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Currency momentum strategies[☆]

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ABSTRACT

We provide a broad empirical investigation of momentum strategies in the foreign exchange market. We find a significant cross-sectional spread in excess returns of up to 10% per annum (p.a.) between past winner and loser currencies. This spread in excess returns is not explained by traditional risk factors, it is partially explained by transaction costs and shows behavior consistent with investor under- and overreaction. Moreover, cross-sectional currency momentum has very different properties from the widely studied carry trade and is not highly correlated with returns of benchmark technical trading rules. However, there seem to be very effective limits to arbitrage that prevent momentum returns from being easily exploitable in currency markets.

1. Introduction

Momentum returns in stock markets provide a strong challenge to standard finance theory. Simply buying assets with high recent returns and selling assets with low recent returns results in a very profitable investment strategy whose returns are difficult to understand by means of standard risk factors (Jegadeesh and Titman, 1993, 2001). Consequently, researchers have proposed various explanations that focus not only on conventional

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risk-based models (see, e.g., Harvey and Siddique, 2000; Chordia and Shivakumar, 2002; Johnson, 2002; Pastor and Stambaugh, 2003; Liu and Zhang, 2011), but also on characteristics such as credit risk (Avramov, Chordia, Jostova, and Phlipov, 2007) or bankruptcy risk (Eisdorfer, 2008), limits to arbitrage (e.g., Chabot, Ghysels, and Jagannathan, 2009), behavioral explanations such as investor underreaction (e.g., Chui, Titman, and Wei, 2010), or high transaction costs (Korajczyk and Sadka, 2004). Despite this progress, the literature does not seem to have settled on a generally accepted explanation for momentum returns yet.

In this paper, we study foreign exchange (FX) markets as a natural laboratory for the analysis of momentum returns. Compared to stock markets, FX markets are more liquid and feature huge transaction volumes and low transaction costs, they are populated largely by sophisticated professional investors, and there are no natural short-selling constraints that prevent the shorting of past loser assets to fully implement momentum strategies. Hence, considering FX markets raises the hurdle for generating significant excess returns from momentum strategies considerably.

Surprisingly, there is little evidence on momentum in the *cross-section* of currencies. Large cross-country data sets were rare in the past so that the earlier literature has generally focused on momentum strategies in the time series of currencies, i.e., momentum strategies where individual currencies are bought and sold over time depending on various sorts of signals such as moving average cross-overs, filter rules, channel breakouts, etc. This literature has shown that certain technical trading rules were temporarily profitable but that their profits often tend to deteriorate over time as more traders learn about these strategies and start to exploit them (e.g., Levich and Thomas, 1993; Pukthuanthong-Le, Levich, and Thomas, 2007; Neely, Weller, and Ulrich, 2009, among others). A survey of this literature is provided by Menkhoff and Taylor (2007). However, some evidence on the existence of cross-sectional momentum profits in the FX market is provided by Okunev and White (2003), Asness, Moskowitz, and Pedersen (2009), and Burnside, Eichenbaum, and Rebelo (2011) in the context of small cross-sections of major currencies. Relative to our paper, these studies have a different focus, however, and do not provide a unifying analysis for understanding returns to cross-sectional currency momentum returns.

The main contribution of this paper is to study the economic anatomy of momentum profits in FX markets. We start by forming currency portfolios where an investor is long in currencies with high past excess returns (so-called "winners") and short in currencies with low past excess returns (so-called "losers"). We take the viewpoint of a U.S. investor and consider exchange rates against the U.S. dollar (USD). Our data cover the period from January 1976 to January 2010, and we study a cross-section of up to 48 currencies. We go beyond earlier research on currency momentum by (a) providing an in-depth analysis of the relative importance of systematic versus unsystematic risk for understanding momentum returns, (b) carefully comparing momentum strategies to carry trades and technical trading rules, (c) quantifying the importance of transaction costs, and investigating nonstandard sources of momentum returns, such as (d) under- and overreaction or (e) limits to arbitrage.

We find large and significant excess returns to currency momentum strategies of up to 10% per annum (p.a). As in Jegadeesh and Titman (2001), we find some evidence of return continuation and subsequent reversals over longer horizons of up to 36 months, which is consistent with behavioral biases, such as investor under- and overreaction, and suggests that momentum effects in different asset classes could share a common source. Importantly, currency momentum is very different from the popular carry trade in FX markets, providing high returns that are largely unrelated to carry trade returns.[4] Currency momentum returns are also different from returns generated by technical trading rules, which have been studied in a large empirical literature (e.g., Dooley and Shafer, 1976; Sweeney, 1986; Levich and Thomas, 1993; Neely, Weller, and Ulrich, 2009).

To rationalize these high excess returns of currency momentum strategies, we investigate whether currency momentum is significantly affected by (i) transaction costs, (ii) business cycle risk and other traditional risk factors, and (iii) different forms of limits to arbitrage. We find that momentum returns are indeed fairly sensitive to transaction costs. Adjusting returns for bid–ask spreads lowers the profitability of momentum strategies significantly since momentum portfolios are skewed towards currencies with high transaction costs. However, transaction costs are unable to completely account for currency momentum returns.

Also, momentum returns in FX markets are not systematically related to standard proxies for business cycle risk, liquidity risk (Brunnermeier, Nagel, and Pedersen, 2009), the carry trade risk factor proposed by Lustig, Roussanov, and Verdelhan (2011), volatility risk (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012), the three Fama and French factors (Fama and French, 1992), or a four-factor model including a U.S. stock return momentum factor (Carhart, 1997). In short, there does not seem to be a systematic risk factor that would explain (net) momentum returns, a result that is akin to the corresponding findings based on U.S. equity momentum.

However, the profitability of currency momentum strategies varies significantly over time, which can induce limits to arbitrage for the major market participants in FX markets (e.g., proprietary traders and hedge funds), who usually have rather short investment horizons and could thus act myopically (e.g., Shleifer and Vishny, 1997).[5]

[4] The carry trade is a popular trading strategy that borrows in currencies with low interest rates and invests in currencies with high interest rates. According to uncovered interest parity, if investors are risk neutral and form expectations rationally, exchange rate changes will eliminate any gain arising from the differential in interest rates across countries. However, a number of empirical studies show that high interest rate currencies tend to appreciate, while low interest rate currencies tend to depreciate. As a consequence, carry trades form a profitable investment strategy, giving rise to the "forward premium puzzle" (Fama, 1984). See Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), Lustig, Roussanov, and Verdelhan (2011), and Menkhoff, Sarno, Schmeling, and Schrimpf (2012).

[5] We use the term "limits to arbitrage" here to mean that trading momentum strategies expose the investor to risks not captured by traditional covariance risk measures so that an anomaly like momentum returns is not easily exploitable. This definition is in line with much of

Furthermore, momentum returns are clearly related to currency characteristics. Returns are much higher in currencies with high (lagged) idiosyncratic volatility (about 8% p.a.) compared to currencies with low idiosyncratic volatility (about 4% p.a.). Returns are also related to measures of country risk, i.e., momentum strategies in countries with a high risk rating tend to yield significantly positive excess returns, whereas momentum strategies in countries with low risk ratings do not. Finally, a similar effect is found for a measure of exchange rate stability risk (i.e., the expected risk of observing large currency movements in the future).

In summary, we provide evidence that, despite FX markets' differences relative to stock markets, the properties of momentum strategies are fairly similar, which suggests that momentum profits in different asset classes could share a common root. Similar to stock markets, the high excess returns of currency momentum strategies can be (only) partially explained by their sensitivity to high transaction costs. Another piece of explanation of why momentum in currency markets persists is that there might be effective obstacles constraining the deployment of arbitrage capital to exploit the phenomenon. We find that currency momentum strategies are risky in that their returns are rather unstable over short time periods and that their exposure is subject to fundamental investment risk, captured by idiosyncratic characteristics of the currencies involved.

The remainder of this paper proceeds as follows. We selectively discuss earlier literature in Section 2. Section 3 details our data and portfolio formation procedure. Section 4 describes momentum returns in FX markets and compares momentum strategies with benchmark technical trading rules and the popular carry trade, while Section 5 discusses the results of our tests seeking to explain the high returns to currency momentum strategies. Section 6 provides robustness checks and Section 7 concludes. Additional results can be found in an Internet Appendix to this paper.

2. Related literature

Academic studies about momentum strategies are mostly focused on stock markets but momentum effects have been also detected in bond and commodity markets. To set the stage, we briefly survey this literature before we turn to FX markets and highlight the contributions of this paper.

Stock market momentum: Momentum effects are well documented in equity markets for almost two decades. The empirical literature is highly influenced by the work of Jegadeesh and Titman (1993), who show in a thorough analysis of the U.S. stock market that simple momentum strategies generate high returns, in the order of about 12% p.a., and are difficult to rationalize by standard asset pricing models. Subsequent studies extend the original research into new domains, including many countries worldwide beyond the U.S. (e.g., Rouwenhorst, 1998, 1999; Chan, Hameed, and Tong, 2000, Chui, Titman, and Wei, 2010) and higher frequencies (Gutierrez and Kelley, 2008).

While equity momentum is an established empirical fact, explanations have been heavily disputed. The major approaches to explain momentum can be classified as (i) risk-based and characteristics-based explanations, (ii) explanations invoking cognitive biases or informational issues, and (iii) explanations based on transaction costs or other forms of limits to arbitrage.

Starting with risk-based and characteristics-based explanations (i), early studies show that momentum returns are difficult to rationalize by covariance risk with standard factors (e.g., Fama and French, 1996; Jegadeesh and Titman, 2001). In the same vein, linking momentum to macroeconomic risk has proven rather challenging.[6] By contrast, firm-specific characteristics have been shown to be linked to momentum, e.g., momentum appears to be stronger among smaller firms (Hong, Lim, and Stein, 2000), among firms with lower credit rating (Avramov, Chordia, Jostova, and Philipov, 2007), and among firms with high revenue growth volatility (Sagi and Seascholes, 2007). Also, momentum returns appear to a large extent concentrated in firms with a high likelihood to go bankrupt (Eisdorfer, 2008).

Empirical work invoking behavioral biases (ii) in explaining momentum – focusing, for example, on investors' underreaction to news – also featured prominently since the beginning of the debate (Jegadeesh and Titman, 1993) and in subsequent work (e.g., Jegadeesh and Titman, 2001; Grinblatt and Han, 2005; Hvidkjaer, 2006).[7] Stressing how information is incorporated into prices, Chan, Jegadeesh, and Lakonishok (1996) provide early evidence that analysts' earnings forecasts respond gradually to news which can generate underreaction. Hong, Lim, and Stein (2000) demonstrate in detail the relation between weak analyst coverage and stronger momentum.[8] A final strand explores the role of transaction costs or limits to arbitrage (iii) in explaining momentum. Lesmond, Schill, and Zhou (2004) state that reasonably high transaction costs could wipe out momentum profits. Korajczyk and Sadka (2004) qualify this finding as they argue that momentum strategies can be designed in a way to limit transaction costs; this will lead to a more moderate cost level so that even very large momentum portfolios (with assets worth more than one billion U.S. dollars) are still highly profitable.

Momentum in bonds and commodities: Momentum has also been shown to exist in other asset classes. Regarding

(*footnote continued*)
the recent literature but it should be noted that the term (originally due to Keynes) initially referred to the market's inability to exploit risk-free arbitrage opportunities. Relative to this more precise definition, our tests are more closely related to "limits to speculation."

[6] For instance, Chordia and Shivakumar (2002) find support for time-varying risk factors explaining momentum returns, whereas Griffin and Martin (2003) and Cooper, Gutierrez, and Hameed (2004) do not.

[7] Behavioral models, e.g., by Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999) account for momentum effects by allowing for deviations from fully rational behavior such as overconfidence, slow updating of investor beliefs, and information imperfections.

[8] In addition, analyst behavior will lead, during the period of information incorporation, to information heterogeneity among investors, which is shown by Verardo (2009) to be related to momentum.

bond markets, momentum strategies do not work for investment-grade bonds (Gebhardt, Hvidkjaer, and Swaminathan, 2005) or bonds at the country level (Asness, Moskowitz, and Pedersen, 2009), but yield positive returns for non-investment grade *corporate* bonds (Jostova, Nikola, Philipov, and Stahel, 2010). Further analysis shows that momentum returns are not related to liquidity but seem to reflect default risk in the winner and loser portfolios. Regarding commodity markets, the high returns to momentum strategies are shown to be related to market states with low levels of inventories that indicate higher risk (Gorton, Hayashi, and Rouwenhorst, 2008). These findings tentatively suggest common sources of momentum profits that seem to be based on the risk characteristics of the underlying assets.

Currency momentum: In contrast to the extensive literature on momentum strategies in stock markets, the literature on currency momentum has mostly developed a somewhat different line of research. The most striking difference is the fact that currency momentum studies generally do not analyze momentum in a cross-section of currencies but in the time series of single exchange rates, often framed as "technical trading rules."[9] This literature is surveyed in Menkhoff and Taylor (2007) and we will discuss it in more depth below. This time-series literature has extensively examined which kinds of trading rules work best.

One exception from the time-series focus is Okunev and White (2003) who analyze a universe of eight currencies over 20 years, from January 1980 to June 2000. At the end of each month, the investor goes long in the currency with the best last-month performance and goes short in the currency with the worst last-month performance. This yields a return of about 6% p.a., which is largely independent of the base currency chosen and of the specific trading rule chosen, i.e., how exactly the best and worst currencies are identified. Thus, there is clear indication that currency momentum strategies can be profitable and thus worthy of a thorough examination.[10] Burnside, Eichenbaum, and Rebelo (2011) investigate returns to an equally weighted momentum portfolio that aggregates over momentum positions in individual currencies. They find (as we do in this paper) that standard risk factors cannot account for currency momentum returns.

Technical trading in FX markets: Technical trading in FX is in most cases the same as trend following, that is, exploiting the momentum of a market. These time-series momentum strategies include filter rules and moving average rules. A filter rule gives the signal to invest (to take a short position) in a currency if a defined upwards (downwards) exchange rate change has occurred, such as a 1% or 2% change. A moving average rule gives signals if short-term exchange rate averages become larger or smaller than longer-term averages.[11] Simple trend following trading strategies of this kind provide attractive returns, even considering interest rate differentials and transaction costs, as, for example, the early studies of Dooley and Shafer (1983) or Sweeney (1986) have demonstrated.[12]

These early studies have been challenged by subsequent work examining whether trend following trading strategies are also profitable in later periods. Whereas Dooley and Shafer (1983) and Levich and Thomas (1993) confirm profitability out-of-sample, studies also covering the 1990s and 2000s find that the above-mentioned simple trend following strategies applied to the same set of exchange rates no longer yield attractive returns (see, e.g., Olson, 2004; Pukthuanthong-Le, Levich, and Thomas, 2007; Neely, Weller, and Ulrich, 2009). However, profits are still found if either new forms of trend following strategies or new exchange rates are considered.[13]

Contributions of this paper: In contrast to the abundance of time-series studies, there is little evidence on cross-sectional aspects of currency momentum, whose importance has clearly risen in face of the realities of today's FX markets. Whereas there were about 10 convertible and liquid currencies in the 1970s, there are more than 30 currencies available to investors today. And while transaction volumes used to be dominated by banks' FX traders, asset managers of various kinds (including hedge funds) have emerged as some of the key players in today's FX markets. Overall, volumes, tradable assets, and participants have changed, which culminates in the perception of FX as a separate asset class, in parallel to, e.g., equities and bonds (King, Osler, and Rime, 2012). Even retail investors nowadays have access to various FX investment strategies via structured products. This naturally leads to studying cross-sectional currency momentum taking into account these new features and industry practices.[14]

In this paper, we go beyond earlier research in a number of directions. First, we analyze a much longer time span and, more importantly, a much larger cross-section of currencies that includes currencies of developed and emerging countries. This extended sample across time and currencies is crucial for our analysis of returns to currency momentum strategies since it allows

[9] See, e.g., Harris and Yilmaz (2009), Neely, Weller, and Ulrich (2009), and Serban (2010) in this respect.

