of the reversal strategies we evaluated in the previous sections has to do with the way the reversal portfolios are constructed. Reversal portfolios are constructed by taking a long position in losers and a short position in winners. Then, at a pre-specified interval the portfolio is rebalanced and stocks that are no longer losers are sold and replaced by newly bottom-ranked stocks. And vice versa, stocks that are no longer winners are bought back and replaced by newly top-ranked stocks. While the portfolio construction approach described above is standard in the academic literature to investigate stock market anomalies, it is suboptimal when a real-live investment strategy is evaluated and transaction costs are taken into account. Namely, replacing stocks that are no longer losers (winners) by newly bottom (top)-ranked stocks only increases the profitability of reversal investment strategies if the difference in expected return between the stocks is larger than the costs associated with the transactions.

In many cases, however, the costs of the rebalances will be larger than the incremental return that is earned by the stock replacements. For example, for our universe of the 1,500 largest stocks we found that past loser stocks on average earn a gross excess return of roughly 9 (= 44.3 / 5; see Table 3) basis points over the subsequent day while stocks in the next decile earn 3 basis points (= 15 / 5; see Table 3). On average, loser (winner) stocks remain ranked in the bottom (top) decile for a period of two-and-a-half days. Consequently, replacing a stock that moved from the top decile to the second decile only increases the profitability of the reversal strategy if the costs of the buy and sell transactions are less than 15 [= (9 - 3) * 2.5] basis points together. When we consider the transaction cost estimates in Table 2, however, we see that single-trip costs are larger than 7.5 basis points in many cases. Therefore a portfolio construction approach that directly sells (buys back) stocks that are no longer losers (winners) is likely to generate excessive turnover and unnecessarily high transaction costs.

A naive approach to cope with this problem would be to lower the rebalancing frequency. However, with this approach one runs the risk to hold stocks that have already reverted. Namely, a loser (winner) stock at a specific point in time might rank among the winner (loser) stocks within the interval at which the portfolio is rebalanced and might therefore have a negative (positive) expected return. In fact, the portfolio weights of loser stocks that have reverted become larger and thereby exacerbate this effect.

We propose a slightly more sophisticated approach that only replaces stocks that are no longer losers by newly losing stocks if the expected return differential between the stocks is larger than the likely costs that are involved with the transactions. We therefore do not directly sell (buy back) stocks that are no longer losers (winners) but wait until these stocks are ranked among the 50 percent of winner (loser) stocks ranked on past return. These stocks are then replaced by the stocks with the lowest (highest) past-week return at that time. As a consequence, this "smart" approach has a substantially lower turnover than the standard approach to construct long-short reversal portfolios. In addition, it is more likely that stocks replacements add incremental return to the reversal strategy because the gross return differential between bottom-ranked stocks in decile 1 and the stocks in decile 6 is larger than the differential between the stocks in deciles 1 and 2 for example. At the same time, this approach enforces that the portfolio does not hold stocks that already reverted. With the “smart” portfolio construction approach we also daily rebalance the portfolio weights such that they are all set to be equal at the begin of each day. It is important to note that the holding period with this approach is flexible for each stock with a minimum of one day and a maximum of theoretically infinity.

We now use the slightly more sophisticated portfolio construction approach outlined above to evaluate the profitability of reversal investment strategies for our samples of the 1,500 and 500 largest stocks.

[INSERT TABLE 6 ABOUT HERE]

The results of this analysis are listed in Table 6. We first consider the results for our sample of the 1,500 largest stocks in Panel A of Table 6. Indeed, the “smart” portfolio construction approach appears to successfully reduce turnover and thereby the impact of transaction costs on the profitability of the reversal strategy. While the turnover of the standard reversal strategy for the 1,500 largest stocks is 780 percent per week, this figure is 321 percent for the “smart” approach. We find that the effective holding period of a stock on average is five days for this strategy. And while transaction costs estimated using the scheme based on the Keim and Madhavan model consume 145 basis points of reversal gross returns of the standard reversal strategy, this figure is 60 basis points for the “smart” approach. We find similar results when we use the transaction cost scheme based on the Nomura model. While trading costs consume 181 basis points of reversal gross returns of the standard reversal strategy, this figure is 73 basis points for the “smart” approach. All in all, it appears that using a slightly more sophisticated portfolio construction approach when engaging in short-term reversal strategies can have a significant impact on trading costs.

Next, we consider the results for the 500 largest stocks in our sample. Also for this sample we see that the “smart” portfolio construction approach appears to successfully reduce turnover. More specifically, while the standard reversal strategy has a turnover of 688 percent per week, this figure is 326 percent for the “smart” reversal strategy. Interestingly, the gross return of the smart strategy is only marginally lower at 65 basis points per week compared to the 71.9 basis points per week we observed earlier for the standard reversal strategy. However, the impact of transaction costs appears to be much lower. Like with the previous analysis for the 500 largest stocks, it is not a surprise to see that the net returns of the reversal strategy computed using Keim and Madhavan (1997) cost estimates are very close to the strategy’s gross return. But also when net returns are computed using the model of Nomura we find that transaction cost now consume 34 basis points of the strategy’s gross return. This figure is 75 basis points for the standard reversal strategy. The resulting 31 basis points that are earned by the “smart” reversal strategy net of transaction costs are highly significant from both a statistical as an economical point of view.

3.4 The profitability of reversal strategies for the 100 largest stocks

We continue our empirical analysis by investigation the profitability of reversal investment strategies for the 100 largest stocks. By focussing on the 100 largest stocks we can fully rule out that market microstructure effects play a role in explaining the reversal profits we document. Secondly, this analysis enables us to further investigate the interactions between market cap segment, reversal profits and trading costs. In our previous analyses we found that reversal profits slightly decrease when small cap stocks are excluded, but that the impact of transaction costs on the strategy's profitability becomes substantially lower when the strategy is applied to exclusively large cap stocks. For this analysis, we employ the scheme we received from Nomura with average trading cost estimates for decile portfolios of S&P500 stocks sorted on their trading volumes presented in Table 3. For completeness, we also use the scheme based on the Keim and Madhavan (1997) model. However, when we evaluate the reversal investment strategies' profitability net of transaction costs we only consider the results using the trading cost estimates from Nomura since we believe that trading cost estimates for this group of large cap stocks are systematically underestimated by the Keim and Madhavan (1997) model. Like in the analysis using the 500 largest stocks we construct quintile portfolios based on stocks' past returns. The results are in Table 7.

[INSERT TABLE 7 ABOUT HERE]

Panel A of Table 7 present the gross and net returns of the standard reversal strategy that is long in the bottom quintile of stocks ranked on their past-week return, and short in the top quintile of stocks. Panel B of Table 7 presents the results for our "smart" reversal strategy that does not directly sell (buy back) stocks that are no longer in the bottom (top) quintile, but waits until these stocks are ranked among the top (bottom) 50 percent of stocks. Interestingly, gross returns of reversal strategies for the 100 largest stocks are not lower than those of reversal strategies for the 500 largest stocks. In fact, with gross returns of 84.2 and 77.9 for the standard strategy and the "smart" strategy, respectively, it seems that the returns are even larger for the universe of the 100 largest stocks. At the same time, we observe that the impact of transaction costs on the reversal strategies' profitability becomes substantially lower. While 75 basis points of the standard reversal strategy's gross return was consumed by transaction costs for the 500 largest stocks, this figure is 53 basis points for the 100 largest stocks. For our "smart" reversal strategy, these figures are 34 and 25 basis points per week, respectively. The results from this analysis indicate that reversal profits are also observed among the largest stocks. In fact, reversal profits appear to be the highest among this group of stocks.