[10] More recently, Asness, Moskowitz, and Pedersen (2009) have also investigated returns to a currency momentum strategy based on 10 currencies. The focus of their paper is very different from ours, however, with its primary objective being to explore the commonality of momentum across asset classes.

[11] For example, a 1,5 (or 5,20) rule suggests to buy Euro against US-dollar, if the 1- (5-) day US-dollar/Euro rate is higher than its 5-day (20-day) average.

[12] These strategies are also implemented in practice and the widespread use has led, e.g., Lequeux and Acar (1998), to build an index based on moving average rules to serve as a benchmark for Commodity Trading Advisors.

[13] Less well known and less studied forms include channel rules, genetic programming-based rules, Markov model-based rules, and others (e.g., Neely, Weller, and Dittmar, 1997). Neely and Weller (2012) provide a recent overview of different trading rules in currency trading. Neely, Weller, and Ulrich (2009) show that these rules are still profitable until the end of their sample period in 2005. Pukthuanthong-Le and Thomas (2008) confirm that standard trading rules in the main exchange rates do not generate profits when recent data are considered, whereas the same rules yield high returns in emerging markets' exchange rates.

[14] We thank the referee for pointing this out. An investment product such as the Currency Momentum ETF of Deutsche Bank, which is accessible even for retail investors, serves as an example of these new trends.

us to better identify return variation over time (and, hence, states of the business cycle) as well as across currencies that are structurally different and should have different exposures to global risk factors. Second, we can take explicit account of transaction costs, which is crucial since momentum returns are only relevant as long as they survive realistic transaction costs. Third, we take a close look at possible limits to arbitrage (which are a key theme in the recent literature on equity momentum) and investigate the role of idiosyncratic return volatility, country risk, and the risk of exchange rate stability. In sum, we provide a detailed account of the economic anatomy and drivers of currency momentum strategies that has been missing in the literature until now.

3. Data and currency portfolios

This section describes our data, the computation of currency excess returns, and the construction of momentum portfolios.

Data source and sample currencies: The data for spot exchange rates and one-month forward exchange rates cover the sample period from January 1976 to January 2010, and are obtained from Barclays Bank International (BBI) and Reuters (via Datastream). We denote the spot and forward rates in logs as s and f, respectively. Spot and forward rates are end-of-month data (last trading day in a given month) and are therefore not averaged over a month.

Our total sample consists of the following 48 countries: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Iceland, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, United Kingdom.

It is worth noting that, compared to, e.g., Lustig, Roussanov, and Verdelhan (2011) or Menkhoff, Sarno, Schmeling, and Schrimpf (2012), whose samples start in 1983 and have seven currency pairs in the beginning of the sample (mainly) based on BBI data quoted against the U.S. dollar, we employ a longer time series that extends back to 1976. We do so by complementing BBI data (which only start in 1983) with Reuters data quoted against the British Pound as in Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011). We have a total of 16 currencies for this longer time span and convert these data to quotations against the U.S. dollar. These 16 countries are: Austria, Belgium, Canada, Denmark, France, Germany, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. In addition to the larger cross-section and longer time series, we also have bid and ask quotes for spot and forward rates available so that we can adjust for transaction costs for the whole period from 1976 to 2010.

Finally, we note that our effective sample size varies over time as data for emerging countries become available or when currencies cease to exist, e.g., due to the adoption of the Euro. To illustrate this point, we plot the number of currencies with available data for each month of our sample in Fig. 1 (solid line). As can be inferred from this graph, our sample does not cover all 48 currencies at the same time since data availability varies naturally due to inclusion and exclusion of currencies. The total sum of actual observations (currency-month combinations) is

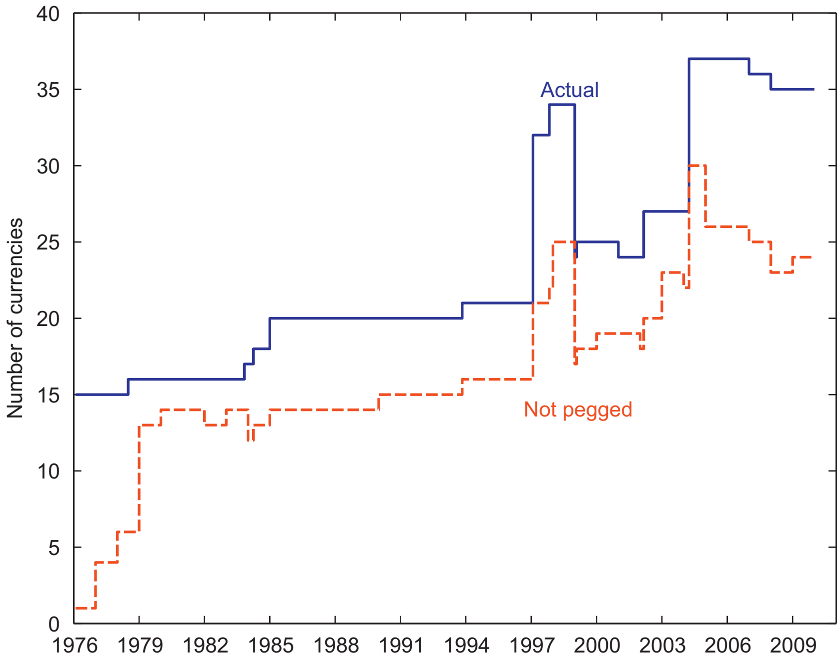

Fig. 1. Number of available currencies. The solid line shows the number of available currencies (i.e., currencies with available data for forward and spot exchange rates) and the dashed line shows the number of currencies with available data when excluding pegged currencies for each month of our sample period runs from January 1976 to January 2010.

9,403 as opposed to the theoretical maximum of 19,584 (408 months $\times$ 48 currencies). Individual start and end dates for each currency are shown in Table A1 in the Internet Appendix.

The dashed line in Fig. 1 also shows the number of available currencies that are not tightly pegged to other currencies. As can be expected, there are fewer currencies of this sort, especially in the very early part of the sample. While it is not problematic per se to perform momentum trading strategies in tightly linked currencies, one would expect that momentum profits should be relatively lower in the very early years of our sample. This is what we find in our empirical analysis below.[15]

Currency excess returns: Monthly excess returns to a U.S. investor for holding foreign currency k are given by

$$rx_{t+1}^{k} \equiv i_t^k - i_t - \Delta s_{t+1}^k \approx f_t^k - s_{t+1}^k, \tag{1}$$

where i^k denotes the one-month interest rate in country k, i without a superscript denotes the interest rate at home (the U.S. in our case), s and f denote the (log) spot and one-month forward rate (foreign currency unit per USD), respectively. Δs denotes the log spot rate change or return. If covered interest rate parity (CIP) holds, interest rate differentials $i_t^k - i_t$ equal forward discounts $f_t^k - s_t^k$. Akram, Rime, and Sarno (2008) show empirically that CIP holds even at very short horizons. Descriptive statistics for excess returns, forward discounts, and bid–ask spreads are reported in the Internet Appendix (Table A1).

For future reference, we also define net currency excess returns, i.e., currency excess returns after bid–ask spreads. These returns only apply when investigating dynamic investment strategies (momentum strategies in our case), where investors form portfolios of currencies. We detail the construction of portfolios below and simply define how we adjust for transaction costs here.

The net return for a currency that enters a portfolio at time t and exits the portfolio at the end of the month is computed as $rx_{t+1}^l = f_t^b - s_{t+1}^a$ for a long position and $rx_{t+1}^s = -f_t^a + s_{t+1}^b$ for a short position. An a (b) superscript indicates the ask (bid) quote. A currency that enters a portfolio but stays in the portfolio at the end of the month has a net excess return $rx_{t+1}^l = f_t^b - s_{t+1}$ for a long position and $rx_{t+1}^s = -f_t^a + s_{t+1}$ for a short position, whereas a currency that exits a portfolio at the end of month t but already was in the current portfolio the month before ($t-1$) has an excess return of $rx_{t+1}^l = f_t^b - s_{t+1}^a$ for a long position and $rx_{t+1}^s = -f_t^a + s_{t+1}^b$ for a short position. Hence, since forward contracts in our sample have a maturity of one month, the investor always incurs transaction costs in the forward leg of his position but does not always have to trade the spot market leg of his position if he stays invested in a foreign currency. In addition, we assume that the investor has to establish a new position in each single currency in the first month (January 1976) and that he has to sell all positions in the last month (at the end of January 2010). Note that bid and ask rates are daily (not averaged over the month) so that they correspond exactly to the end-of-month data for spot and forward rates.

[15] We thank the referee for pointing this out.

However, one has to bear in mind that bid–ask spreads from BBI/Reuters are based on indicative quotes that are "too high" (see, e.g., Lyons, 2001) relative to actual effective spreads in FX markets so that our results with net returns (after deducting the bid–ask spread) should be understood as undercutting the lower bound on the profitability of momentum strategies and not as the "exact" return. For this reason, we frequently provide results with and without transaction costs below in our empirical analysis. We denote returns or spot rate changes after deducting bid–ask spreads as "net returns" and "net spot rate changes," respectively.

Portfolio construction: At the end of each month, we form six portfolios based on lagged returns over the previous $f=1,3,6,9,12$ months (f denotes the formation period) and these portfolios are held for $h=1,3,6,9,12$ months (h denotes the holding period). The one-sixth of all available currencies in a given month that have the lowest lagged returns are allocated to the first portfolio (denoted "Low"), the next sixth is allocated to portfolio 2, and so on, and the one-sixth of all currencies with the highest lagged returns are allocated to the sixth portfolio (denoted "High"). Hence, this procedure yields a time series of six currency momentum portfolios' excess returns and is analogous to the construction of momentum portfolios in the equity market literature.[16]

However, since interest rate differentials (forward discounts) contribute a significant share of the excess return of currency investments, we also track the pure spot rate changes of momentum portfolios themselves and report them separately in many tables. This way, we can check whether currency momentum is mainly driven by interest rate differentials or whether it occurs in spot rates, too.

Finally, in most analyses we work with the portfolio that is long in the winner currencies (portfolio "High") and short in the loser currencies (portfolio "Low"). These portfolios are denoted $MOM_{f,h}$ where f and h represent the formation and holding period, respectively, as defined above. We also refer to these portfolios simply as "long–short" momentum portfolios or "high-minus-low" portfolios. An important feature of these long–short portfolios is that they are dollar neutral, since the dollar component cancels out when taking the difference between (any) two portfolios.

4. Characterizing currency momentum returns

In this section, we present our main empirical results regarding the profitability and characteristics of currency

[16] Lustig and Verdelhan (2007) were the first to form portfolios of currency excess returns to be able to explain returns to the carry trade. This approach of forming currency portfolios has proved very useful in uncovering the economic drivers of carry trade risk premia and has been followed by several other papers afterwards. This way of constructing momentum returns differs from much of the earlier literature on technical trading in currency markets that mostly works in the time series of individual currency pairs (and then potentially aggregates across all currencies in the sample). Our approach is closer to how momentum is studied in the equity market literature and it is also closely related to how the financial industry sets up tradable momentum portfolios. For example, Deutsche Bank offers a currency momentum ETF based on G10 currencies and the underlying index is long (short) in the three best (worst) performing currencies over the last 12 months (Deutsche Bank, 2010).

momentum strategies (Section 4.1), the stability of the strategies out of sample (Section 4.2), the difference between currency momentum and technical trading rules (Section 4.3), the difference between currency momentum and carry trades (Section 4.4), and the long-run return behavior of momentum strategies (Section 4.5).

4.1. Returns to momentum strategies in currency markets

Table 1, Panel A, shows average annualized excess returns (left panel) and spot rate changes (right panel) for a number of high-minus-low momentum portfolios with formation and holding periods each varying between one and 12 months: $f,h = 1,3,6,9,12$. Average excess returns in the left panel are based on sorting on lagged excess returns, and average spot rate changes in the right panel are based on sorting on lagged spot rate changes. To provide a perspective on profitability of FX momentum relative to risk, Panel B of Table 1 reports Sharpe Ratios for the same strategies.

Turning to excess returns in the left panel first, we find that momentum strategies yield substantial (and statistically highly significant) excess returns of about 6–10% for short holding periods of one month and their profits slowly fade out when increasing the holding period. The latter finding is quite pronounced since there is a monotone decline in average excess returns when moving from short holding periods to longer holding periods h for a given formation period f. However, we find many instances of significant momentum returns for strategies with longer holding periods as well, so that momentum is not confined to very short holding periods.

In the right panel of Table 1, Panel A, we also report the average difference between spot rate changes for the high and low portfolio. For ease of exposition, we actually report the negative of the log spot rate change (in the notation of Section 3) so that higher values indicate a positive contribution of spot rate movements to a momentum strategy's total excess return. Interestingly, the profitability of currency momentum strategies is also clearly visible in spot rate changes themselves and is thus not mostly driven by the interest rate differential as is the case for carry trades (see, e.g., Lustig, Roussanov, and Verdelhan, 2011). In fact, the strategy with a 12-month formation period is completely driven by favorable spot rate changes and the interest rate differential reduces the excess return somewhat.

Table 1
Momentum returns and Sharpe Ratios.

This table shows annualized average returns for different momentum strategies $(\overline{r^{f,h}})$ in Panel A. The rows show formation periods (f) whereas the columns indicate holding periods (h) in months. Numbers in brackets are t-statistics based on Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) standard errors. The left part of the table shows currency excess returns (spot rate changes adjusted for interest rate differentials) whereas the right part shows pure spot rate returns. Panel B shows annualized Sharpe Ratios. t-Statistics based on a moving block-bootstrap are in squared brackets. The right panel shows average annualized spot rate changes (in percent) divided by the annualized standard deviation of mean exchange rate changes. The sample period is January 1976–January 2010 and we employ monthly returns.