Our finding that reversal investment strategies can yield a significant return up to 50 basis points per week net of transaction costs present a serious challenge to standard rational asset pricing model and has important implications for the practical implementation of reversal investment strategies. The key lesson is that investors striving to earn superior returns by engaging in reversal trading are more likely to realize their objectives by using smart portfolio construction rules that limit turnover and by trading in liquid stocks with relatively low transaction costs.

3.5 The profitability of a standard reversal strategy with a weekly rebalancing frequency

Next, we evaluate a naive portfolio construction approach that reduces the turnover of reversal strategies by increasing the rebalancing frequency to five days. All the other settings are exactly the same as with the standard approach. As mentioned earlier, the main disadvantage of this approach compared to the "smart" portfolio construction approach described in the previous section is that one runs the risk to hold stocks that have already reverted. We evaluate this portfolio construction approach for our samples of the largest 1,500, 500 and 100 largest stocks over the period January 1990 to December 2009. The results are in Table 8.

[INSERT TABLE 8 ABOUT HERE]

It appears that using a five-day rebalancing frequency indeed substantially lowers portfolio turnover. For example, the turnover of the standard reversal strategy for the 1,500 largest stocks was 780 percent per week. This figure is 337 percent per week for the "smart" reversal strategy. Also for our samples of the largest 500 and 100 stocks, the turnover of the reversal strategy that uses a five-day rebalancing frequency is less than half of the turnover of the strategy that rebalances at a daily frequency. As a consequence of the lower turnover, the impact of transaction costs is substantially lower for reversal strategy that uses a five-day rebalancing frequency than for the strategy that uses a daily frequency. While transaction costs consume 145 basis points of the profits of the daily strategy for the 1,500 largest stocks using the scheme based on the Keim and Madhavan (1997) model, this figure is only 76 basis points for the weekly strategy. These figures are very similar when we use the Nomura model. Nonetheless, the net returns of the weekly reversal strategy for the 1,500 largest stocks are significantly negative because the gross returns of the strategy are also much lower than for the daily strategy. While the daily strategy yields a gross return of 93 basis points per week, the weekly strategy yields only 55 basis points. For our samples of the largest 500 and 100 stocks we observe similar effects: transaction costs become substantially lower when the rebalancing frequency is increased from one day to five days, but so do gross returns. The effects seem to offset each other so that the profitability of the reversal strategies remains the same.

3.6 Results over January 2000 through December 2009

We continue our empirical analysis by investigating the profitability of the reversal profits over the most recent decade in our sample. As we mentioned earlier, financial markets have undergone important changes over time. We conjecture that it might well be the case that the decimalization of the quotation systems and the increase in stock trading volumes might affected the profitability of reversal profits. To this end, we evaluate the profitability of our “smart” reversal strategy for the 1,500, 500, and 100 largest stocks over the period January 2000 to December 2009. Again for our sample of the 1,500 largest stocks, stocks are sorted into reversal deciles, and for our samples of the 500 and 100 largest stocks into quintiles. The results are presented in Table 9.

[INSERT TABLE 9 ABOUT HERE]

It appears that the gross profitability of reversal investment strategies has become lower for small cap stocks, while it remained constant for large cap stocks. While the gross return of a long-short strategy for the 1,500 largest U.S stocks was 81.5 basis points per week over the period 1990 to 2009, we find this figure to be 40.7 basis points over the subperiod 2000 to 2009. For the 500 and 100 largest stocks in our sample, the gross returns are 65 and 77.9 basis points per week over our entire sample period, and 53 and 78.6 basis points per week over the subperiod 2000 to 2009, respectively. It also appears that the impact of trading costs has remained constant over time. Using trading cost estimates based on the Nomura model, we find that transaction costs consume roughly 56 basis points of the profitability of the reversal profits for the largest 1,500 stocks For our samples of the largest 500 and 100 stocks transaction consume roughly 31 basis points of the reversal profits for the largest 500 stocks, and 20 basis points for the 100 largest stocks. All in all, the net profitability of our “smart” reversal investment strategy seems to be quite constant over our sample period. For the 1,500 largest stocks, the “smart” reversal strategy yields a negative return of minus 7 basis points per week after transaction costs. For our sample of the 500 largest stocks, the net return decreased from 30.5 to 22.1 basis points per week. And for our sample of the largest 100 stocks, the net return slightly increased from 53.1 basis points to 59.0 basis points per week. The reversal profits earned for our samples of the 500 and 100 largest stocks over the period 2000 to 2009 are statistically and economically still highly significant.

3.7 Implications for explanations for reversal effects

Our findings have important implications for some of the explanations that have been put forward in the literature to explain the reversal anomaly. Apart from the stream of literature that attributes reversal effects to trading frictions in securities markets that weaken the arbitrage mechanism, several other explanations have been put forward.

Short-term stock reversals are sometimes regarded as evidence that the market lacks sufficient liquidity to offset price effects caused by unexpected buying and selling pressure and that market makers set prices in part to control their inventories. Grossman and Miller (1988) and Jegadeesh and Titman (1995b) argue that the reversals are induced by inventory imbalances by market makers and the contrarian profits are a compensation for bearing inventory risks. Related to this stream of literature, Madhavan and Smidt (1993), Hasbrouck and Sofianos (1993), Hansch, Naik, and Viswanathan (1998), and Hendershott and Seasholes (2006) find that prices quoted by dealers are inversely related to their inventory supporting the notion that dealers actively manage their inventories. This liquidity explanation projects that reversals in U.S. stock markets should have become smaller over time since market liquidity dramatically increased. It also predicts that reversals are stronger for small cap stocks than large cap stocks that typically have lower turnover. In fact, under the liquidity hypothesis reversals may even not be present among large cap stocks at all. However, our findings that net reversal profits are large and positive for the 500 and 100 largest U.S. stocks and did not diminish over the second decade in our sample rules out this explanation.

Another explanation for reversal effects that has been put forward in the literature is from Lo andMacKinlay (1990) and Boudoukh, Richardson, and Whitelaw (1994) who note that nonsynchronous trading contributes to contrarian profits. This explanation assumes information diffuses gradually in financial markets and that large cap stocks react more quickly to information than small cap stocks that are covered by fewer analysts. As a consequence of this, the returns of large cap stocks might lead the returns of small cap stocks. For example, if the price of large cap stock A appreciates and the price of small cap stock B follows subsequently, a reversal strategy may profit from buying stock B. And vice versa, a reversal strategy may profit from selling stock B when the price of stock A drops. However, our finding that reversal profits are not convincingly larger for the 1,500 largest U.S. stocks than for the 500 and even 100 largest stocks is inconsistent with this explanation since nonsynchronous trading predicts a size-related lead-lag-effect in stock returns and higher reversal profits among small cap stocks.

The only explanation that has been put forward in the literature whose projections are not inconsistent with our findings is the behavioural explanation that market prices tend to overreact to information in the short run [see, e.g., Jegaseesh and Titman (1995a)]. It should be stressed that our study does not provide any direct evidence supporting this behavioural hypothesis. Of course, it is not our goal to explain the reversal effect in this study; our main point is to show that reversal profits are present after trading costs. Nonetheless, we believe that our results help to better understand the reversal anomaly since it rules out several competing explanations that have been put forward in the literature.

4. EUROPEAN RESULTS

In this section we investigate the reversal profits and trading costs in European equity markets. Despite their size, European markets have generally been underinvestigated in our opinion (Abnormal profits of short-term reversal strategies are also documented in non-US equity markets. Chang, Liu and Ni (1995) find abnormal profits of short-term contrarian strategies in the Japanese stock market. Schiereck, DeBondt, and Weber (1999) and Hameed and Ting (2000) find the same in the German and Malaysian stock markets, respectively. And Griffin, Kelly, and Nardari (2010) investigate reversal profits in 56 developed and emerging countries).

An attractive feature of the trading cost model we obtained from Nomura Securities is that it has also been calibrated using European trade data which enables us to investigate trading costs and reversal profits in these markets. To our best knowledge, this study is the first to provide a comprehensive overview of trading costs and to investigate trading cost impact on the profitability of short-term reversal investment strategies in European equity markets.

We use return data for the 1,000 largest stocks that were constituents of the Citigroup European Broad Market Index (BMI) during the period January 1995 and December 2009. The reason why we start in 1995 instead of 1990 as we did in our analysis using U.S data is that Nomura does not have the data necessary to accurately estimate trading costs for European stocks before 1995. Daily stock returns including dividends, market capitalizations and price volumes are also obtained from FactSet. Table 13 presents as overview of the distributions of the stocks' market capitalization, daily trading volumes, illiquidity, and turnover over our sample period.

[INSERT TABLE 10 ABOUT HERE]

Panel A of Table 10 shows the distributions of the European stocks' market capitalization. It appears that our sample of U.S. stocks has a larger market capitalization. Over the period January 1995 to December 2009, the median market capitalization for the 1,000 largest European stocks is USD 1.1 billion. For comparison, this figure is USD 1.4 billion for the 1,500 largest U.S. stocks. Nonetheless, with a market capitalization of USD 22.2 billion for the 5 percent largest stocks, the European equity market can be considered to be sizable.

Panel B of Table 10 shows the distributions of the stock's trading volumes. While we also observe a tremendous increase in trading volumes over time for European stocks, volumes seem to be higher in the U.S. markets. The median trading volume of USD 5.2 million per day for European stocks is substantially lower than the USD 12.2 billion per day for the 1,500 largest U.S. stocks over the period January 1995 to December 2009. While we observe large trading volumes over USD 100 million per day in the European markets, we do not observe levels over USD 300 million as in the U.S.

When we consider the stocks' illiquidity in Panel C of Table 10, it appears that the European markets also have been very liquid over our sample period. Compared to the U.S markets, the illiquidity level is slightly higher: the median illiquidity measure is 0.005 for the European markets, while this figure is 0.002 for the largest 1,500 U.S. stocks over the period

January 1995 to December 2009. The largest value we observe is 0.217 for the 95th percentile of stocks in 1995.

Finally, Panel D of Table 10 shows the distributions of the stocks' turnover. It appears that the turnover levels are somewhat lower in Europe compared to the U.S. which is not surprising given the substantially higher volume levels we see in the U.S. Nonetheless, the turnover figures are very low with a median value of 0.3 percent in our sample.

All in all, the lower market capitalizations and trading volumes in the European markets make us expect that trading cost in Europe will be somewhat higher than in the U.S. To compare trading costs, we list the trading costs estimates we received from Nomura Securities for the largest 1,000 and 600 European stocks in Table 11. We asked the researchers of Nomura to use the same settings to compute trading costs in Europe as they used to compute costs in the U.S. So, for example, trades are closed within one day, and the trade size is one million USD per stock by the end of 2009 which is deflated back in time with 10 percent per annum. As estimates for broker commissions a again use a 5 basis points rate per trade during the 1990s and a 3 basis points rate over the most recent 10 years of our sample period.

[INSERT TABLE 11 ABOUT HERE]

When we compare the trading costs estimates for the 1,500 largest U.S. stocks to those for the 1,000 largest European stocks in Panel A of Table 11, it appears that costs in Europe indeed are somewhat higher. For example, the trading costs for the 10 percent least liquid stocks are 76 basis points for the European stocks, while the costs are 64 basis points for U.S. stocks. The differences become larger when we move to the more liquid segment of the market: while the median trading costs for stocks in deciles 5 and 6 are 34 basis points for the European stocks, the corresponding figure for U.S. stocks is 13 basis points over the period January 1995 to December 2009. For the 10 percent most liquid stocks, trading costs are even three times higher in Europe compared to the U.S.: while the most liquid stocks trade against 6 basis points in the U.S., this figure is 19 basis points in Europe. Because trading costs are larger in Europe than in the U.S. we expect the impact of trading costs on reversal profits to be larger in Europe.

To investigate this issue, we perform several analyses that are very similar to our previous analyses. Using the methodology outlined in Section 3.1, we construct quantile portfolios for the 1,000 largest European stocks and quintile portfolios for the 600 and 100 largest European stocks for compute the returns of long-short reversal portfolios. Additionally, we apply the "smart" portfolio construction for these stock samples where we do not directly sell (buy back) stocks that are no longer losers (winners) but wait until these stocks are ranked among the top (bottom) 50 percent of stocks based on past-week returns. For all the reversal strategies we compute gross returns, and returns net of transaction costs using the Nomura model. The results are presented in Table 12.

[INSERT TABLE 12 ABOUT HERE]

It appears that reversal profits gross of costs are also very large in Europe. The gross returns of the various reversal strategies we evaluate ranges between 69.2 basis points per week to 96.5 basis points. However, as we expected the impact of trading costs appears to be very large. For our universes of the 1,000 and 600 largest European stocks we do not find positive returns net of trading costs. Even not when we apply our “smart” portfolio construction rule. Once we exclusively focus on the 100 largest stocks and apply the “smart” portfolio construction, we document significantly positive net reversal profits up to 20 basis points per week.

5. ROBUSTNESS CHECKS

In this final section we present the results of several robustness checks we performed.

5.1 “Smart” portfolio construction using alternative trade rules

Although the trade rules we propose for “smart” portfolio construction are reasonable in our view, the choice to buy or sell stocks once their rank on past-week return crosses the median is quite arbitrary. We therefore examine the sensitivity of our findings to alternate rule choices. More specifically, we evaluate the profitability of reversal investment strategies for the 500 largest U.S. stocks that sells (buys back) stocks once their rank on past-week return is above (below) the 30th (70th) percentile; the 40th (60th) percentile; the 70th (30th) percentile; the 80th (20th) percentile; and the 90th (10th) percentile. The results of these analyses are listed in Table 13.

[INSERT TABLE 13 ABOUT HERE]

The results in Panel A of Table 13 point out that reducing portfolio turnover a little bit already has a large impact on the profitability of reversal strategies after trading costs. Once we require loser (winner) stocks to rank above (below) the 30^{th} (70^{th}) percentile to be sold (bought back), reversal net profits become highly significant at 20.1 basis points per week. This compares to minus 3 basis points per week for the standard reversal strategy (see Table 5). While gross returns become somewhat lower when turnover is reduced, the impact of trading costs on performance becomes substantially smaller. The optimum in terms of net return is reached using a trade rule that sells (buys back) stocks once their rank on past-week return is above (below) the 70th (30th) percentile. Interestingly, it appears that reversal profits are both statistically and economically highly significant for all trade rules, ranging from 20.1 to 35.3 basis points per week. We can therefore safely conclude that our findings are robust to our choices of trade rule.