Panel A: Excess returns and spot rate changes

	Excess returns						Spot rate changes				
	Holding period h						Holding period h				
f	1	3	6	9	12	f	1	3	6	9	12
1	9.46	7.00	6.17	5.15	5.75	1	7.91	4.42	3.38	4.75	3.13
	[5.31]	[4.11]	[3.13]	[2.73]	[3.6]		[4.55]	[3.07]	[1.93]	[2.94]	[2.02]
3	9.40	6.32	4.96	4.67	4.43	3	8.54	5.73	5.28	4.63	5.10
	[5.30]	[3.80]	[3.03]	[2.92]	[2.74]		[5.10]	[3.59]	[3.66]	[2.88]	[3.51]
6	8.54	6.31	3.66	3.25	3.14	6	6.50	5.75	3.47	3.64	3.17
	[4.78]	[3.63]	[2.06]	[1.79]	[1.69]		[3.88]	[4.00]	[2.15]	[2.32]	[1.80]
9	7.18	6.80	5.36	3.86	3.24	9	8.33	7.06	6.50	4.91	4.09
	[3.80]	[3.65]	[2.86]	[2.05]	[1.67]		[4.82]	[4.23]	[3.91]	[2.87]	[2.35]
12	6.16	5.48	3.02	2.05	1.89	12	7.59	6.04	3.94	3.19	3.03
	[3.40]	[3.24]	[1.75]	[1.17]	[1.04]		[4.63]	[4.02]	[2.59]	[1.97]	[1.92]

Panel B: Sharpe Ratios and normalized spot rate changes

	Excess returns						Spot rate changes				
	Holding period h						Holding period h				
f	1	3	6	9	12	f	1	3	6	9	12
1	0.95	0.76	0.59	0.56	0.61	1	0.84	0.53	0.37	0.57	0.37
	[5.48]	[4.10]	[3.15]	[2.47]	[2.95]		[5.52]	[4.23]	[3.25]	[2.81]	[3.21]
3	0.88	0.60	0.50	0.53	0.51	3	0.86	0.57	0.58	0.50	0.63
	[5.37]	[3.70]	[3.04]	[2.74]	[2.42]		[5.17]	[3.73]	[3.45]	[2.99]	[2.61]
6	0.79	0.60	0.37	0.34	0.33	6	0.64	0.60	0.38	0.41	0.35
	[4.55]	[3.53]	[1.94]	[1.76]	[1.48]		[4.76]	[3.70]	[2.06]	[2.05]	[1.43]
9	0.67	0.63	0.50	0.36	0.30	9	0.85	0.71	0.66	0.51	0.41
	[3.76]	[3.61]	[2.95]	[1.95]	[1.57]		[3.99]	[3.66]	[3.07]	[2.12]	[1.84]
12	0.61	0.56	0.32	0.21	0.19	12	0.77	0.64	0.44	0.35	0.33
	[3.18]	[3.05]	[1.64]	[1.17]	[1.05]		[3.48]	[3.32]	[1.89]	[1.27]	[1.14]

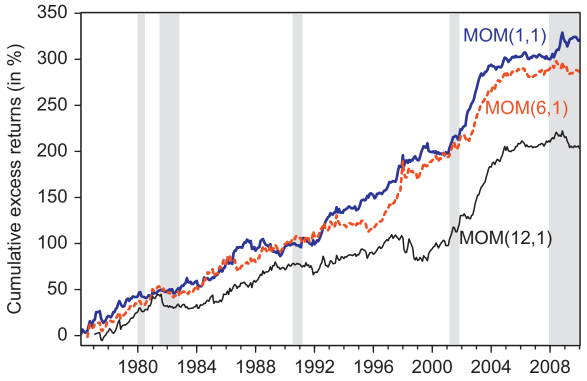

Fig. 2. Cumulative excess returns of momentum strategies. This figure shows cumulative log excess returns (not adjusted for transaction costs) accruing to three different momentum returns. The momentum strategies are for a formation period of 1, 6, and 12 months, respectively, and the holding period is one month. The bold line shows returns to the momentum strategy with a one-month formation period (MOM(1,1) in the figure), the dashed line shows returns to a strategy with a six-month formation period (MOM(6,1)), whereas the thin, black line shows returns to a momentum strategy with a 12-month formation period (MOM(12,1)). Shaded areas correspond to NBER recessions.

As noted above, results tend to be strongest for a holding period of $h=1$ month. We therefore focus on these strategies in most of the following analysis as they seem to present the hardest challenge when trying to understand momentum returns in currency markets. Since the level of average excess returns is also clearly dependent on the formation period f, we provide results for the three strategies with $f=1,6$, and 12 months in our empirical analyses below. In sum, most of our analysis in the remainder of the paper focuses on the three benchmark strategies $MOM_{1,1}$, $MOM_{6,1}$, and $MOM_{12,1}$.[17]

As a first and simple means of investigating a possible link between momentum returns and the state of the business cycle, and to provide a graphical exposition of momentum returns accruing to investors, Fig. 2 shows cumulative excess returns for the three benchmark momentum strategies $MOM_{1,1}$,$MOM_{6,1}$, and $MOM_{12,1}$ over the full sample period. Shaded areas correspond to NBER recessions. As illustrated by the figure, there is no obvious correlation of momentum returns with the state of the business cycle (as examined later in Section 5.2). However, the three benchmark momentum strategies show some comovement but are not perfectly correlated.

Sharpe Ratios: To get a first measure of risk-adjusted returns, Panel B of Table 1 presents Sharpe Ratios for the momentum strategies shown in Table 1 above in Panel A, and "normalized spot rate changes" (average spot rate changes divided by their standard deviation) in Panel B. Corroborating the evidence above, currency momentum strategies seem highly profitable, at least for a subset of strategies. For example, the annualized Sharpe Ratio of the MOM(1,1) strategy is 0.95, which seems very high, even in comparison to carry trades. See, e.g., Menkhoff, Sarno, Schmeling, and Schrimpf (2012) who report an annualized Sharpe Ratio of 0.82 for a carry trade strategy. Hence, even when taking risk into account on the basis of Sharpe Ratios, momentum strategies seem highly attractive. In addition, we see from Panel B of Table 1 that this performance is largely driven by spot rate changes and that it is not dominated by the interest rate component of excess returns.

Momentum returns and size of the cross-section: As noted above in the previous section, our effective sample size never exceeds 40 currencies and is therefore relatively small compared to sample sizes used in, e.g., the equity momentum literature. However, it is well known from earlier work that even small portfolios of currencies can yield large gains from diversification since currencies tend to be less correlated than stocks (e.g., Burnside, Eichenbaum, and Rebelo, 2008). To explore the link between the size of the cross-section and the magnitude of momentum returns, we conduct a stylized simulation experiment as follows. In each run i, we randomly draw (without replacement) a set of N currencies from the set of all 48 currencies while imposing the restriction that we have data for at least six currencies in each month of the sample period from January 1976 to January 2010. We then calculate average annualized momentum excess returns for a MOM(1,1) strategy and save this result. We do this 5,000 times for each cross-section size N and average over momentum profits to obtain an estimate of the "typical" momentum profit conditional on observing a cross-section of size N. For $N=48$, we simply report the momentum profit from Table 1.

Fig. 3 shows results from this exercise and it can be seen that expanding the size of the cross-section is very useful for small cross-sections but much less important for larger cross-sections. In other words, there are decreasing gains from expanding the size of the tradable currency universe. The maximum level of returns is roughly obtained for a

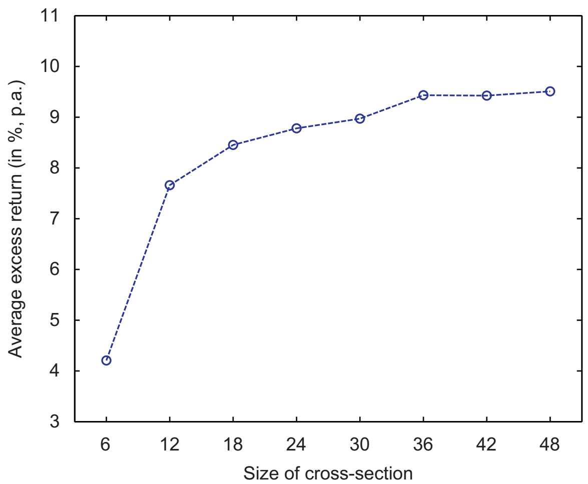

Fig. 3. Size of the cross section and momentum returns. This figure shows average annualized excess returns for a MOM(1,1) strategy implemented on a cross section of 6, 12, 18,…,48 currencies. We draw 5,000 random combinations of currencies for each size of the cross section (imposing the restriction that we have at least six currencies at each point in time) and plot the average (across simulations) annualized mean excess return of a MOM(1,1) strategy.

[17] One might worry that some currencies were not always tradable during our sample period due to, e.g., capital account restrictions. We provide robustness checks on this issue in Section 6.1.

Table 2
Momentum^2.

This table shows average momentum excess returns and Sharpe Ratios (SR) for momentum strategies based on other momentum portfolios. We first calculate monthly excess returns for all 144 possible momentum portfolios based on formation and holding periods of $f=1,2,\ldots,12$ and $h=1,2,\ldots,12$. Next we run a momentum strategy on these 144 momentum portfolios and sort momentum strategies from the first step into nine portfolios based on their lagged returns over an evaluation period. Lagged returns over the evaluation period (shown in the first column) vary from one to 120 months. We report results for the nine portfolios from the second stage (from "Worst" lagged strategy to "Best" lagged strategy) and a high-minus-low portfolio (best strategy minus worst strategy, "B−W") that is long in the best 16 (144/9) strategies and short in the worst 16 (144/9) strategies from the first step. Numbers in brackets are HAC t-statistics based on Newey and West (1987). The sample period is January 1976–January 2010 and we employ monthly returns.

		Momentum^2-Portfolios									
Lag		Worst	2	3	4	5	6	7	8	Best	B−W
1	Mean	1.03	2.45	3.44	3.78	4.34	5.46	5.82	6.85	8.70	7.67
	t	[0.79]	[1.74]	[2.40]	[2.54]	[2.90]	[3.50]	[3.76]	[4.46]	[5.68]	[4.31]
	SR	0.14	0.31	0.42	0.45	0.49	0.62	0.63	0.75	0.94	0.73
3	Mean	1.21	3.02	3.85	3.53	4.51	5.14	5.72	6.67	7.62	6.41
	t	[1.04]	[2.28]	[2.71]	[2.46]	[3.03]	[3.37]	[3.72]	[4.24]	[5.05]	[4.12]
	SR	0.20	0.43	0.50	0.43	0.53	0.58	0.62	0.72	0.83	0.71
6	Mean	3.40	2.99	3.47	3.92	3.93	4.69	6.09	6.54	7.88	4.48
	t	[2.87]	[2.39]	[2.63]	[2.87]	[2.62]	[3.17]	[3.94]	[4.27]	[5.04]	[3.08]
	SR	0.54	0.45	0.48	0.52	0.47	0.54	0.67	0.72	0.85	0.54
9	Mean	3.59	3.82	4.04	4.61	4.81	5.28	5.55	6.07	7.10	3.51
	t	[3.02]	[3.11]	[3.13]	[3.43]	[3.44]	[3.43]	[3.69]	[3.89]	[4.52]	[2.53]
	SR	0.57	0.57	0.56	0.60	0.59	0.60	0.63	0.68	0.79	0.44
12	Mean	3.29	4.57	4.57	4.42	4.86	4.98	5.54	5.87	7.25	3.96
	t	[2.76]	[3.69]	[3.39]	[3.28]	[3.46]	[3.51]	[3.44]	[3.75]	[4.83]	[3.14]
	SR	0.53	0.66	0.62	0.58	0.59	0.59	0.61	0.66	0.81	0.51
60	Mean	3.83	3.75	4.24	4.82	4.15	5.28	5.18	5.42	5.92	2.09
	t	[2.70]	[2.60]	[2.90]	[3.27]	[2.75]	[3.62]	[3.25]	[3.49]	[3.86]	[1.88]
	SR	0.55	0.53	0.58	0.63	0.52	0.66	0.60	0.64	0.68	0.33
120	Mean	3.69	4.21	4.82	4.60	4.54	5.01	5.75	5.76	6.40	2.70
	t	[2.16]	[2.48]	[2.80]	[2.61]	[2.62]	[2.88]	[3.20]	[3.18]	[3.59]	[2.03]
	SR	0.49	0.56	0.61	0.55	0.55	0.61	0.68	0.65	0.74	0.41

cross-section of size $N=36$. Hence, although our cross-section is far from what is used in the equity market literature, one can be confident that the results are quite representative of the currency market as a whole.

4.2. Out-of-sample perspective

Our setup to illustrate FX momentum profits, which is akin to the equity literature, has a clear out-of-sample component, since we form portfolios based on lagged information only. Hence, the momentum strategies discussed above are implementable in real time. However, average returns can vary markedly across different strategies (that is, different combinations of formation and holding period), and can also be fairly low. For example, the strategy with a 12-month formation and holding period only yields 1.89% p.a. over the full sample whereas the strategy with a one-month formation and holding period experienced an annualized average return close to 10%. This particular information is only available ex post and an investor could not have conditioned on this information in 1976. Hence, it is interesting to examine whether investors could have actually exploited these momentum profits taking into account that there is ex ante uncertainty about which specific momentum strategy to follow.[18] Put differently, do specific momentum strategies identified to be attractive in-sample continue to do well?

We tackle this question by investigating returns to what we term "Momentum^2" strategies. To do so, we imagine an investor who can invest in 144 different strategies (all combinations of $f=1,2,\ldots,12$ and $h=1,2,\ldots,12$) and has to rely on some mechanism to select between these different strategies. A natural mechanism in our context is to let the investor rely on momentum in lagged momentum returns (as measured over an evaluation period). More specifically, we form nine portfolios out of the universe of 144 possible momentum strategies. These nine portfolios are based on a ranking *of the momentum strategies* themselves by their lagged returns during an evaluation period, hence the term Momentum^2. Results for this exercise are shown in Table 2 which reports returns for all nine Momentum^2 portfolios (from "worst" lagged returns to "best" lagged returns) and a "best minus worst" portfolio. For robustness we show

[18] Silber (1994) also investigates whether trading strategies identified as profitable over an in-sample period continue to perform well in an out-of-sample period.

results for lags of 1,3,6,9,12,60, and 120 months over which individual momentum strategies are evaluated. As can be seen, using lagged momentum returns to identify future momentum returns seems feasible. For example, conditioning just on last month's return across all possible strategies leads to an annualized average excess return of 7.67% p.a. As for the simple momentum strategies above, we see a declining pattern in returns when moving to longer selection windows. For example, using a window of 120 months leads to much lower returns of only 2.70% p.a., which, however, are still significantly different from zero. Most importantly, these results indicate, however, that specific FX momentum strategies that performed well in the past tend to continue to do well and are thus quite stable.

While the above analysis confirms that momentum returns are exploitable in an out-of-sample setting, we further examine this issue from a somewhat different angle by a simple investigation of the subsample stability of momentum profits. To do so, Table A.2 in the Internet Appendix shows average annualized excess returns and Sharpe Ratios for four subperiods of equal length. We report results for formation periods of $f=1,3,6,9,12$ and a holding period of one month. As can be seen, the ranking of these five different strategies is fairly stable over the four subperiods. In other words, it is never the case that one strategy does extremely well in one subperiod but then produces large losses in the next subperiod. Overall, we conclude that it should have been possible for an investor to exploit momentum strategies in real time.

4.3. Comparing momentum and technical trading rules

The results presented above suggest that momentum effects in the cross-section of currencies are quite strong and that momentum strategies consequently yield high excess returns and Sharpe Ratios. However, an important question is whether the currency momentum returns documented above can be regarded as a novel phenomenon per se or whether they merely reflect returns to technical trading strategies that have been documented extensively in the earlier literature.

To investigate this issue, we compute returns to three benchmark moving average cross-over rules that have been employed frequently in earlier work on technical trading in FX markets. These strategies are based on moving averages of 1 and 20 days (1,20), 1 and 50 days (1,50), and 1 and 200 days (1,200) (see, among others, Dooley and Shafer, 1983; Levich and Thomas, 1993, Neely, Weller, and Ulrich, 2009).[19] While it is clearly not the case that these three strategies are perfect proxies for *all* possible technical trading strategies, their prominence in the earlier literature makes them interesting for comparison with our cross-sectional currency momentum strategies.

To set the stage, we first compute returns to these moving average rules for all currencies in our sample individually and then aggregate these strategies into an equally weighted portfolio. Panel A of Table 3 reports descriptive statistics for the three rules, which show that these strategies are profitable, with annual mean excess returns around 5% and high annual Sharpe Ratios between 0.77 and 0.88. Hence, these strategies form an interesting benchmark for our momentum returns.

To assess whether returns to the moving average rules described above capture returns to the currency momentum strategies, we run regressions of momentum returns for the MOM(1,1), MOM(6,1), and MOM(12,1) strategies on returns of the three moving average rules. Results are shown in Panel B of Table 3.

It can be seen that, even though moving average rule returns and currency momentum are to some extent correlated, the largest R^2 only amounts to 26%. More importantly, all intercept estimates (α's) are large in economic terms and strongly significant in statistical terms. Hence, it seems fair to conclude that currency momentum is not closely related to benchmark technical trading strategies as studied in the earlier literature, and that controlling for returns of these trading rules does not wipe out returns to our cross-sectional currency momentum.

In addition, we also examine returns to individual currencies' momentum strategies, i.e., where an investor is long or short in each currency depending on lagged returns in the same currency. This strategy is also studied in Moskowitz, Ooi, and Pedersen (2012). We report descriptive statistics for returns of each currency in Panel A of Table A.3 in the Internet Appendix, along with the average across countries, an equally weighted portfolio of all individual currencies' strategies, and, for comparison, the cross-sectional momentum strategy employed in this paper in Panel B. It can be seen that most of these time-series momentum strategies are profitable on average (Panel A of Table A.3) but that an aggregate strategy (the equally weighted portfolio, EW, in Panel B) is less profitable than a cross-sectional momentum strategy (MOM(1,1) in Panel B), as the latter strategy has a much higher average excess return (almost twice as high) and Sharpe Ratio.

4.4. Comparing currency momentum and the carry trade

An important question is to what extent momentum strategies simply capture the same information as the popular carry trade strategy in FX markets, where investors go long in high interest rate currencies and short in low interest rate currencies. After all, interest rate differentials are strongly autocorrelated and spot rate changes do not seem to adjust to compensate for this interest rate differential, which is well-known in the literature as the "forward premium puzzle" (Fama, 1984). Hence, it might be the case that lagged high returns simply proxy for lagged high interest rate differentials and that, therefore, currency momentum returns are very similar to carry trade returns. To address this concern, we perform a comprehensive comparison between momentum returns and carry trade returns in this section. The results clearly show that carry trade and momentum strategies, as well as their associated returns, are in fact very different.

Return correlations: Table 4, Panel A, shows correlation coefficients between returns to momentum portfolios and

[19] These trading strategies generate a buy (sell) signal, when the shorter moving average crosses the longer moving average from below (above).

Table 3
Moving average rules and cross-sectional momentum.
This table shows means, Sharpe Ratios (SR), standard deviations, skewness, and kurtosis for excess returns to three benchmark moving average (MA) rules in Panel A. Panel B shows results from regressions of cross-sectional momentum excess returns (i.e., high-minus-low portfolios) on a constant and excess returns to each of the three MA rules. Note that the adjusted R^2's in Panel B are in percent. The sample period is January 1976–January 2010 and we employ monthly returns.

Panel A: Descriptive statistics for MA rules

	(1,20)	(5,20)	(1,200)
Mean	5.27	5.14	5.23
	[5.56]	[5.73]	[4.64]
SR	0.88	0.83	0.77
St. dev.	5.98	6.22	6.81
Skewness	0.67	0.40	0.09
Kurtosis	4.63	4.71	4.97

Panel B: Regressions of cross-sectional momentum returns on MA rule returns

	MOM(1,1)			MOM(6,1)			MOM(12,1)		
$\alpha_{(1,20)}$	7.74			7.63			6.21		
	[4.54]			[4.60]			[3.62]		
$\beta_{(1,20)}$	0.33			0.17			−0.01		
	[3.57]			[1.41]			[−0.12]		
$\alpha_{(5,20)}$		7.80			7.49			5.84	
		[4.52]			[4.45]			[3.35]	
$\beta_{(5,20)}$		0.32			0.21			0.06	
		[3.95]			[1.72]			[0.60]	
$\alpha_{(1,200)}$			6.90			4.16			7.39
			[3.97]			[2.46]			[2.82]
$\beta_{(1,200)}$			0.47			0.81			0.03
			[5.67]			[7.56]			[0.16]
$\overline{R}^2$ (in %)	3.62	3.88	10.34	0.68	1.17	26.00	−0.25	−0.10	−0.23

carry trade portfolios. We show results for the long–short momentum strategies $MOM_{1,1}$, $MOM_{6,1}$, and $MOM_{12,1}$, and always report the correlation between corresponding portfolios; e.g., the correlation of momentum portfolio 2 and carry trade portfolio 2, or the correlation between the high-minus-low (H−L) carry trade and momentum portfolios. It can be seen that the correlations of excess returns for the six portfolios are rather high but that there is basically no correlation between the high-minus-low portfolios, and the latter represent the way carry trade and momentum strategies are typically implemented by market participants. Thus, the return to following a currency momentum strategy is basically uncorrelated with carry trade returns and this finding holds true regardless of the respective formation period underlying a momentum strategy.

In contrast, we show in Panel B that the high-minus-low portfolios of the three momentum strategies are much more highly correlated and reach correlations of more than 70% for $MOM_{6,1}$ and $MOM_{12,1}$. Hence, it seems fair to conclude that returns to different momentum strategies are likely to share a strong common component.

That excess returns to carry trades and momentum strategies are basically uncorrelated in FX markets appears in line with real-world strategies of many currency investors who combine momentum and carry trade positions in their portfolios to take advantage of an alleged diversification benefit from following the two strategies simultaneously.[20] For example, during the recent financial crisis from July 2007 to June 2009, the benchmark momentum strategy with $h=f=1$ experienced an average monthly return of 0.80% whereas the carry trade yielded a negative average monthly return of −0.05%. The return correlation of these two strategies was as low as −31% over these two years. Hence, the two strategies showed a clearly different behavior during this period.

Comparing portfolio properties: We additionally investigate characteristics of momentum and carry trade portfolios, which are reported in Table A.4 in the Internet Appendix. The table shows descriptive statistics for the six momentum portfolios with a formation and holding period of one month and six carry trade portfolios where currencies are sorted into portfolios depending on their lagged interest rate, as in, e.g., Lustig, Roussanov, and

[20] Patton and Ramadorai (in press), for example, show in a general universe of hedge funds (not necessarily currency funds) that there is significant exposure to carry trade and momentum-type returns and that this exposure is time-varying. Pojarliev and Levich (2010) show via style regressions that currency fund managers engage in both carry trade and momentum-type strategies. Melvin and Shand (2011) show that currency managers follow momentum strategies but that their exposure to momentum and the way momentum strategies are implemented change over time.

Table 4
Correlation of momentum and carry trade returns.

This table shows correlation coefficients between portfolio returns. Panel A shows correlation coefficients between momentum returns based on strategies with formation horizons of f equal to one, six, and 12 months and holding periods of $h=1$ month (denoted $MOM_{1,1}$, $MOM_{6,1}$, $MOM_{12,1}$, respectively) and forward discount-sorted portfolio returns (denoted C since they form the basis of the carry trade). Returns are based on six portfolios and a long-short portfolio for both momentum and the carry trade. We only report correlations for corresponding pairs of portfolios. For example, in row $\rho(M_{1,1},C)$, we report the correlation of the "Low" momentum portfolio with the "Low" carry trade portfolio in column "Low," the correlation of the third momentum portfolio with the third carry trade portfolio, and so on for all six portfolios and the long-short portfolios. Row $\rho(M_6,C)$ shows the correlations between portfolio pairs of the momentum strategy with a six-month formation period with the carry trade and row $\rho(M_{12},C)$ shows the correlations between portfolio pairs of the 12-month formation period momentum strategy and the carry trade. Panel B shows correlations for momentum portfolios with different formation horizons. The sample period is January 1976–January 2010 and we employ monthly returns.

Panel A: Momentum and carry trade portfolios

	Low	2	3	4	5	High	H−L
$\rho(MOM_{1,1},C)$	0.68	0.84	0.83	0.85	0.81	0.73	0.04
$\rho(MOM_{6,1},C)$	0.63	0.84	0.82	0.83	0.81	0.74	0.01
$\rho(MOM_{12,1},C)$	0.67	0.85	0.81	0.87	0.82	0.74	0.07

Panel B: Momentum portfolios

	Low	2	3	4	5	High	H−L
$\rho(MOM_{1,1},MOM_{6,1})$	0.77	0.83	0.88	0.85	0.83	0.79	0.45
$\rho(MOM_{1,1},MOM_{12,1})$	0.66	0.81	0.86	0.87	0.80	0.78	0.28
$\rho(MOM_{6,1},MOM_{12,1})$	0.82	0.89	0.89	0.89	0.91	0.89	0.73

Verdelhan (2011) or Menkhoff, Sarno, Schmeling, and Schrimpf (2012).[21]

As can be inferred from this table, there is a monotonically increasing pattern in average returns for both cross-sections but no clear pattern in higher moments of the return distribution. While the level of average returns and standard deviations of the high-minus-low momentum and carry trade portfolios is roughly similar, we find that the two long-short portfolios are clearly different in terms of their skewness. While the carry trade produces negatively skewed excess returns (Brunnermeier, Nagel, and Pedersen, 2009), we find a slightly positive skewness for the momentum strategy.

More interestingly, the last two rows of each panel show lagged average returns and lagged average forward discounts for each portfolio at the time of portfolio formation. Momentum portfolios do have a positive spread in forward discounts and carry trade portfolios have a positive spread in lagged returns, but these spreads are much lower in absolute value than the spread in the characteristic used for sorting currencies into portfolios. More specifically, the average cross-sectional spread in forward discounts (in annualized terms) at the time of portfolio formation is about 4.6% (5.13% versus 0.44%) for the momentum cross-section but averages more than 15% for the carry trade cross-section. Similarly, the average spread in lagged returns is almost 6% for the momentum portfolios (2.94% versus −2.93%) but only 0.84% for the carry trade cross-section. Hence, momentum and carry trade strategies seem far from being identical.

Double sorts: Next, we provide results based on double sorts. To this end, we first double sort currencies into two portfolios depending on whether a currency has a lagged forward discount above or below the median (of all available currencies), and then into three portfolios depending on their lagged excess return. Portfolios are rebalanced each month (i.e., $h=1$). Table 5 shows results for these double sorts for formation periods of $f=1,3,12$ months. There is no material difference between momentum returns among high versus low interest rate currencies. For example, the high-minus-low momentum return for a strategy with a one-month formation period based on low interest rate currencies is 5.06% p.a., on average, whereas it is 5.36% p.a. for high interest rate currencies. Hence, the difference between these two high-minus-low momentum portfolios is less than 0.30% p.a. and not statistically significant (with a t-statistic of only 0.17). Findings for the other two formation periods are very similar.

As above, we do not find a strong relation between momentum and carry trade strategies and the double sorts suggest that the two strategies are largely independent. In fact, going long in currencies with high lagged returns and high interest rates whilst shorting currencies with low returns and low interest rates generates an excess return of 10.52% p.a. that is even larger than the spread in both momentum or carry trade portfolios taken individually.

Cross-sectional regressions: Finally, we want to separate the effects of lagged excess returns and lagged interest rate differentials on future excess returns. To this end, we run Fama-MacBeth type cross-sectional regressions of currency excess returns (or spot rate changes) on (i) lagged excess returns over the last l months, (ii) lagged forward discounts, and/or (iii) lagged spot rate changes for each month of our sample, i.e.,

$$rx_t^k = \alpha_t + \beta_{rx,t} rx_{t-\ell;t-1}^k + \beta_{FD,t}(f_{t-1} - s_{t-1}) + \beta_{\Delta s,t} \Delta s_{t-\ell;t-1}^k + \varepsilon_t, \tag{2}$$

where the subscript $t-\ell;t-1$ refers to a variable defined over the last ℓ months using information available at time $t-1$. This procedure yields a time-series of coefficient estimates (α_t, β_t) and we report the mean of these time series and t-statistics based on Newey and West (1987) standard errors in Table 6 in the spirit of the approach by Fama and MacBeth (1973).[22]

These cross-sectional regressions serve to disentangle the information contained in lagged returns (or spot rate changes) and forward discounts for future excess returns (or spot rate changes) in a regression framework and on the level of individual currencies. Momentum strategies

[21] To conserve space in this table, we focus on the momentum strategy with $f=1$ and $h=1$. Results are similar for the other strategies.

[22] See, for example, Gutierrez and Kelley (2008), who employ a similar methodology.

Table 5
Double sorts.

This table shows annualized mean excess returns for double-sorted portfolios. All currencies in the sample are first sorted on lagged forward discounts (FD) into two portfolios along the median. Next, currencies within each of the two subgroups are allocated into three momentum portfolios depending on their lagged excess returns over $f=1$,6, or 12 months. Hence, row FD_L denotes the 50% of all currencies with the lowest (lagged) forward discount whereas FD_H denotes the 50% of all currencies with the highest (lagged) forward discounts. Columns M_L, M_M, and M_H denote the 33% of all currencies with the lowest, intermediate, and the highest (lagged) returns, respectively. Columns Δ_M show the return difference between high and low momentum portfolios (M_H-M_L) for each subgroup of currencies whereas, e.g., Δ_{FD} shows the return difference between the forward discount-sorted portfolios for each momentum subgroup. The lower-right cell in each subpanel shows the return difference between the two momentum "high-minus-low" portfolios of each forward discount category. We report annualized excess returns in percent for each portfolio and all high-minus-low portfolios. Numbers in brackets are Newey and West (1987) HAC t-statistics and the sample runs from January 1976 to January 2010.

	Carry trade and momentum											
	$f=1$, $h=1$				$f=6$, $h=1$				$f=12$, $h=1$			
	M_L	M_M	M_H	Δ_M	M_L	M_M	M_H	Δ_M	M_L	M_M	M_H	Δ_M
FD_L	−4.52	−0.90	0.54	5.06	−4.40	−0.35	0.06	4.46	−3.94	−0.40	0.09	4.04
	[−2.90]	[−0.55]	[0.34]	[3.81]	[−2.81]	[−0.21]	[0.04]	[3.63]	[−2.34]	[−0.24]	[0.06]	[2.86]
FD_H	0.64	3.20	6.00	5.36	2.38	2.43	6.34	3.96	2.86	3.21	5.98	3.12
	[0.34]	[1.68]	[3.18]	[3.30]	[1.14]	[1.45]	[3.29]	[2.43]	[1.49]	[1.80]	[3.10]	[2.02]
Δ_{FD}	5.16	4.10	5.45	0.30	6.77	2.78	6.27	−0.50	6.80	3.61	5.89	−0.91
	[4.00]	[3.43]	[3.89]	[0.17]	[4.33]	[2.57]	[4.58]	[−0.26]	[4.71]	[3.22]	[4.56]	[−0.49]

Table 6
Cross-sectional regressions.

This table shows results for cross-sectional regressions of individual currencies' excess returns (left part) or spot rate changes (right part) on lagged excess returns, lagged forward discounts, and/or lagged spot rate changes. Numbers in parentheses are standard errors of the cross-sectional R^2's. For ease of interpretation, we have multiplied spot rate changes by minus one so that higher values indicate an appreciation of the foreign currency against the USD. The sample runs from January 1976 to January 2010.