5.2 Fama-French regressions

Another important aspect of the profitability of reversal strategies that should be taken into account is the extent to which the profits can be attributed to exposures to common risk factors. To investigate this issue, we regress the weekly gross and net returns of the "smart" long-short reversal portfolios for the largest 1,500, 500 and 100 U.S. stocks on the Fama-French risk factors (French, 2010) for market, size and value [see, e.g., Fama and French (1993, 1995, 1996)]. The alphas, betas and adjusted R-squared values from these regressions are listed in Table 14.

[INSERT TABLE 14 ABOUT HERE]

Panel A presents the results for the 1,500 largest U.S. stocks, Panel B presents the results for the 500 largest U.S. stocks, and Panel C presents the results for the 100 largest U.S. stocks. In all cases the explanatory power of the Fama-French risk factors is only very small. The highest adjusted R-squared value we observe is 5 percent. The explanatory power seems to become smaller the more we move to the large cap segment of the market. The coefficients estimates for market (RMRF), size (SMB) and value (HML) are very close to zero. Not surprisingly, we economic magnitude and the statistical significance of the resulting alphas are virtually identical to those of the raw reversal returns. It appears that basically nothing of the reversal profits we document can be attributed to exposures to common risk factors.

5.3 Results when industry neutrality is imposed

The next issue we investigate is related to findings from several authors that the Fama and French factors do not fully suffice to describe the returns on industry portfolios [see, e.g., Fama and French (1997)]. While our reversal profits appear to be unrelated to the Fama-French factors, the strategies are not necessarily neutral to industries. In this subsection we investigate what portion of the reversal profits can be attributed to industries and is not captured by the Fama and French factors.

To impose industry neutrality we rank stocks on their past return relative to stocks that have the same industry classification. This approach ensures that there is an equal number of stocks from each industry in all decile portfolios. We use the Global Industry Classification Standard (GICS) developped by MSCI Barra to define ten industries. The gross and net returns of this strategy are reported in Table 15.

[INSERT TABLE 15 ABOUT HERE]

It appears that imposing industry neutrality lowers reversal returns to some extent. While the long-short gross return of our base case “smart” reversal strategy is 81.5 basis points per week for the 1,500 largest stocks, this figure is 77.4 basis points for the industry-neutral strategy. For the 500 largest stocks, these figures are 65 and 57.8 basis points per week, respectively. And for the 100 largest stocks, these figures are 77.9 and 66.2 basis points. However, at the same time it seems that the risk involved with the strategy also substantially drops once industry neutrality is imposed. While the *t*-statistic of the reversal strategy for the 1,500 largest stocks is 9.7, this figure is 13.9 for the industry-neutral variant. For the 500 largest stocks, the *t*-statistic increases from 8.7 to 13.2. And for the 100 largest stocks the *t*-statistic increases from 9.4 to 12.2. The impact of transaction costs remains virtually unchanged in all cases. Overall, the profitability of our "smart" reversal investment strategy seems to be somewhat lower once we impose industry neutrality, but at the same time, risk-adjusted performance seems to improve. We therefore conclude that the profitability of reversal investment strategies is robust to industry effects.

6. SUMMARY AND CONCLUDING COMMENTS

This paper shows that the finding of several studies that transaction costs prevent profitable execution of reversal investment strategies can largely be attributed to excessively trading in small cap stocks.

Excluding small cap stocks and applying a slightly more sophisticated portfolios construction approach to reduce turnover when engaging in reversal trading has a tremendous impact on the returns that reversal investment strategies deliver net of transaction costs.

Our finding that reversal strategies generate 30 to 50 basis points per week net of transaction costs poses a serious challenge to standard rational asset pricing models. Our results also have important implications for the practical implementation of reversal investment strategies.

Another important issue that came to light in this study is that trading cost estimates of the Keim and Madhavan (1997) model that are typically used in this stream of literature to evaluate the profitability of trading strategies net of transaction costs should be interpreted with caution in some cases. More specifically, it seems that cost estimates of this model for both small cap stocks with low trading volumes and large cap stocks with high trading volumes are systematically biased downwards. The comprehensive overview presented in this study on trading costs estimates for S&P1500 and S&P500 stocks resulting from the proprietary transaction cost models of Nomura Securities, one of world's largest stock brokers, provides new opportunities for future research to re-evaluate the profitability of investment strategies based on well-documented anomalies such as the value and the momentum effects.

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TABLE 1. Summary statistics for U.S. stocks.

Table 1 present an overview of the distributions of U.S. stock market capitalization, daily trading volumes, Amihud's (2002) illiquidity measure, and turnover over January 1990 to December 2009. Trading volumes and turnover are median values over the past three months.

Percentile	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average
Panel A. Market capitalization (USD bln)																					
5%	0.1	0.1	0.1	0.2	0.2	0.3	0.3	0.4	0.5	0.5	0.5	0.5	0.4	0.4	0.7	0.8	1.0	1.0	0.5	0.5	0.4
25%	0.1	0.2	0.2	0.2	0.3	0.3	0.4	0.5	0.6	0.6	0.7	0.6	0.6	0.7	0.9	1.1	1.2	1.3	0.9	0.7	0.6
50%	0.3	0.4	0.4	0.5	0.5	0.6	0.7	0.9	1.0	1.0	1.1	1.2	1.1	1.2	1.7	2.0	2.3	2.5	1.8	1.4	1.1
75%	1.0	1.1	1.2	1.4	1.5	1.7	1.9	2.4	2.7	3.0	3.1	3.1	2.8	3.2	4.2	5.0	5.6	6.0	4.9	3.6	3.0
95%	5.5	5.8	6.3	7.0	7.0	7.8	10.0	13.5	17.2	20.2	20.5	22.1	18.3	19.3	23.3	25.6	28.2	34.1	28.1	22.0	17.1
Panel B. Volume (USD mln)																					
5%	0.1	0.0	0.1	0.1	0.2	0.2	0.3	0.5	0.6	0.8	1.1	1.0	1.0	1.1	2.3	3.2	4.1	5.9	4.1	3.1	1.5
25%	0.2	0.3	0.4	0.7	0.7	0.9	1.3	1.8	2.3	2.7	4.1	3.7	3.7	4.0	6.1	7.8	9.8	12.8	11.2	7.5	4.1
50%	0.8	0.9	1.2	1.7	1.9	2.4	3.6	4.7	5.7	7.6	11.2	9.7	8.8	9.5	13.0	16.1	20.4	25.8	25.4	18.7	9.4
75%	2.6	3.0	3.5	4.8	5.5	7.2	9.8	12.0	15.2	21.7	31.5	29.3	26.3	26.4	32.7	39.1	50.7	62.7	71.8	55.8	25.6
95%	14.7	15.6	17.1	22.5	23.0	33.2	45.1	59.0	76.4	114.7	183.3	163.8	131.5	124.2	143.3	160.9	211.8	284.1	335.9	256.0	120.8
Panel C. Illiquidity (times 100)																					
5%	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
25%	0.6	0.4	0.4	0.3	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
50%	2.0	1.5	1.2	0.8	0.8	0.5	0.4	0.3	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.0	0.1	0.1	0.5
75%	7.3	5.9	3.8	2.2	2.0	1.3	0.9	0.7	0.7	0.6	0.5	0.5	0.5	0.3	0.2	0.1	0.1	0.1	0.2	0.3	1.4
95%	33.6	38.6	22.5	8.9	8.0	4.9	3.7	2.3	2.3	2.0	1.5	1.6	1.5	1.0	0.5	0.3	0.2	0.2	0.8	0.8	6.8
Panel D. Turnover (%)																					
5%	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.5	0.5	0.2
25%	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4	0.4	0.4	0.4	0.5	0.5	0.7	0.9	0.8	0.4
50%	0.2	0.2	0.3	0.3	0.3	0.3	0.4	0.4	0.4	0.5	0.7	0.7	0.7	0.7	0.7	0.7	0.8	1.0	1.3	1.2	0.6
75%	0.4	0.5	0.5	0.6	0.5	0.6	0.8	0.8	0.9	1.2	1.7	1.4	1.2	1.2	1.2	1.2	1.3	1.5	1.9	1.8	1.1
95%	1.3	1.4	1.5	1.7	1.9	2.4	2.7	2.6	2.5	4.5	4.8	4.0	3.1	2.8	2.7	2.4	2.7	3.0	3.7	3.6	2.8