Dependent: Excess returns					Dependent: Spot rate changes				
Const.	rx	$f-s$	Δs	R^2	Const.	rx	$f-s$	Δs	R^2
Panel A: One month									
−0.02	0.16			0.15	−0.16	0.08			0.13
[−0.17]	[5.65]			(0.01)	[−1.52]	[2.95]			(0.01)
0.00		0.63		0.14	0.00		−0.37		0.09
[0.01]		[4.87]		(0.01)	[0.01]		[−2.89]		(0.01)
0.02			0.13	0.13	−0.16			0.13	0.14
[0.22]			[4.46]	(0.01)	[−1.59]			[4.55]	(0.01)
−0.07	0.12	0.57		0.26	−0.07	0.12	−0.43		0.20
[−0.76]	[4.42]	[4.68]		(0.01)	[−0.76]	[4.42]	[−3.52]		(0.01)
−0.07		0.68	0.14	0.26	−0.07		−0.32	0.14	0.21
[−0.72]		[5.89]	[4.82]	(0.01)	[−0.72]		[−2.83]	[4.82]	(0.01)
Panel B: Six months									
0.06	0.30			0.17	−0.05	0.15			0.15
[0.57]	[5.65]			(0.01)	[−0.46]	[3.07]			(0.01)
0.04		0.46		0.13	0.04		−0.52		0.09
[0.33]		[2.98]		(0.01)	[0.31]		[−3.33]		(0.01)
0.12			0.19	0.14	−0.03			0.25	0.15
[1.20]			[3.24]	(0.01)	[−0.30]			[4.87]	(0.01)
0.08	0.21	0.36		0.27	0.07	0.23	−0.64		0.24
[0.82]	[3.89]	[2.36]		(0.02)	[0.82]	[4.39]	[−4.20]		(0.01)
0.06		0.57	0.23	0.27	0.07		−0.41	0.23	0.24
[0.71]		[4.01]	[4.27]	(0.02)	[0.77]		[−2.90]	[4.33]	(0.01)
Panel C: 12 Months									
−0.05	0.28			0.16	−0.17	0.12			0.15
[−0.52]	[3.97]			(0.01)	[−1.66]	[1.79]			(0.01)
0.04		0.42		0.12	0.03		−0.51		0.09
[0.36]		[2.66]		(0.01)	[0.29]		[−3.22]		(0.01)
0.03			0.20	0.14	−0.05			0.32	0.14
[0.24]			[2.45]	(0.01)	[−0.47]			[4.52]	(0.01)
−0.06	0.20	0.28		0.25	−0.06	0.25	−0.66		0.24
[−0.66]	[2.58]	[1.74]		(0.01)	[−0.62]	[3.21]	[−4.06]		(0.01)
−0.04		0.48	0.24	0.25	−0.04		−0.42	0.27	0.24
[−0.47]		[3.21]	[3.14]	(0.01)	[−0.42]		[−2.70]	[3.41]	(0.01)

require individual currencies' excess returns to vary cross-sectionally in a way that is predictable by lagged returns. Cross-sectional regressions allow us to test for this effect while simultaneously controlling for interest rate differentials and, hence, complement the double sorts above, which work on a portfolio level, and do not necessarily control for both factors at the same time due to sequential sorting.

Panel A shows results for regressions where we use lagged excess returns, forward discounts, and/or spot rate changes over the last month as explanatory variables, whereas Panels B and C show results for values of l equal to six and 12 months, respectively.[23]

Turning to results for excess returns first (left part of Table 6), we find that lagged returns, lagged forward discounts, as well as lagged spot rate changes are cross-sectionally positively related to subsequent currency returns even when including them in joint specifications. Hence, momentum effects are robust to controlling for forward discounts (interest rate differentials). Furthermore, it is noteworthy that lagged spot rate changes do about as well as lagged excess returns in the cross-sectional regressions so that momentum seems to originate from spot rate changes and not from lagged interest rate differentials, which corroborates our finding that carry trades and momentum are different.

The right part of Table 6 shows the same calculations but with spot rate changes as dependent variables. While the effect of lagged returns or spot rate changes is very similar to our results described above, we find that the forward discount has a *negative* impact on future spot rate changes. However, the coefficients based on univariate regressions are always smaller than one in absolute value. Hence, a one percent higher interest rate in a foreign country is only followed by a depreciation smaller than one percent relative to other currencies' excess returns against the USD, consistent with the existence of a forward bias (Fama, 1984). Note that these are cross-sectional regressions so that results do not necessarily translate into a time-series setting in which the forward premium puzzle has typically been studied.

4.5. Post-formation momentum returns

Jegadeesh and Titman (2001) suggest that momentum returns are driven by slow information diffusion that leads to underreaction and persistence in returns (see also Chui, Titman, and Wei, 2010). This initial underreaction can furthermore be accompanied by subsequent overreaction that magnifies the drift in returns but has to be corrected over the long run. To investigate these issues, Jegadeesh and Titman (2001) study the post-formation holding period returns of momentum strategies over longer time spans (i.e., the returns over long horizons after portfolio formation where the portfolio composition is held constant). They find a (roughly) "inverted U-shaped pattern", i.e., returns tend to increase for several months up to one year after portfolio formation but then peak and start to decrease significantly. Jegadeesh and Titman interpret this pattern as evidence of initial underreaction that drives prices and subsequent overreaction to the series of high returns, pushing prices up above the fundamental value of the asset. This overreaction is then corrected over longer periods, leading to the observed predictable pattern of increasing and decreasing returns after portfolio formation.[24]

As a first check of this hypothesis for currency markets, we plot cumulative post-formation excess returns over periods of 1,2,…,60 months for the zero-cost long-short momentum portfolios with a one, six, and 12 months formation periods (i.e., MOM_1, MOM_6, and MOM_{12}) in Fig. 4. Returns in the post-formation period are overlapping since we form new portfolios each month but track these portfolios for 60 months. There is a clear pattern of increasing returns that peaks after 8–12 months across strategies and a subsequent period of declining excess returns. The decline is more pronounced for momentum strategies with longer formation periods. Thus, on the face of it, this evidence looks very similar to the pattern identified in equity markets as in Jegadeesh and Titman (2001). This result is interesting since it suggests that currency and equity market momentum could have similar origins.[25]

In sum, these results on currency momentum are consistent with those on stock market momentum, where momentum returns could be (at least partly) driven by slow information processing and investor overreaction. However, given the highly liquid FX market, which is dominated by professional traders and investors, it is hard to believe that investor irrationalities of this kind are not quickly arbitraged away. Thus, it is worthwhile to examine possible limits to arbitrage activity that could explain the persistence of momentum profits in FX markets. This is addressed in the next section.

5. Understanding the results

5.1. Transaction costs

What role do transaction costs play for momentum returns? To address this question, we first report momentum returns after transaction costs in Table 7, Panel A,

[23] For ease of interpretation, we multiply spot rate changes by minus one, so that higher values mean that the foreign currency is appreciating against the USD.

[24] There is relatively little work on behavioral effects in currency markets (compared to equity markets). Burnside, Han, Hirshleifer, and Wang (2011) recently show, however, that concepts from behavioral finance can be useful to understand FX phenomena as well. In addition, Bacchetta and van Wincoop (2010) argue that many FX portfolios are still not actively managed but that portfolio decisions are often taken infrequently, which can be fully rational due to the costs of portfolio adjustments. This mechanism could also account for slow diffusion of information into prices in FX markets. Investors' infrequent portfolio adjustment decisions, slow-moving capital deployed to exploit arbitrage opportunities, and the implications of these aspects for the dynamics of asset price movements are also demonstrated recently in Duffie (2010).

[25] We also provide the same results for post-formation drift in cumulative spot rate changes in Fig. A1 in the Internet Appendix and find a very similar pattern (although with a somewhat lower magnitude with respect to the initial price increases) so that the result discussed above does not seem to be driven by interest rate differentials but also stems from price changes.

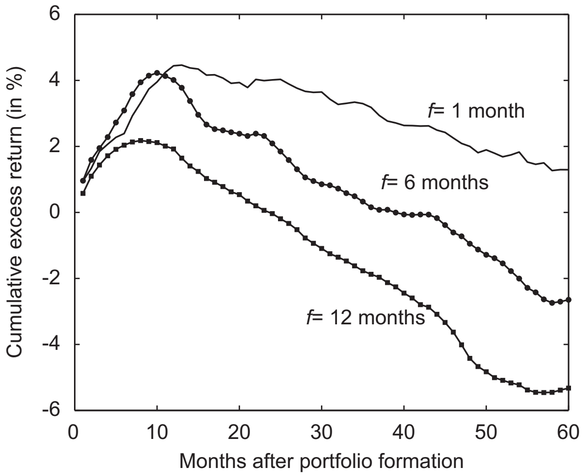

Fig. 4. Long-horizon momentum excess returns. This figure shows cumulative average excess returns to three different long-short currency momentum portfolios after portfolio formation. Momentum portfolios differ in their formation period ($f=1,6,12$ months) and post-formation returns are shown for 1,2,…,60 months following the formation period (i.e., we build new portfolios each months but track these portfolios for the first 60 months after their formation so that we are effectively using overlapping horizons). Excess returns are monthly and the sample period runs from January 1976 to January 2010.

where we impose the full quoted bid–ask spread. This spread is known to be too large relative to actual effective spreads Lyons (2001). Hence, these results are likely to underestimate momentum returns (or equivalently to provide a lower bound on profitability), whereas neglecting spreads clearly overstates momentum returns.

The results show that transaction costs could be an important factor for understanding momentum returns in currency markets (Burnside, Eichenbaum, Kleshchelski, and Rebelo, 2006; Burnside, Eichenbaum, and Rebelo, 2007). When applying the full spread, returns for the best strategy (with f, $h=1$) drop from nearly 10% to about 4% p.a. and they wipe out most of the profit of many other strategies. Interestingly, the effects of transaction costs on the average spot rate changes of portfolios, which are adjusted for bid–ask spreads in an analogous fashion to excess returns, are relatively less affected. To make the full effect of transaction costs more transparent, we also plot cumulative net excess returns (after transaction costs) for the three baseline strategies $MOM_{1,1}$, $MOM_{6,1}$, and $MOM_{12,1}$ in Fig. A2 in the Internet Appendix. Again, shaded areas correspond to NBER recessions. It can be seen that FX momentum strategies are much more profitable (after transaction costs) in the later part of the sample, but momentum strategies do not always deliver

Table 7
Momentum returns after transaction costs.

This table shows annualized average returns for different momentum strategies ($\overline{r^{f,h}}$) after adjusting for bid–ask spreads. Panel A shows results for net excess returns (left part) and net spot rate changes (right part) when deducting the full quoted spread. Numbers in brackets are t-statistics based on Newey and West (1987) standard errors. Panel B shows results only for net excess returns and for the case that effective spreads equal 75% (left part) or 50% (right part) of the quoted spread. The sample period is January 1976–January 2010 and we employ monthly returns.

Panel A: Quoted spreads

	Net excess returns						Net spot rate changes				
	Holding period h						Holding period h				
f	1	3	6	9	12	f	1	3	6	9	12
1	3.92	2.02	1.26	0.38	0.39	1	4.84	3.36	2.69	4.43	2.53
	[2.20]	[1.16]	[0.61]	[0.18]	[0.20]		[2.81]	[2.37]	[1.57]	[2.76]	[1.65]
3	4.41	2.12	0.88	0.97	−0.07	3	6.80	4.58	4.72	4.33	4.86
	[2.39]	[1.20]	[0.53]	[0.58]	[-0.04]		[3.99]	[2.81]	[3.18]	[2.58]	[3.32]
6	3.86	2.12	−0.27	−0.92	−1.28	6	5.06	4.83	3.06	3.27	3.29
	[2.09]	[1.19]	[−0.15]	[−0.49]	[−0.67]		[3.03]	[3.37]	[1.94]	[2.08]	[1.88]
9	2.48	2.43	0.99	−0.40	−1.06	9	7.53	6.73	6.19	4.81	3.84
	[1.26]	[1.27]	[0.51]	[−0.21]	[−0.54]		[4.34]	[4.00]	[3.69]	[2.88]	[2.20]
12	1.40	0.80	−1.46	−1.98	−2.44	12	6.65	5.53	3.75	2.92	2.77
	[0.74]	[0.45]	[−0.84]	[−1.11]	[−1.31]		[4.01]	[3.66]	[2.47]	[1.79]	[1.73]

Panel B: Effective spreads and net excess returns

	Effective spread of 75%						Effective spread of 50%				
	Holding period h						Holding period h				
f	1	3	6	9	12	f	1	3	6	9	12
1	5.28	3.24	2.51	1.53	1.69	1	6.64	4.47	3.77	2.69	3.00
	[2.98]	[1.89]	[1.25]	[0.76]	[0.88]		[3.76]	[2.62]	[1.89]	[1.36]	[1.61]
3	5.61	3.16	1.86	1.85	0.97	3	6.81	4.20	2.83	2.74	2.00
	[3.07]	[1.82]	[1.12]	[1.12]	[0.59]		[3.76]	[2.45]	[1.72]	[1.68]	[1.23]
6	5.03	3.17	0.70	0.15	−0.18	6	6.20	4.23	1.68	1.21	0.92
	[2.76]	[1.80]	[0.39]	[0.08]	[−0.10]		[3.43]	[2.41]	[0.94]	[0.66]	[0.49]
9	3.66	3.56	2.16	0.68	0.08	9	4.85	4.69	3.33	1.75	1.24
	[1.89]	[1.89]	[1.13]	[0.35]	[0.04]		[2.53]	[2.52]	[1.76]	[0.93]	[0.64]
12	2.60	1.97	−0.35	−0.94	−1.36	12	3.80	3.13	0.78	0.09	−0.28
	[1.39]	[1.12]	[−0.20]	[−0.53]	[−0.74]		[2.07]	[1.81]	[0.45]	[0.05]	[−0.15]

high returns to investors. Instead, there is much variation in profitability.

Next, given that the quoted spread is known to be too high relative to effective spreads, we follow Goyal and Saretto (2009) and report results for momentum excess returns after transaction costs of 75% (Panel B, left part) and 50% (Panel B, right part) of quoted spreads in Table 7. Results for these more realistic bid–ask spread adjustments indicate that transaction costs clearly matter but that they are not the sole driver of FX momentum returns as we find that many strategies still yield economically high and statistically significant returns on average.

Further scrutinizing this issue, we can break up the importance of transaction costs into turnover across portfolios and bid–ask spreads across portfolios. We provide results on both issues in the Internet Appendix (Table A.5). Two main conclusions emerge from this exercise. First, turnover can be extremely high, reaching values of more than 70% per month for the strategy with a one-month formation and holding period. Second, the winner and loser currencies do have higher transaction costs than the average exchange rate and the markup ranges from about 2.5 to 7 basis points per month. Accordingly, trading in the winner and loser currencies (as is necessary to set up a momentum strategy) is more costly than trading in the average currency pair. Hence, transaction costs clearly matter to a considerable extent.

However, given that transaction costs should be expected to decline over time due to more efficient trading technologies (such as electronic trading networks operated by, e.g., Electronic Broking Services (EBS) and Reuters), it seems unclear whether transaction costs are able to fully explain momentum returns. Fig. A3 in the Internet Appendix shows average bid–ask spreads across currencies for each month in our sample and separately for all countries and for the subsample of 15 developed countries as defined above. While there is a lot of time-series variation in average spreads, it is the case that spreads have trended downwards over our sample period. This downward trend is most clearly seen for the sample of developed countries for which we have almost complete data histories and for which average spreads are not driven by the frequent inclusion of emerging market currencies that induce some large spikes in average spreads when looking at the sample of all countries. Overall, the downward trend in bid–ask spreads seems to suggest that new technology has swamped the positive effect of volatility on bid–ask spreads. Thus, it is interesting to also investigate momentum strategies over a later part of our sample where bid-ask spreads tend to be lower on average since lower transaction costs could either imply (i) higher momentum returns due to lower trading costs or (ii) lower momentum returns since lower trading costs facilitate more capital being deployed for arbitrage activity.

Internet Appendix Table A12 shows results for the same calculations underlying Table 1 but we only include the period January 1992 to January 2010 to learn about whether the profitability of momentum strategies increases or declines over this recent period of low transaction costs. We find that unadjusted momentum returns reach levels similar to those for the full sample (Panel A) but that transaction cost-adjusted net excess returns (Panel B) are clearly higher and, for example, reach average annualized values of more than 7% for the one-month strategy $MOM_{1,1}$. Thus, lower bid–ask spreads do not necessarily lead to lower (unadjusted) excess returns, which further indicates that transaction costs are not the sole driving force behind momentum effects. This evidence also indicates that momentum returns are a phenomenon that is still exploitable nowadays.

5.2. Momentum returns and business cycle risk

Table 8, Panel A, shows results from univariate time-series regressions of momentum returns on various risk factors or business cycle state variables. See, e.g., Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) or Sarno, Schneider, and Wagner (2012) for similar regressions in the context of currency returns. These factors include macrovariables or other risk factors from the earlier literature: "Consumption" stands for real growth in non-durables and services consumption expenditures, "Employment" denotes U.S. total nonfarm employment growth, "ISM" denotes the ISM manufacturing index, "IP" denotes growth in real industrial production, "CPI" denotes the inflation rate, "M2" is the growth in real money balances, "Disp inc" is growth in real disposable personal income, "TED" denotes the TED spread (the difference between 3-month interbank rate, Libor and 3-month T-bill rate), "Term" denotes the term spread (20-year maturity minus 3-month T-bill rate), HML_{FX} is the return to the carry trade long-short portfolio (Lustig, Roussanov, and Verdelhan, 2011), and VOL_{FX} is a proxy for global FX volatility (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012). We note that the alphas in these regressions cannot be interpreted as a measure of risk-adjusted returns for most specifications since we are mainly employing macrovariables or other nonreturn-based factors here. Statistical significance at the 5% level or below is indicated by bold numbers. However, looking across momentum strategies and macro-finance risk factors, there is little evidence that exposure to these factors is able to account for momentum returns. The adjusted R^2's are generally tiny and most slope coefficients are insignificantly different from zero.[26]

Panel B of Table 8 shows a multivariate regression of momentum returns on the three Fama-French factors augmented by the U.S. stock momentum factor (UMD), and it can again be seen that there is basically no explanatory power. Moreover, the alphas in these regressions, which are annualized and in percentages, can be

[26] As mentioned earlier, one exception is the momentum strategy with a 12-month formation period and global FX volatility. We find a highly significant slope coefficient here and a positive R^2. Menkhoff, Sarno, Schmeling, and Schrimpf (2012) show for this momentum strategy that innovations to global FX volatility do indeed capture a large amount of the cross-sectional spread in returns and that volatility risk is significantly priced. However, we do not find that FX volatility risk helps much for understanding momentum returns of the strategies with short formation periods of one month or six months.

Table 8
Macro risk.
This table shows time-series regression estimates of currency momentum returns (long–short portfolios $MOM_{1,1}$,$MOM_{6,1}$, and $MOM_{12,1}$) on various macrofactors and other risk factors. Consumption is real consumption growth, Employment denotes U.S. total nonfarm employment growth, ISM denotes the ISM manufacturing index, IP denotes growth in real industrial production, CPI denotes the inflation rate, M2 is the growth in real money balances, Disp inc is growth in real disposable personal income, TED denotes the TED spread, Term denotes the term spread (20 years minus 3 months), HML_{FX} is the return to the carry trade long–short portfolio (Lustig, Roussanov, Verdelhan, 2011), and VOL_{FX} is a proxy for global FX volatility (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012). MKTRF, HML, and SMB are the Fama-French factors and UMD denotes the return to a long–short U.S. momentum portfolio. Panel A shows results for univariate regressions (intercepts α, slope coefficients β, and the adjusted R^2) whereas Panel B shows results from a multivariate regression of momentum returns on the three Fama-French factors and UMD. Bold numbers indicate significance at the 5%-level or below.

Panel A: Univariate regressions

	$MOM_{1,1}$			$MOM_{6,1}$			$MOM_{12,1}$		
	α	β	R^2	α	β	R^2	α	β	R^2
Consumption	**9.65**	−0.05	0.00	**8.95**	−0.12	0.00	**6.03**	0.07	0.00
Employment	**10.57**	−0.72	0.00	**7.74**	0.62	0.00	**5.86**	0.23	0.00
ISM	**9.46**	0.04	0.00	**8.60**	0.03	0.00	**6.14**	0.04	0.00
IP	**9.72**	0.11	0.00	**8.72**	0.04	0.00	**6.26**	0.03	0.00
CPI	**11.73**	−0.55	0.00	**9.11**	−0.12	0.00	**6.60**	−0.10	0.00
M2	**9.97**	0.34	0.00	**8.68**	0.02	0.00	**6.18**	−0.01	0.00
Disp inc	**9.33**	0.07	0.00	**8.42**	0.10	0.00	**5.95**	0.10	0.00
TED	**13.64**	**−0.38**	0.01	**11.95**	−0.30	0.01	**9.73**	−0.32	0.01
Term	4.48	**0.22**	0.01	**7.54**	0.05	0.00	5.05	0.05	0.00
HML_{FX}	**9.50**	0.04	0.00	**8.65**	0.02	0.00	**6.21**	0.08	0.00
VOL_{FX}	**11.70**	−0.44	0.00	**18.75**	−2.04	0.01	**27.59**	**−4.29**	0.04

Panel B: Multivariate regressions

	$MOM_{1,1}$			$MOM_{6,1}$			$MOM_{12,1}$		
	α	β	R^2	α	β	R^2	α	β	R^2
MKTRF	**8.73**	0.00	0.00	**8.02**	0.04	0.00	**5.16**	0.02	0.00
SMB		0.97			−0.54			0.71	
HML		0.06			0.01			0.06	
UMD		0.02			0.03			0.04	

interpreted as the risk-adjusted performance of momentum returns since the factors are excess returns in this case. Across strategies, the alphas are fairly high, as judged by this particular model for returns. Based on earlier research for the U.S. stock market, this result does not come as a surprise regarding the three Fama-French factors but it seems noteworthy that currency momentum is also unrelated to the UMD factor.[27]

In sum, there is little evidence that standard business cycle variables or portfolio-based risk factors help to understand momentum returns, i.e., it seems that the latter are largely disconnected from U.S. business cycle risk. This finding squares well with earlier results for U.S. equity momentum, which is hard to explain by relying on its covariance with macrorisk factors (e.g., Griffin and Martin, 2003; Cooper, Gutierrez, and Hameed, 2004).

5.3. Limits to arbitrage: time variation in momentum profitability

Next, we are interested in the stability of momentum returns over time. Since FX market participants (e.g., proprietary trading desks, asset managers, and hedge funds) generally have short investment horizons, time variation in momentum profits could also represent an important obstacle for taking arbitrage positions in FX markets.

Fig. 5 plots average excess returns to the three long-short momentum portfolios $MOM_{1,1}$, $MOM_{6,1}$, and $MOM_{12,1}$ over rolling windows of 36 months. The left part shows unadjusted returns while the right part of the figure shows net excess returns after transaction costs. It can be seen that the profitability of momentum strategies is time-varying and that both adjusted and unadjusted returns appear to be higher over the second part of the sample. In fact, momentum returns for all three strategies have been rather high between 2000 and 2005 reaching levels of monthly net excess returns of about 2% per month.

Most importantly, this figure also illustrates that momentum returns are far from being constant even over intermediate time intervals of several years. Hence, an investor seeking to profit from momentum returns has to have a long enough investment horizon. This result seems important, since the bulk of currency speculation is accounted for by professional market participants and proprietary traders who have a rather short horizon over which their performance is evaluated (Lyons, 2001). Hence, momentum strategies are potentially risky for myopic market participants, so that large time variation in the performance of

[27] We have also experimented with more elaborate cross-sectional asset pricing tests for both macrofactors and return-based factors but, as could be expected on the basis of the time-series results reported in Table 8, did not find any improvement in results.

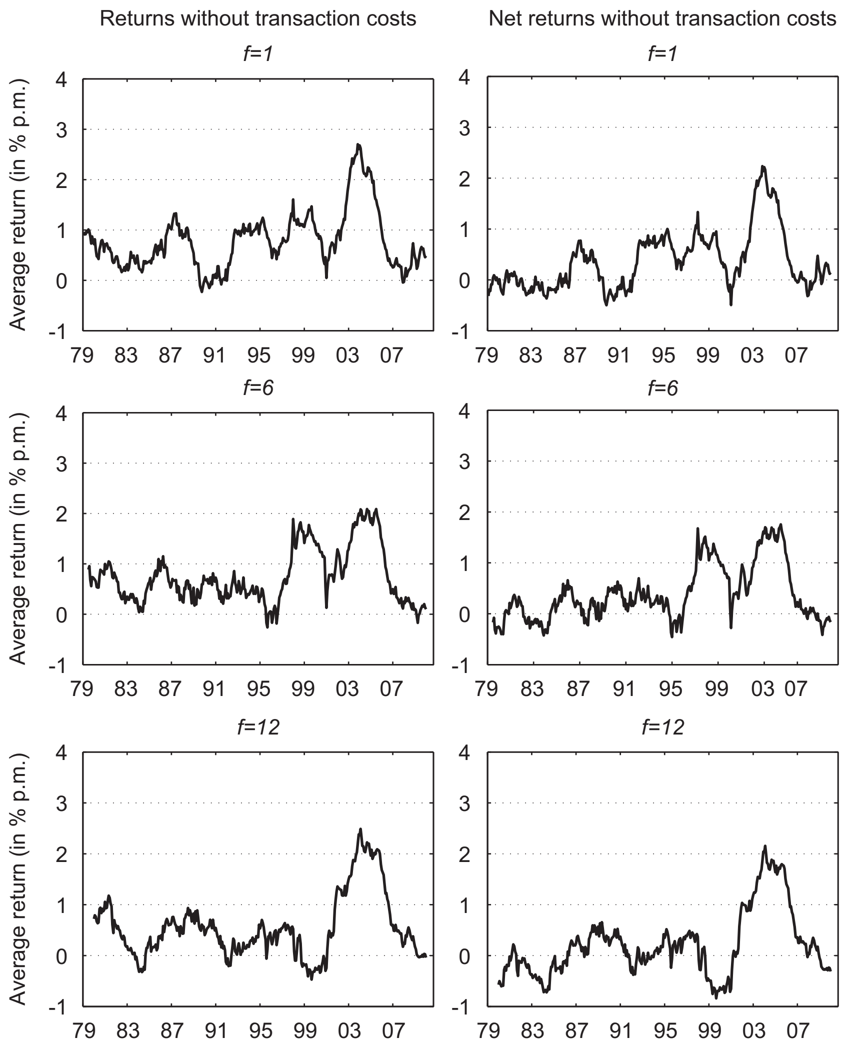

Fig. 5. Rolling average returns for three momentum strategies. This figure shows average excess returns per month (p.m.) over rolling windows of 36 months for three long-short momentum strategies: $MOM_{1,1}$, $MOM_{6,1}$, and $MOM_{12,1}$, where $MOM_{j,h}$ denotes the return difference between a portfolio long in currencies with the highest lagged excess returns (measured over the last *f* months) and a portfolio short in currencies with the lowest excess return over the last *f* months. Portfolios are held for $h=1$ month and we use excess returns without transaction costs (left part of the table) and net excess returns adjusted for transaction costs (right part). The sample runs from January 1976 to January 2010.

momentum returns could impede arbitrage activity by some of the key FX market players.[28]

5.4. Limits to arbitrage: idiosyncratic volatility

Unlike in stock markets, there are no natural short-selling constraints in FX markets. However, to conduct arbitrage in currency markets, an investor obviously has to set up positions that he may wish to hedge such that the position becomes a pure bet on return continuation but not on any sort of systematic risk. Hence, we investigate whether momentum returns are different between currencies with high or low idiosyncratic volatility (relative to an FX asset pricing model). Finding that currency momentum is stronger among high idiosyncratic volatility currencies would imply that attempts to arbitrage these momentum returns away could be risky since it will be hard to find a second pair of currencies that can be used as a hedge factor unrelated to simple return continuation.

To this end, Panel A of Table 9 shows results from double-sorting currencies first into two portfolios depending on whether a currency has a lagged idiosyncratic volatility above or below the median (of all available currencies), and then into three portfolios depending on their lagged

[28] The role of frictions (e.g., margin and capital constraints) on the deployment of arbitrage capital to investment opportunities by institutional investors is stressed, for instance, in recent work by Mitchell, Pedersen, and Pulvino (2007). Excellent recent surveys on limits to arbitrage and slow-moving capital that provide an obstacle to the corrective actions of rational arbitrageurs are provided by Duffie (2010) and Gromb and Vayanos (2010).

Table 9
Double sorts on idiosyncratic volatility or risk ratings and momentum.
The setup of this table is identical to Table 5 but here we sort on idiosyncratic volatility and momentum (Panel A), country risk and momentum (Panel B), and exchange rate stability risk and momentum (Panel C). We report annualized excess returns in percent for each portfolio and all high-minus-low portfolios. Numbers in brackets are Newey and West (1987) HAC *t*-statistics and the sample runs from January 1976 to January 2010.