TABLE 2. Transaction cost estimates for the 1,500 largest U.S. stocks.
Table 2 presents an overview of the single-trip transaction cost estimates in basis points for volume deciles of our sample of the 1,500 largest U.S. stocks resulting from the Keim and Madhavan model (Panel A) and the estimates for volume deciles of S&P1500 stocks we received from Nomura Securities (Panel B). Volume deciles are based on stocks' three-month median trading volumes. It is assumed that the trades are closed within one day and the trade size is one million per stock by the end of 2009. The trade size is deflated back in time with 10 percent per annum.

Volume Decile	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average
Panel A. Keim-Madhaven average buy and sell																					
D1 (bottom)	71	78	47	28	29	27	21	12	13	18	21	26	30	29	13	12	10	11	38	63	30
D2	82	74	53	32	33	30	20	10	14	20	27	29	38	36	15	13	9	8	37	66	32
D3	64	72	51	32	30	25	18	11	15	19	24	24	39	35	19	10	7	7	40	61	30
D4	56	53	38	30	32	25	15	12	14	18	21	29	42	32	19	15	6	8	34	58	28
D5	48	39	32	30	25	22	15	9	11	17	15	27	43	38	15	16	6	4	24	37	24
D6	38	29	23	22	20	14	10	8	8	11	15	23	41	26	14	11	6	1	16	34	18
D7	24	20	18	13	14	8	6	1	4	5	6	15	26	22	8	2	2	-6	15	28	11
D8	16	11	9	8	4	4	1	-3	-5	-6	0	13	14	10	2	-6	-11	-14	7	21	4
D9	0	-3	-5	-5	-2	-6	-6	-11	-12	-13	-10	0	3	0	-9	-17	-16	-21	-5	8	-7
D10 (top)	-20	-20	-19	-19	-17	-19	-22	-26	-28	-31	-25	-14	-5	-11	-17	-25	-26	-31	-21	-15	-20
Panel B.Nomura buy or sell																					
D1 (bottom)	86	77	83	75	73	54	52	66	53	76	65	88	80	76	76	65	53	41	51	70	68
D2	72	60	60	55	51	34	27	35	31	65	67	61	56	50	41	30	24	20	25	50	46
D3	58	50	45	41	38	23	19	22	23	47	47	37	30	24	20	17	15	14	17	33	31
D4	48	41	36	30	30	17	12	18	18	30	28	23	20	17	14	13	12	11	13	23	23
D5	41	34	30	26	25	15	14	14	17	21	19	16	15	13	12	11	10	9	11	17	19
D6	33	26	22	21	20	13	13	12	14	16	14	13	12	11	10	9	9	8	9	14	15
D7	26	23	21	18	17	11	17	11	11	13	11	10	9	9	8	8	8	7	8	11	13
D8	22	20	18	16	14	10	17	13	10	11	9	8	8	8	7	7	6	6	6	9	11
D9	17	15	14	13	13	9	11	11	10	9	7	7	7	6	6	6	6	5	6	7	9
D10 (top)	13	14	14	13	13	10	9	8	8	7	5	5	5	5	5	5	5	5	5	5	8

TABLE 3. Transaction cost estimates for the 500 largest U.S. stocks.
Table 3 presents an overview of the transaction cost estimates in basis points for volume deciles of our sample of the 500 largest U.S. stocks resulting from the Keim and Madhavan model (Panel A) and the estimates for volume deciles of S&P500 stocks we received from Nomura Securities (Panel B). Volume deciles are based on stocks' three-month median trading volumes. It is assumed that the trades are closed within one day and the trade size is one million USD per stock by the end of 2009. The trade size is deflated back in time with 10 percent per annum.

Volume Decile	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average
Panel A. Keim-Madhaven average buy and sell																					
D1 (bottom)	14	6	2	1	8	8	2	-4	0	6	9	8	4	3	-4	-9	-11	-16	-5	51	4
D2	14	10	3	1	3	0	-1	-8	-8	-5	-4	-3	5	7	-3	-9	-12	-16	-4	46	1
D3	12	6	5	1	1	-2	-8	-11	-10	-8	-6	-3	3	-1	-8	-13	-16	-19	-2	40	-2
D4	8	7	3	0	0	-2	-7	-11	-12	-11	-11	-6	2	-1	-11	-15	-19	-19	-6	39	-4
D5	9	5	1	-2	-2	-3	-10	-12	-14	-15	-12	-10	0	-1	-11	-16	-21	-21	-10	28	-6
D6	6	1	-4	-7	-3	-7	-11	-15	-16	-16	-17	-11	2	-3	-14	-21	-18	-23	-7	26	-8
D7	1	-5	-6	-8	-5	-10	-12	-17	-17	-16	-20	-8	1	-2	-15	-16	-18	-22	-11	15	-10
D8	-7	-10	-9	-10	-9	-12	-15	-17	-19	-24	-21	-9	0	0	-14	-16	-21	-28	-8	16	-12
D9	-12	-10	-13	-15	-14	-17	-21	-25	-27	-30	-29	-16	-9	-12	-14	-24	-22	-27	-17	2	-18
D10 (top)	-24	-25	-27	-24	-24	-27	-29	-34	-38	-39	-38	-19	-4	-22	-27	-30	-32	-34	-24	-16	-27
Panel B.Nomura buy or sell																					
D1 (bottom)	23	15	13	15	22	31	25	24	23	23	34	36	34	38	40	28	19	15	13	21	25
D2	12	11	10	12	16	22	13	14	16	27	26	20	17	17	14	11	10	9	10	14	15
D3	11	10	9	11	14	14	11	17	14	16	16	13	12	12	10	9	9	8	8	12	12
D4	10	9	9	11	12	12	12	12	12	13	12	11	10	10	9	8	8	7	7	11	10
D5	9	9	8	10	11	12	12	11	10	11	10	9	9	9	8	7	7	6	7	9	9
D6	8	8	8	9	10	13	12	11	10	10	9	8	8	8	7	7	6	6	6	9	9
D7	8	8	8	9	9	11	11	10	9	11	8	7	7	7	7	6	6	6	6	8	8
D8	8	8	7	8	9	11	11	10	10	9	7	6	7	7	6	6	6	5	6	7	8
D9	7	7	7	7	9	10	9	9	9	8	6	6	6	6	6	5	5	5	5	6	7
D10 (top)	7	7	6	7	8	10	9	8	8	7	4	5	5	5	5	5	5	4	4	5	6

TABLE 4. Profitability of reversal investment strategies for the 1,500 largest U.S. stocks.