Panel A: Idiosyncratic volatility and momentum

	$f=1,h=1$				$f=6,h=1$				$f=12,h=1$			
	M_L	M_M	M_H	Δ_M	M_L	M_M	M_H	Δ_M	M_L	M_M	M_H	Δ_M
$IVOL_L$	−1.04	0.92	2.93	3.97	−0.85	1.08	2.82	3.67	0.15	1.13	2.27	2.12
	[−0.65]	[0.55]	[1.75]	[2.81]	[−0.50]	[0.66]	[1.79]	[3.04]	[0.10]	[0.67]	[1.31]	[1.58]
$IVOL_H$	−3.52	1.00	4.57	8.09	−2.22	0.24	4.77	6.99	−0.78	0.20	4.38	5.16
	[−1.83]	[0.57]	[2.48]	[4.72]	[−1.16]	[0.14]	[2.44]	[4.28]	[−0.41]	[0.11]	[2.30]	[3.01]
Δ_{IVOL}	−2.48	0.07	1.64	4.11	−1.38	−0.84	1.95	3.33	−0.93	−0.94	2.11	3.04
	[−1.86]	[0.07]	[1.28]	[2.18]	[−1.15]	[−0.86]	[1.52]	[2.05]	[−0.80]	[−0.89]	[1.63]	[1.79]

Panel B: Country risk and momentum

	M_L	M_M	M_H	Δ_M	M_L	M_M	M_H	Δ_M	M_L	M_M	M_H	Δ_M
$CRISK_L$	0.01	3.41	4.51	4.50	0.95	3.14	4.26	3.31	1.65	3.24	3.86	2.21
	[0.01]	[1.78]	[2.52]	[3.12]	[0.49]	[1.67]	[2.33]	[2.67]	[0.80]	[1.67]	[2.10]	[1.51]
$CRISK_H$	−0.67	3.82	8.04	8.72	0.89	3.39	7.24	6.35	2.58	2.70	8.65	6.07
	[−0.34]	[1.90]	[3.72]	[4.19]	[0.40]	[1.94]	[3.24]	[2.92]	[1.29]	[1.43]	[3.56]	[2.34]
Δ_{CRISK}	−0.68	0.41	3.53	4.22	−0.06	0.25	2.97	3.04	0.93	−0.54	3.79	3.87
	[−0.46]	[0.35]	[2.21]	[2.12]	[−0.04]	[0.20]	[2.02]	[1.72]	[0.54]	[−0.45]	[2.61]	[1.93]

Panel C: Exchange rate stability risk and momentum

	M_L	M_M	M_H	Δ_M	M_L	M_M	M_H	Δ_M	M_L	M_M	M_H	Δ_M
$XSTAB_L$	1.27	0.15	3.25	1.98	1.56	0.30	3.60	2.04	0.80	1.40	3.22	2.42
	[0.83]	[0.10]	[2.17]	[1.39]	[0.96]	[0.23]	[2.32]	[1.31]	[0.50]	[1.04]	[2.15]	[1.70]
$XSTAB_H$	−0.48	4.04	6.09	6.56	0.51	3.35	6.06	5.55	1.58	3.38	6.36	4.78
	[−0.24]	[2.02]	[3.09]	[4.06]	[0.24]	[1.77]	[2.93]	[3.31]	[0.77]	[1.80]	[3.12]	[2.50]
Δ_{XSTAB}	−1.75	3.89	2.84	4.59	−1.05	3.05	2.47	3.51	0.78	1.98	3.14	2.35
	[−1.06]	[2.47]	[1.58]	[2.44]	[−0.59]	[2.01]	[1.31]	[1.70]	[0.43]	[1.21]	[1.82]	[1.11]

excess return.[29] For all three formation periods we study (i.e., f is either 1,6, or 12), we find that momentum returns are higher among currencies with high idiosyncratic volatility than among currencies with low idiosyncratic volatility (*IVOL*). The returns differences are quite large in economic terms. For example, sorting on lagged idiosyncratic volatility and lagged one-month returns leads to an annualized momentum excess return of 3.97% among currencies with low *IVOL*, whereas a momentum strategy among currencies with high *IVOL* yields an average excess return of 8.09% p.a. Thus, momentum strategies are much more profitable among currencies with high idiosyncratic risk.

5.5. Limits to arbitrage: country risk

A natural limit to arbitrage in foreign exchange markets is country risk. Institutional constraints such as country limits, for instance, can prevent position-taking in currencies of high risk countries. Arbitrage activity involving these countries' currencies also exposes investors to the risk of potential sudden capital account restrictions and sharp exchange rate moves. This implies that arbitrage strategies involving these countries' currencies are much more risky compared to those involving currencies of well-developed and highly stable countries with low risk ratings.

We now perform the same analysis as above but sort instead on a measure of country risk (*CRISK*) and a measure of exchange rate stability risk (*XSTAB*). These data are based on the International Country Risk Guide (ICRG) database from the Political Risk Services (PRS) group.[30] We employ the composite country risk rating, which comprises economic, political, and financial risk of a country, as a general proxy for the riskiness of a given country and exchange rate stability risk as a specific proxy for the risk of sharp currency movements.[31] Data for these risk proxies start in January 1985 and we employ the log

[29] Idiosyncratic volatility for each currency j in month t is computed from a regression of currency returns on a constant, the Dollar risk factor, and the HML_{FX} factor of Lustig, Roussanov, and Verdelhan (2011). Idiosyncratic volatility is then computed as the absolute value of the regression residual in month t. We find similar results to those reported below when we employ the volatility risk factor proposed by Menkhoff, Sarno, Schmeling, and Schrimpf (2012).

[30] These data are quite common as proxies for country risk; see, e.g., Bekaert, Harvey, Lundblad, and Siegel (2007), who also use risk indicators from this database.

[31] The exchange rate stability risk proxy measures the perceived risk of large exchange rate movements in the near future.

deviation of the risk rating of a country from the rating of the U.S. as a proxy of relative risk for a U.S. investor.

The setup here is somewhat akin to Avramov, Chordia, Jostovy, and Phlipov (2007, in press), who show that U.S. stock momentum is mainly concentrated in high credit risk firms that are illiquid and hard to sell short.[32] Hence, credit risk proxies for hurdles to arbitrage activity. In our context, we focus on country risk as a natural proxy for limits to arbitrage in FX markets. High risk countries are more politically unstable, economically less developed and more volatile so that establishing positions in the associated currencies poses nontrivial threats of sudden capital account restrictions and nonconvertibility of currency. In short, arbitrage activity involving these countries' currencies should be clearly more risky compared to well-developed and highly stable countries with low risk ratings similar to the U.S.

Panels B and C of Table 9 show results for double sorts on either country risk or exchange rate stability risk and momentum. Corroborating our earlier findings for idiosyncratic volatility, we find that momentum returns are significantly positive and always larger in high-risk countries than in low-risk countries, where momentum strategies do not yield significant excess returns. Hence, for an investor to profit from currency momentum strategies, it is necessary to operate in markets for currencies of risky countries. This is especially important since, unlike momentum strategies in domestic U.S. stocks, investments in foreign currency are always subject to risks of capital controls and nonconvertibility. Therefore, country risk should be an important limit to arbitrage activity in FX markets.

Finally, we examine whether our findings above are driven by country risk being related linearly to the cross-sectional spread in momentum returns and whether momentum is differently affected than carry trades. Table A16, which, as an example, is based on the strategy with a one month formation and holding period, in the Internet Appendix shows a clear pattern. Country risk and exchange rate stability risk are high for both winner *and* loser currencies (Panel A) in the momentum strategy. Hence, it is not the case that these risk ratings are simple proxies for interest rate differentials that drive our results. Instead, currency momentum strategies require that an investor has to go long and short in the most risky countries. This is especially true since momentum profits stem from both the long and short side of the position (see Table A.4, Panel A) so that it is necessary to set up both positions. Contrary to this, the cross-section of forward discount-sorted portfolios that form the basis of the carry trade (Table A16, Panel B) shows a very different pattern. Country risk is highest for carry trade target currencies (high interest rate currencies) and lowest for carry trade funding currencies (low interest rate currencies). This squares well with the finding that most of the carry trade return comes from the long position of the strategy (A.4, Panel B). In any case, these results indicate that country risk has a nonlinear impact on the cross-sectional spread in momentum portfolios' returns and, again, that the anatomy of carry trade strategies is very different from currency momentum.

Developed countries: Finally, a shortcut to looking at country risk could also be to define a sample of clearly developed countries that have stable exchange rate regimes and are most liquid. Table A13 in the Internet Appendix shows results before and after transaction costs similar to those in Table 1 but we limit the cross-section to 15 developed countries.[33] It is clear from this table that momentum returns are much smaller and basically nonexistent after transaction costs when looking at currencies of developed countries. This finding is interesting since it suggests that the profitability of momentum strategies depends on whether smaller and presumably less liquid currencies are included in the investment universe or not. Again, this shows that limits to arbitrage are an important factor in explaining the persistence of momentum returns in FX markets.

6. Robustness and additional tests

6.1. Capital account restrictions and tradability

We have shown above that momentum returns are large in FX markets when examining a broad cross-section that also includes smaller currencies from emerging markets. A potential concern regarding these results is whether all currencies have actually been tradable throughout the sample period as there can be capital controls for some countries or other issues rendering trading in these currencies infeasible. Many of these smaller currencies do indeed show up in the loser and winner portfolios quite frequently which is shown in Table A.6 in the Internet Appendix. This table reports the frequency with which each currency is included in the winner and loser portfolio of the MOM(1,1) strategy. The table shows, quite expectedly, that several larger currencies (e.g., Australia, Canada, Japan, New Zealand, Switzerland, United Kingdom) are often included in the momentum strategy but this dominance rests at least partly on the longer sample periods available for these currencies. However, the table also shows large inclusion frequencies for emerging markets such as Brazil, Indonesia, Poland, or Singapore. Hence, it seems worthwhile to investigate whether issues of tradability (or convertibility) affect our results.

As a first exercise, we limit the sample to currencies that have a positive score on the capital account openness index of Chinn and Ito (2006), both in the formation and holding period, to control for the possibility that some currencies are not tradable or that they are only traded in more opaque offshore markets which would not be adequately reflected in the data. We report results for

[32] In a similar vein, Jostova, Nikolova, Philipov, and Stahel (2010) show that momentum profits in U.S. corporate bond returns derive solely from long and short positions in non-investment grade bonds.

[33] These countries are Australia, Belgium, Canada, Denmark, Euro area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom.

Table 10
Momentum returns and capital controls.
The setup of this table is identical to Table 1 but here we exclude countries with capital controls. More specifically, at each point in time, we only include currencies of countries that have a score in excess of zero (Panel A) or a score higher than one (Panel B) in the updated capital account openness index of Chinn and Ito (2006). The sample periods runs from January 1976 to January 2010.

	Excess returns						Spot rate changes				
	Holding period h						Holding period h				
f	1	3	6	9	12	f	1	3	6	9	12
Panel A. Chinn-Ito index > 0											
1	9.22	6.46	6.02	4.54	4.63	1	5.14	3.07	3.75	2.84	2.90
	[4.61]	[3.47]	[2.87]	[2.42]	[2.39]		[2.79]	[1.86]	[1.86]	[1.58]	[1.57]
3	9.90	7.07	6.18	5.39	5.33	3	7.04	5.33	4.91	3.62	4.00
	[5.30]	[3.96]	[3.42]	[3.44]	[3.07]		[3.81]	[2.81]	[2.70]	[2.06]	[2.30]
6	9.65	8.11	4.71	3.42	4.22	6	6.48	7.29	3.32	2.14	1.33
	[5.29]	[4.52]	[2.52]	[1.74]	[2.26]		[3.30]	[4.11]	[1.72]	[1.14]	[0.68]
9	8.95	8.46	5.60	4.53	2.64	9	6.83	5.76	5.30	3.64	1.82
	[4.53]	[4.48]	[2.85]	[2.21]	[1.37]		[3.42]	[2.81]	[2.66]	[1.79]	[0.92]
12	6.90	6.51	3.77	2.54	1.40	12	4.61	4.20	1.73	1.42	−0.53
	[3.61]	[3.58]	[2.06]	[1.38]	[0.77]		[2.33]	[2.20]	[0.96]	[0.78]	[−0.28]
Panel B. Chinn-Ito index > 1											
1	8.97	5.80	6.51	4.65	4.25	1	5.06	2.96	4.10	2.27	2.75
	[4.61]	[3.01]	[3.07]	[2.48]	[2.02]		[2.79]	[1.77]	[2.02]	[1.25]	[1.45]
3	9.85	7.12	5.98	5.53	5.34	3	7.51	5.41	4.74	4.43	3.52
	[5.10]	[3.95]	[3.28]	[3.54]	[2.87]		[3.91]	[2.85]	[2.70]	[2.51]	[2.08]
6	10.50	8.86	5.40	3.43	2.34	6	6.19	6.61	3.17	2.43	−0.39
	[5.45]	[4.76]	[2.83]	[1.55]	[1.32]		[3.02]	[3.46]	[1.58]	[1.24]	[−0.20]
9	9.22	8.16	5.51	4.87	2.46	9	6.69	5.46	5.19	2.83	1.80
	[4.47]	[3.97]	[2.66]	[2.11]	[1.18]		[3.18]	[2.55]	[2.48]	[1.35]	[0.91]
12	6.88	6.05	2.63	2.18	1.54	12	4.73	3.72	1.46	1.09	−0.20
	[3.42]	[3.09]	[1.16]	[1.21]	[0.83]		[2.34]	[1.86]	[0.77]	[0.61]	[−0.10]

this restricted subset in Table 10, Panel A. As can be seen, the results are not affected by excluding these currencies. Moreover, countries with negative capital account openness index values do not account for a large share of the relevant corner portfolios (less than 20%, on average). While a positive score in the Chinn-Ito index already excludes a number of countries (even developed countries, e.g., the U.K. from 1976 to 1978), we additionally run the same exercise under the constraint that a country has to have an index score of at least one. This requirement eliminates several currencies almost completely from the sample (e.g., Brazil, Philippines, Poland, and South Korea) and significantly reduces the investable sample period for other countries (e.g., Belgium only becomes investable in the 1990s). Results for this filter are shown in Panel B of Table 10 but also do not indicate that momentum is primarily driven by currencies that exhibit limitations to investability.

While the above analysis suggests that tradability issues do not wipe out momentum profits in FX markets, we additionally ran a small survey among four large brokers in FX markets (Goldman Sachs, Deutsche Bank, UBS, Nomura) and asked which currencies would have been impossible (or nearly impossible) to trade in a dynamic portfolio strategy that requires frequent rebalancing. Based on their answers, we restricted our set of tradable currencies and computed momentum returns on the resulting sample. The following restrictions were imposed: Czech Republic (not tradable before 1999), Hungary (2000), Indonesia (1999), Malaysia (1999), Philippines (1999), Singapore (1999), South Africa (2001), Taiwan (1999), Hong Kong (1986), and Thailand (1999).[34] Results for this limited sample are shown in Table 11, Panel A. Corroborating the evidence based on the Chinn/Ito index above, we find that momentum profits are still significant after taking into account likely restrictions on tradability of countries.

As a final check, we augmented the market practitioner's list by eliminating all currencies with large trading in non-deliverable forwards in offshore markets that might not be adequately covered by our price and interest rate data. These currencies include: Brazil, Egypt, India, Indonesia, South Korea, Malaysia, the Philippines, and Taiwan. Results for this even more restricted set of currencies are shown in Panel B of Table 11 but only strengthen our findings above.

In sum, we find that accounting for capital account restrictions (or other trading restrictions) does not significantly weaken average momentum returns despite excluding many smaller emerging markets from our sample. This finding seems to be driven by the fact that most minor currencies, which are more likely to be subject to capital controls, only enter our sample very

[34] Most of the survey respondents' other restrictions, for example, regarding Egypt or Saudi Arabia, were actually already reflected in our data where data histories of several currencies start very late at the end of the 1990s or early 2000s (see Table A1 in the Internet Appendix).

Table 11
Momentum and tradability.
This table shows average annualized excess returns for six momentum portfolios sorted on lagged one-, six-, and 12-month returns and the corresponding high-minus-low momentum portfolios (H−L). Panel A shows results for a set of investable currencies as identified in a survey of FX professionals in major investment banks. Panel B additionally excludes all currencies with non-deliverable forward (NDF) trading in offshore markets. We refer to Section 6 in the main text for details. Numbers in brackets are *t*-statistics based on Newey and West (1987) and the sample period runs from January 1976 to January 2010.

Panel A: "Investable" currency universe

f	L	2	3	4	5	H	H−L
1	−3.28	−0.17	0.67	2.58	2.47	5.48	8.76
	[−1.89]	[−0.09]	[0.38]	[1.45]	[1.50]	[2.99]	[4.90]
6	−1.85	−0.79	1.45	1.16	2.31	5.81	7.65
	[−1.05]	[−0.44]	[0.88]	[0.68]	[1.36]	[2.98]	[4.80]
12	−2.14	0.38	0.94	1.43	2.97	4.75	6.89
	[−1.15]	[0.22]	[0.55]	[0.83]	[1.69]	[2.55]	[4.05]

Panel B: "Investable" currency universe ex NDF

f	L	2	3	4	5	H	H−L
1	−2.80	0.31	0.98	1.99	2.58	5.30	8.10
	[−1.64]	[0.17]	[0.52]	[1.07]	[1.56]	[2.88]	[4.69]
6	−1.68	−0.20	1.53	1.15	2.38	5.66	7.34
	[−0.97]	[−0.11]	[0.87]	[0.65]	[1.38]	[2.79]	[4.58]
12	−1.74	0.23	1.04	1.85	2.82	4.63	6.36
	[−0.97]	[0.13]	[0.58]	[1.04]	[1.58]	[2.37]	[3.58]

recently and, thus, do not drive the lion's share of our result.