Table 4 presents the weekly gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio based on reversal deciles for the 1,500 largest U.S. stocks relative to the equally weighted average return of the stock universe. In addition, the table presents the turnover of the long-short portfolio. Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the Keim and Madhavan (1997) model and the transaction cost model of Nomura Securities listed in Table 2. A minimum of zero is imposed for the transaction cost estimates resulting from the Keim and Madhavan model.

	Return long (bps)	Return short (bps)	Return long-short (bps)	t-stat	Turnover (%)
Gross return	44.3	-48.1	92.9	10.1	780
Net return using KM estimates	-29.9	23.0	-52.8	-5.7	"
Net return using Nomura estimates	-47.9	40.7	-88.2	-9.6	"

TABLE 5. Profitability of reversal investment strategies for the 500 largest U.S. stocks.

Table 5 presents the weekly gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio based on reversal quintiles for the 500 largest U.S. stocks relative to the equally weighted average return of the stock universe. In addition, the table presents the turnover of the long-short portfolio. Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the Keim and Madhavan (1997) model and the transaction cost model of Nomura Securities listed in Table 3. A minimum of zero is imposed for the transaction cost estimates resulting from the Keim and Madhavan model.

	Return long (bps)	Return short (bps)	Return long-short (bps)	t-stat	Turnover (%)
Gross return	35.3	-36.4	71.9	9.1	688
Net return using KM estimates	32.5	-33.6	66.4	8.4	"
Net return using Nomura estimates	-2.7	0.3	-3.0	-0.4	"

TABLE 6. Profitability of "smart" reversal investment strategies for the 1,500 and 500 largest U.S. stocks.

Table 6 presents the weekly gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio based on reversal quantiles relative to the equally weighted average return of the stock universe. In addition, the table presents the turnover of the long-short portfolio. The reversal portfolios are constructed using an approach that does not directly sell (buy back) stocks that are no longer losers (winners), but waits until these stocks are ranked among the top (bottom) 50 percent of stocks. Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the Keim and Madhavan (1997) model and the transaction cost model of Nomura Securities listed in Tables 2 and 3. A minimum of zero is imposed for the transaction cost estimates resulting from the Keim and Madhavan model. Panel A presents the results based on reversal deciles for the 1,500 largest U.S. stocks and Panel B presents the results based on reversal quintiles for the 500 largest U.S. stocks.

	Return long (bps)	Return short (bps)	Return long-short (bps)	t-stat	Turnover (%)
Panel A. 1,500 largest U.S. stocks					
Gross return	36.5	-44.6	81.5	9.7	321
Net return using KM estimates	6.5	-14.4	21.0	2.5	"
Net return using Nomura estimates	0.4	-7.9	8.3	1.0	"
Panel B. 500 largest U.S. stocks					
Gross return	30.7	-34.0	65.0	8.7	326
Net return using KM estimates	29.4	-32.7	62.3	8.4	"
Net return using Nomura estimates	13.7	-16.8	30.5	4.1	"

TABLE 7. Profitability of reversal investment strategies for the 100 largest U.S. stocks.

Table 7 presents the weekly gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio based on reversal quintiles for the 100 largest U.S. stocks relative to the equally weighted average return of the stock universe. In addition, the table presents the turnover of the long-short portfolio. Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the Keim and Madhavan (1997) model and the transaction cost model of Nomura Securities listed in Table 5. A minimum of zero is imposed for the transaction cost estimates resulting from the Keim and Madhavan model. Panel A presents the results using a standard portfolio construction approach that is long (short) in the 20 percent of stocks with the lowest (highest) returns over the past week. Panel B shows the results for a slightly more sophisticated portfolio construction approach that does not directly sell (buy back) stocks that are no longer losers (winners), but waits until these stocks are ranked among the top (bottom) 50 percent of stocks.

	Return long (bps)	Return short (bps)	Return long-short (bps)	t-stat	Turnover (%)
Panel A. Standard reversal strategy for 100 largest U.S. stocks					
Gross return	43.7	-40.3	84.2	9.8	711
Net return using KM estimates	42.8	-39.4	82.5	9.6	"
Net return using Nomura estimates	17.1	-14.4	31.5	3.7	"
Panel B. Smart reversal strategy for 100 largest U.S. stocks					
Gross return	40.9	-36.7	77.9	9.4	337
Net return using KM estimates	40.5	-36.3	77.1	9.3	"
Net return using Nomura estimates	28.6	-24.4	53.1	6.4	"

TABLE 8. Profitability of reversal investment strategies using a five-day rebalancing frequency.

Table 8 present the weekly gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio based on a standard reversal strategy using a five-day rebalancing frequency for the largest 1,500, 500 and 100 U.S. stocks. In addition, the table presents the turnover of the long-short portfolio. Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the Keim and Madhavan (1997) model and the transaction cost model of Nomura Securities listed in Tables 2 and 3. A minimum of zero is imposed for the transaction cost estimates resulting from the Keim and Madhavan model. Panel A presents the results based on reversal deciles for the 1,500 largest U.S. stocks, Panel B presents the results based on reversal quintiles for the 500 largest U.S. stocks, and Panel C presents the results based on reversal quintiles for the 100 largest U.S. stocks.

	Return long (bps)	Return short (bps)	Return long-short (bps)	t-stat	Turnover (%)
Panel A. Standard reversal strategy for 1,500 largest U.S. stocks with a 5-day rebalancing frequency					
Gross return	23.3	-31.7	55.1	7.6	337
Net return using KM estimates	-7.3	-0.7	-6.7	-0.9	"
Net return using Nomura estimates	-14.2	6.7	-20.8	-2.9	"
Panel B. Standard reversal strategy for 500 largest U.S. stocks with a 5-day rebalancing frequency					
Gross return	20.2	-23.7	44.0	7.1	310
Net return using KM estimates	18.8	-22.5	41.4	6.7	"
Net return using Nomura estimates	3.5	-7.1	10.6	1.7	"
Panel C. Standard reversal strategy for 100 largest U.S. stocks with a 5-day rebalancing frequency					
Gross return	25.3	-26.7	52.2	7.9	315
Net return using KM estimates	24.8	-26.5	51.5	7.8	"
Net return using Nomura estimates	13.7	-15.3	29.0	4.4	"

TABLE 9. Profitability of reversal investment strategies over the period January 2000 to December 2009.

Table 9 present the weekly gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio based on a reversal strategy over the period January 2000 to December 2009 for the largest 1,500, 500 and 100 U.S. stocks. In addition, the table presents the turnover of the long-short portfolio. The reversal portfolios are constructed using an approach that does not directly sell (buy back) stocks that are no longer losers (winners), but waits until these stocks are ranked among the top (bottom) 50 percent of stocks. Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the Keim and Madhavan (1997) model and the transaction cost model of Nomura Securities listed in Tables 2 and 5. A minimum of zero is imposed for the transaction cost estimates resulting from the Keim and Madhavan model. Panel A presents the results based on reversal deciles for the 1,500 largest U.S. stocks, Panel B presents the results based on reversal quintiles for the 500 largest U.S. stocks, and Panel C presents the results based on reversal quintiles for the 100 largest U.S. stocks.

	Return long (bps)	Return short (bps)	Return long-short (bps)	t-stat	Turnover (%)
Panel A. Smart reversal strategy for 1,500 largest U.S. stocks over the period 2000 to 2009					
Gross return	9.6	-31.0	40.7	2.7	321
Net return using KM estimates	-16.5	-3.5	-13.0	-0.9	"
Net return using Nomura estimates	-17.1	-2.2	-14.9	-1.0	"
Panel B. Smart reversal strategy for 500 largest U.S. stocks over the period 2000 to 2009					
Gross return	22.2	-30.7	53.0	4.0	320
Net return using KM estimates	20.3	-28.7	49.2	3.7	"
Net return using Nomura estimates	7.1	-14.9	22.1	1.7	"
Panel C. Smart reversal strategy for 100 largest U.S. stocks over the period 2000 to 2009					
Gross return	40.0	-38.3	78.6	5.5	329
Net return using KM estimates	39.3	-37.5	77.1	5.4	"
Net return using Nomura estimates	30.3	-28.5	59.0	4.1	"

TABLE 10. Summary statistics for European stocks.

Table 10 present an overview of the distributions of European stock market capitalization, daily trading volumes, Amihud's (2002) illiquidity measure, and turnover over January 1995 to December 2009. Trading volumes and turnover are median values over the past three months.

Percentile	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average
Panel A. Market capitalization (USD bln)																
5%	0.2	0.3	0.3	0.4	0.4	0.4	0.3	0.3	0.3	0.4	0.6	0.8	1.0	0.4	0.4	0.4
25%	0.3	0.4	0.4	0.5	0.5	0.5	0.4	0.4	0.4	0.6	0.8	1.1	1.3	1.0	0.6	0.6
50%	0.6	0.7	0.8	0.9	0.9	0.9	0.7	0.7	0.8	1.2	1.5	2.0	2.5	1.8	1.2	1.1
75%	1.7	1.9	2.3	2.9	2.7	2.8	2.5	2.3	2.6	3.7	4.3	5.5	6.6	4.9	3.4	3.3
95%	8.8	9.7	13.6	18.5	18.8	20.1	19.0	16.3	16.6	22.2	27.0	34.1	45.5	36.0	26.6	22.2
Panel B. Volume (USD mln)																
5%	0.0	0.0	0.1	0.1	0.2	0.2	0.3	0.5	0.6	0.7	1.1	0.9	1.0	1.1	2.3	0.6
25%	0.2	0.3	0.4	0.6	0.6	0.8	1.3	1.8	2.4	2.6	3.7	3.7	3.6	3.8	6.2	2.1
50%	0.8	0.9	1.1	1.7	1.8	2.2	3.4	4.4	5.7	7.1	10.5	9.8	8.2	8.9	12.3	5.2
75%	2.5	2.9	3.4	4.5	5.1	6.4	9.2	11.3	14.5	19.7	29.2	28.7	25.0	25.7	32.0	14.7
95%	13.7	14.6	16.0	20.6	23.2	30.4	42.7	57.1	75.5	116.5	185.3	168.1	129.1	117.4	137.1	76.5
Panel C. Illiquidity (times 100)																
5%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
25%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
50%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
75%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
95%	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.1
Panel D. Turnover (%)																
5%	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.0	0.0
25%	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.2	0.2	0.2
50%	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.4	0.4	0.4	0.3	0.3
75%	0.2	0.3	0.4	0.4	0.5	0.6	0.6	0.6	0.5	0.5	0.6	0.7	0.7	0.7	0.6	0.5
95%	1.6	1.8	2.0	2.1	2.4	3.0	2.9	2.4	2.5	2.9	3.2	4.5	4.3	4.2	4.1	2.9

TABLE 11. Transaction cost estimates for the 1,000 and 600 largest European stocks.

Table 11 presents an overview of the single-trip transaction cost estimates in basis points for volume deciles of our sample of the 1,000 (Panel A) and 600 (Panel B) largest European stocks we received from Nomura Securities. Volume deciles are based on stocks' three-month median trading volumes. It is assumed that the trades are closed within one day and the trade size is one million per stock by the end of 2009. The trade size is deflated back in time with 10 percent per annum.

Volume Decile	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average
Panel A.1,000 largest European stocks																
D1 (bottom)	75	75	77	77	77	71	75	77	79	72	74	76	71	79	88	76
D2	64	64	57	62	68	64	71	74	75	68	62	53	48	71	82	66
D3	46	46	43	48	51	54	60	63	63	48	48	39	35	56	75	52
D4	38	37	35	41	41	46	50	53	52	38	42	32	30	46	66	43
D5	33	31	31	34	35	40	44	43	43	31	35	27	26	38	56	37
D6	27	28	27	28	31	34	35	36	33	27	30	24	24	32	46	31
D7	24	24	24	25	26	27	28	29	27	23	25	22	23	28	40	26
D8	22	22	22	23	23	22	23	23	23	21	22	20	20	25	31	23
D9	22	21	20	21	21	19	20	20	20	19	20	19	19	21	25	20
D10 (top)	21	20	20	20	19	17	19	19	19	18	19	18	18	20	22	19
Panel B.600 largest European stocks																
D1 (bottom)	72	72	69	68	75	64	71	72	72	66	63	57	50	66	80	68
D2	54	51	44	50	53	55	61	62	62	48	46	33	30	48	67	51
D3	36	36	34	38	39	44	45	49	47	31	36	27	25	35	51	38
D4	30	29	29	30	32	34	36	35	39	27	29	25	24	30	42	31
D5	26	26	26	27	28	29	30	30	32	23	26	23	22	27	39	28
D6	23	24	24	25	25	24	25	26	26	21	23	21	22	26	34	25
D7	22	22	22	22	23	22	22	22	23	20	21	20	20	23	28	22
D8	22	21	21	22	21	19	20	20	21	19	20	19	18	21	25	21
D9	21	20	19	20	20	18	19	19	20	19	19	19	18	20	23	20
D10 (top)	21	20	18	19	18	16	19	19	19	18	18	18	17	19	21	19

TABLE 12. Profitability of reversal investment strategies for the 1,000, 600, and 100 largest European stocks.

Table 12 presents the weekly gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio based on reversal quintiles for the 1,000, 600 and 100 largest European stocks relative to the equally weighted average return of the stock universe. In addition, the table presents the turnover of the long-short portfolio. Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the transaction cost model of Nomura Securities listed in Table 14.

	Return long (bps)	Return short (bps)	Return long-short (bps)	t-stat	Turnover (%)
Panel A. Standard reversal strategy for 1,000 largest European stocks					
Gross return	45.0	-41.2	86.5	10.49	789
Net return using Nomura estimates	-115.7	112.4	-225.6	-27.2	"
Panel B.Smart reversal strategy for 1,000 largest European stocks					
Gross return	41.4	-41.3	83.1	10.71	318
Net return using Nomura estimates	-22.7	22.8	-45.4	-5.85	"
Panel C. Standard reversal strategy for 600 largest European stocks					
Gross return	34.3	-34.6	69.2	9.6	683
Net return using Nomura estimates	-81.3	76.8	-156.9	-21.8	"
Panel D.Smart reversal strategy for 600 largest European stocks					
Gross return	35.0	-34.2	69.5	10.0	323
Net return using Nomura estimates	-18.6	19.8	-38.3	-5.5	"
Panel E. Standard reversal strategy for 100 largest European stocks					
Gross return	48.0	-48.1	96.5	9.8	700
Net return using Nomura estimates	-24.9	22.9	-47.7	-4.9	"
Panel F.Smart reversal strategy for 100 largest European stocks					
Gross return	46.3	-43.8	90.5	9.5	332
Net return using Nomura estimates	11.9	-9.7	21.6	2.3	"

TABLE 13. “Smart” portfolio construction using alternative trade rules. Table 13 presents the weekly gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio based on reversal quantiles relative to the equally weighted average return of the stock universe. In addition, the table presents the turnover of the long-short portfolio. The reversal portfolios are constructed using an approach that does not directly sell (buy back) stocks that are no longer losers (winners), but waits until these stocks are ranked above (below) the 30th (70th) percentile (Panel A); the 40th (60th) percentile (Panel B); the 60th (40th) percentile (Panel C); the 70th (30th) percentile (Panel D); the 80th (20th) percentile (Panel E); and the 90th (10th) percentile (Panel F). Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock’s volume rank using the schemes based on the transaction cost model of Nomura Securities listed in Table 3.

	Return long (bps)	Return short (bps)	Return long-short (bps)	t-stat	Turnover (%)
Panel A. Smart reversal strategy for 500 largest U.S. stocks using 30/70 trade rule					
Gross return	34.0	-37.2	71.5	9.12	479
Net return using Nomura estimates	8.1	-11.9	20.1	2.56	"
Panel B.Smart reversal strategy for 500 largest U.S. stocks using 40/60 trade rule					
Gross return	32.1	-35.8	68.2	8.89	387
Net return using Nomura estimates	11.5	-15.4	27.0	3.51	"
Panel C. Smart reversal strategy for 500 largest U.S. stocks using 60/40 trade rule					
Gross return	30.9	-33.0	64.1	8.9	275
Net return using Nomura estimates	16.7	-18.5	35.2	4.9	"
Panel D.Smart reversal strategy for 500 largest U.S. stocks using 70/30 trade rule					
Gross return	28.1	-30.5	58.7	8.6	225
Net return using Nomura estimates	16.7	-18.6	35.3	5.2	"
Panel E. Smart reversal strategy for 500 largest U.S. stocks using 80/20 trade rule					
Gross return	24.3	-27.3	51.7	8.2	170
Net return using Nomura estimates	15.8	-18.3	34.2	5.4	"
Panel F.Smart reversal strategy for 500 largest U.S. stocks using 90/10 trade rule					
Gross return	15.9	-18.3	34.2	6.4	100
Net return using Nomura estimates	11.1	-13.1	24.2	4.6	"

TABLE 14. Fama-French regressions.

Table 14 present the results of Fama-French regressions on weekly gross and net returns of the long-short portfolio based on a reversal strategy for the largest 1,500, 500 and 100 U.S. stocks. The reversal portfolios are constructed using an approach that does not directly sell (buy back) stocks that are no longer losers (winners), but waits until these stocks are ranked among the top (bottom) 50 percent of stocks. Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the transaction cost model of Nomura Securities listed in Tables 2 and 5. Panel A presents the results based on reversal deciles for the 1,500 largest U.S. stocks, Panel B presents the results based on reversal quintiles for the 500 largest U.S. stocks, and Panel C presents the results based on reversal quintiles for the 100 largest U.S. stocks.

	Alpha (bps)	t-stat	RMRF	SMB	HML	Adj.Rsq
Panel A. Smart reversal strategy for 1,500 largest U.S. stocks						
Gross return	83.6	10.2	0.0	0.0	0.0	5%
Net return using KM estimates	23.3	2.8	0.0	0.0	0.0	5%
Net return using Nomura estimates	10.8	1.3	0.0	0.0	0.0	5%
Panel B. Smart reversal strategy for 500 largest U.S. stocks						
Gross return	66.8	9.1	0.0	0.0	0.0	3%
Net return using KM estimates	64.2	8.8	0.0	0.0	0.0	3%
Net return using Nomura estimates	32.6	4.4	0.0	0.0	0.0	3%
Panel C. Smart reversal strategy for 100 largest U.S. stocks						
Gross return	80.7	9.9	0.0	0.0	0.0	2%
Net return using KM estimates	79.9	9.8	0.0	0.0	0.0	2%
Net return using Nomura estimates	56.1	6.8	0.0	0.0	0.0	2%

TABLE 15. Profitability of reversal investment strategies with industry neutrality imposed.

Table 15 present the weekly gross and net returns of the long portfolio, the short portfolio, and the long-short portfolio based on a standard reversal strategy for the largest 1,500, 500 and 100 U.S. stocks when industry neutrality is imposed. In addition, the table presents the turnover of the long-short portfolio. The reversal portfolios are constructed using an approach that does not directly sell (buy back) stocks that are no longer losers (winners), but waits until these stocks are ranked among the top (bottom) 50 percent of stocks. Net returns for each stock are computed at each point in time by taking the trading cost estimates associated with the stock's volume rank using the schemes based on the Keim and Madhavan (1997) model and the transaction cost model of Nomura Securities listed in Tables 2 and 5. A minimum of zero is imposed for the transaction cost estimates resulting from the Keim and Madhavan model. Panel A presents the results based on reversal deciles for the 1,500 largest U.S. stocks, Panel B presents the results based on reversal quintiles for the 500 largest U.S. stocks, and Panel C presents the results based on reversal quintiles for the 100 largest U.S. stocks.

	Return long (bps)	Return short (bps)	Return long-short (bps)	t-stat	Turnover (%)
Panel A. Smart reversal strategy for 1,500 largest U.S. stocks with industry neutrality					
Gross return	37.7	-39.4	77.4	13.9	328
Net return using KM estimates	4.7	-6.3	11.0	2.0	"
Net return using Nomura estimates	-4.1	3.0	-7.0	-1.3	"
Panel B. Smart reversal strategy for 500 largest U.S. stocks with industry neutrality					
Gross return	28.1	-29.5	57.8	13.2	342
Net return using KM estimates	26.7	-28.1	55.0	12.6	"
Net return using Nomura estimates	9.2	-10.4	19.7	4.5	"
Panel C. Smart reversal strategy for 100 largest U.S. stocks with industry neutrality					
Gross return	38.5	-27.5	66.2	12.2	391
Net return using KM estimates	38.0	-27.0	65.2	12.0	"
Net return using Nomura estimates	23.9	-12.9	36.9	6.8	"

FIGURE 1. Illustration of potential impact of misspecification of relation between trading volume and transaction costs.

Figure 1 illustrates the potential impact of misspecification of relation between trading volume and transaction costs. The solid line represents the true quadratic relation between trading volume and transaction costs. The dotted line represents the logarithmic fitted function. The figure shows that both cost estimates for stocks with a relatively high and low trading volume might be biased downwards, while the cost estimates for the average stock might be biased upwards.