6.2. Additional tests

Different base currencies: So far, we have investigated momentum profits from the viewpoint of a U.S. investor. For robustness, we also present results for a British (GBP), Swiss (CHF), Canadian (CAD), and Swedish (SEK) investor, i.e., we convert all data such that they are quoted against one of these four alternative numeraires. The effective size of the cross-section is, of course, unchanged since we lose one currency (the numeraire) but include the USD as a "new" currency.

Results are shown in Tables A.7 and A.8 in the Internet Appendix for excess returns and spot rate changes, respectively. It can be seen that results are basically unchanged relative to the benchmark case so that momentum is not a U.S. dollar phenomenon. This result is reasonable since our momentum portfolios are dollar neutral by construction (the USD component cancels out in the long minus short portfolio). Hence, changing the numeraire has little to no effect on the profitability of momentum strategies.

Furthermore, we also run regressions of momentum excess returns for the four different base currencies on a set of risk factors to rule out the possibility that momentum returns are more closely linked to traditional risk factors for non-U.S. investors. Due to data limitations, we cannot obtain data for all risk factors considered in Table 8 so that we focus on the following set of risk factors that should suffice to capture broad economic conditions in these four countries: growth in real industrial production (IP), CPI inflation, growth in real money balances, changes in the term spread, and (local) stock market returns. Results are reported in Table A.9 in the Internet Appendix and we find (similar to the U.S. case in Table 8) that momentum returns are not closely linked to any of these standard macro-finance risk factors.

Currency regimes: Another question of relevance is whether momentum strategies can be enhanced by considering information about currency regimes. Intuitively, currencies that are pegged or are only allowed to move in very small bands (or target zones) should be less useful in setting up a momentum strategy than freely floating currencies or currencies that are allowed to move in larger bands. To address this issue, we limit our sample of currencies to (i) free floats, managed floats, preannounced crawling bands (wider than or equal to $\pm 2\%$), de facto crawling bands (narrower than or equal to $\pm 5\%$), moving bands (narrower than or equal to $\pm 2\%$) or (ii) free floats only. Sample (i) corresponds to category 3 whereas sample (ii) corresponds to category 4 of the International Monetary Fund (IMF) coarse classification of exchange rate regimes available on Carmen Reinhart's Web page.[35]

Results for these two samples of less heavily managed currencies are shown in Table A10. The sample period starts in 1986 here to have a large enough cross-section for free floats (also see Fig. 1). Panel A reports descriptive statistics for six momentum portfolios and the long minus short portfolio for sample (i). There is a monotonically increasing spread in average excess returns and a significantly positive average excess return for the momentum strategy long in winners and short in losers regardless of the formation period. Panel B shows results for sample (ii) that only comprises free floats. Average excess returns tend to be somewhat lower for formation periods of one and six months but somewhat higher for the 12-month formation period.

In sum, there does not seem to be a clear benefit from concentrating on only freely floating currencies. While freely floating currencies have more room for large price swings, excluding less flexible exchange rates results in a smaller cross-section and excludes a number of slowly trending rates that are managed in crawling bands.

Central bank interventions: Central bank interventions have been considered as one potential source of momentum profits early in the literature. For example, Silber (1994) shows that technical trading rules are more valuable when government agencies intervene in the market. However, later papers reach different conclusions so that the relation between official intervention and momentum trading is less

[35] http://www.carmenreinhart.com/data/browse-by-topic/topics/12. IMF categories 1 and 2 correspond to more restrictive regimes. It is important to note that for the last several years, the IMF classification of each country (published in the Annual Report on Exchange Arrangements and Exchange Restrictions) is based on the country's actual (de facto) policy, as determined by the IMF. For some countries, this classification could differ from the country's official (de jure) stated policy. For most of our sample, only the official stated policy is reported by the IMF.

clear-cut. In this vein, Neely (2002) finds that interventions do not influence technical trading profits and that momentum profits are more likely to precede intervention rather than being caused by them.[36]

Given the prominence of this topic in the earlier literature, we briefly examine the relationship between intervention and momentum returns in Table A11 in the Internet Appendix. We report results for regressions of momentum excess returns for our three benchmark strategies on contemporaneous and lagged central bank intervention activity. Intervention activity is proxied for by the sum of absolute intervention amounts of all central banks in the USD (against any foreign currency). Data for this exercise are obtained from the Federal Reserve Bank of St. Louis. Our results show that interventions are not very powerful in capturing momentum returns, broadly consistent with the findings in Neely (2002). However, it should be noted that our analysis is intentionally simple and that there are serious data issues with central bank interventions which are usually not made public.

European Monetary System (*EMS*): As an additional robustness check, we calculate momentum profits where we exclude all countries participating in the EMS (except for the Deutschmark) and focus on the 1990s where currencies of these countries moved in lock-step.[37] Since momentum in any of these countries should be very short-lived, it seems likely that excluding these currencies will yield larger momentum profits. We plot cumulative momentum excess returns (for the MOM(1,1) strategy) from 1990 to 1998 in Fig. A4 in the Internet Appendix and do indeed find that excluding EMS member countries leads to a somewhat better performance. Hence, the results reported in the main text seem conservative and it should be possible to increase the profitability of momentum strategies by carefully accounting for the correlation structure of currencies.

7. Conclusion

We have empirically investigated momentum strategies in FX markets, which rely on return continuation among winner and loser currencies. We find that these strategies yield surprisingly high unconditional average excess returns of up to 10% per year and that these returns are hard to understand in a framework that relies on covariance risk with standard risk factors. In contrast to an explanation based on systematic risk, we find evidence for under- and subsequent overreaction in long-horizon momentum returns. In this sense, the evidence for currency momentum seems similar to what has been found for equity markets in the earlier literature.

We also find that momentum returns are different from more conventional technical trading rules. As technical trading mostly aims at exploiting trends or momentum in currency movements, it could be expected that returns to these strategies are positively related to our cross-sectional momentum returns. We find, however, that returns to benchmark technical trading rules are somewhat lower and that the correlation with our momentum strategies is rather small. Moreover, currency momentum strategies are very different from the popular carry trade in FX markets. Hence, it comes as no surprise that momentum is not well captured by the global factors that have been shown to be related to carry trade returns in the earlier literature. Rather, momentum and the carry trade are different phenomena that require a different explanation.

However, currency momentum returns do not come as a free lunch for investors trying to exploit these strategies. We find that momentum portfolios in the FX market are significantly skewed towards minor currencies that have relatively high transaction costs, accounting for roughly 50% of momentum returns. Also, the concentration of minor currencies in momentum portfolios raises the need to set up trading positions in currencies with higher idiosyncratic volatility, higher country risk, and higher expected risk of exchange rate instabilities, which clearly imposes risks to investors that are not captured by standard risk factors in a covariance risk framework. Hence, there seem to be effective limits to arbitrage that prevent a straightforward exploitation of momentum returns. Furthermore, momentum profits are highly time-varying, which can also pose an obstacle to arbitrage activity for some of the key FX market participants (e.g., proprietary traders and hedge funds) who typically have fairly short-term investment horizons.

Seen from a broader perspective, there is mounting evidence that momentum can be seen as an ubiquitous phenomenon in financial markets (e.g., Asness, Moskowitz, and Pedersen, 2009). A key contribution of this paper is to show that momentum strategies deliver high excess returns in FX markets, comparable in magnitude to the excess returns documented in stock markets. This occurs despite the special characteristics of currency markets, such as huge trading volume, mostly professional traders, no short-selling constraints, and a considerable degree of central bank interference. However, we show that FX momentum returns are not driven by policy measures including monetary regimes, currency intervention, or the implementation of capital account controls. Momentum returns stem primarily from currencies that are hard to hedge and have high country risk, which is similar to recent findings that equity momentum is concentrated in stocks with high credit risk (Avramov, Chordia, Jostova, and Philipov, 2007), and momentum in corporate bonds is concentrated in non-investment grade bonds (Jostova, Nikolova, Philipov, and Stahel, 2010). In sum, these findings suggest that there could be a common source of momentum profits across asset classes.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jfineco.2012.06.009.

[36] Also, see Neely (1998) for an overview of several findings in the literature on interventions and returns to technical trading. See Sarno and Taylor (2001) for a comprehensive survey on the impact of official intervention on exchange rates.

[37] Neely and Weller (1999) investigate returns to technical trading rules in EMS currencies over the period from 1986 to 1996 and find that they generate significant excess returns.

References

Akram, Q.F., Rime, D., Sarno, L., 2008. Arbitrage in the foreign exchange market: turning on the microscope. Journal of International Economics 76, 237–253.

Asness, C., Moskowitz, T., Pedersen, L., 2009. Value and momentum everywhere. Unpublished working paper. AQR Capital Management, University of Chicago, Copenhagen Business School.

Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2007. Momentum and credit rating. Journal of Finance 62, 2503–2520.

Avramov, D., Chordia, T., Jostova, G., Philipov, A. Anomalies and financial distress. Journal of Financial Economics, in press.

Bacchetta, P., van Wincoop, E., 2010. Infrequent portfolio decisions: a solution to the forward discount puzzle. American Economic Review 100, 870–904.

Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. Journal of Financial Economics 49, 307–343.

Bekaert, G., Harvey, C., Lundblad, C., Siegel, S., 2007. Global growth opportunities and market integration. Journal of Finance 62, 1081–1137.

Brunnermeier, M., Nagel, S., Pedersen, L., 2009. Carry trades and currency crashes. In: NBER Macroeconomics Annual 2008, vol. 23, pp. 313–347.

Burnside, C., Eichenbaum, M., Kleshchelski, I., Rebelo, S., 2006. The returns to currency speculation. NBER Working Paper No. 12489.

Burnside, C., Eichenbaum, M., Kleshchelski, I., Rebelo, S., 2011. Do peso problems explain the returns to the carry trade? Review of Financial Studies 24, 853–891.

Burnside, C., Eichenbaum, M., Rebelo, S., 2007. The returns to currency speculation in emerging markets. American Economic Review, Papers and Proceedings 97, 333–338.

Burnside, C., Eichenbaum, M., Rebelo, S., 2008. Carry trade: the gains of diversification. Journal of the European Economic Association 6, 581–588.

Burnside, C., Eichenbaum, M., Rebelo, S., 2011. Carry trade and momentum in currency markets. Annual Review of Financial Economics 3, 511–535.

Burnside, C., Han, B., Hirshleifer, D., Wang, T., 2011. Investor overconfidence and the forward premium puzzle. Review of Economic Studies 78, 523–558.

Carhart, M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

Chabot, B., Ghysels, E., Jagannathan, R., 2009. Momentum cycles and limits to arbitrage: evidence from Victorian England and post-depression us stock markets. NBER Working Paper No. W15591.

Chan, K., Hameed, A., Tong, W., 2000. Profitability of momentum strategies in the international equity markets. Journal of Financial and Quantitative Analysis 35, 153–172.

Chan, L., Jegadeesh, N., Lakonishok, J., 1996. Momentum strategies. Journal of Finance 51, 1681–1713.

Chinn, M.D., Ito, H., 2006. What matters for financial development? Capital controls, institutions, and interactions. Journal of Development Economics 81, 163–192.

Chordia, T., Shivakumar, L., 2002. Momentum, business cycle, and time-varying expected returns. Journal of Finance 62, 985–1019.

Chui, A., Titman, S., Wei, K., 2010. Individualism and momentum around the World. Journal of Finance 65, 361–392.

Cooper, M., Gutierrez, R., Hameed, A., 2004. Market states and momentum. Journal of Finance 59, 1345–1365.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. Journal of Finance 53, 1839–1885.

Deutsche Bank, 2010. Exchange Rate Perspectives: 30 Years of FX Investment Returns. February 8, 2010.

Dooley, M., Shafer, J., 1976. Analysis of short-run exchange rate behavior: March 1973 to September 1975. International Finance Discussion Papers, No. 76. Federal Reserve System, Washington, DC.

Dooley, M., Shafer, J., 1983. Analysis of short-run exchange rate behavior: March 1973 to November 1981. In: Bigman, D., Taya, T. (Eds.), Exchange Rate and Trade Instabilities: Causes, Consequences, and Remedies, Ballinger Publishing, Cambridge, MA, pp. 43–70.

Duffie, D., 2010. Presidential address: asset price dynamics with slow-moving capital. Journal of Finance 65, 1237–1267.

Eisdorfer, A., 2008. Delisted firms and momentum profits. Journal of Financial Markets 11, 160–179.

Fama, E., 1984. Forward and spot exchange rates. Journal of Monetary Economics 14, 319–338.

Fama, E., French, K., 1992. The cross-section of expected stock returns. Journal of Finance 47, 427–465.

Fama, E., French, K., 1996. Multifactor explanations of asset pricing anomalies. Journal of Finance 51, 55–84.

Fama, E., MacBeth, J., 1973. Risk, return and equilibrium: empirical tests. Journal of Political Economy 81, 607–636.

Gebhardt, W., Hvidkjaer, S., Swaminathan, B., 2005. Stock and bond market interaction: Does momentum spill over? Journal of Financial Economics 75, 651–690.

Gorton, G., Hayashi, F., Rouwenhorst, K., 2008. The fundamentals of commodity futures returns. Yale ICF Working Paper No. 07-08.

Goyal, A., Saretto, A., 2009. Cross-section of option returns and volatility. Journal of Financial Economics 94, 310–326.

Griffin, J., Martin, J., 2003. Momentum investing and business cycle risk: evidence from pole to pole. Journal of Finance 58, 2515–2547.

Grinblatt, M., Han, B., 2005. Prospect theory, mental accounting, and momentum. Journal of Financial Economics 78, 311–339.

Gromb, D., Vayanos, D., 2010. Limits of arbitrage: the state of the theory. Annual Review of Financial Economics 2, 251–275.

Gutierrez Jr, R., Kelley, E., 2008. The long-lasting momentum in weekly returns. Journal of Finance 63, 415–447.

Harris, R.D., Yilmaz, F., 2009. A momentum trading strategy based on the low frequency component of the exchange rate. Journal of Banking and Finance 33, 1575–1585.

Harvey, C., Siddique, A., 2000. Conditional skewness in asset pricing tests. Journal of Finance 55, 1263–1295.

Hong, H., Lim, T., Stein, J., 2000. Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. Journal of Finance 55, 265–295.

Hong, H., Stein, J., 1999. A unified theory of underreaction, momentum trading and overreaction in asset markets. Journal of Finance 54, 2143–2184.

Hvidkjaer, S., 2006. A trade-based analysis of momentum. Review of Financial Studies 19, 457–491.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. Journal of Finance 48, 65–91.

Jegadeesh, N., Titman, S., 2001. Profitability of momentum strategies: an evaluation of alternative explanations. Journal of Finance 56, 699–720.

Johnson, T., 2002. Rational momentum effects. Journal of Finance 57, 585–608.

Jostova, G., Nikolova, S., Philipov, A., Stahel, C., 2010. Momentum in corporate bond returns. Unpublished working paper, George Washington University, U.S. Securities and Exchange Commission, George Mason University, U.S. Securities and Exchange Commission.

King, M., Osler, C., Rime, D., 2012. Foreign exchange market structure, players and evolution. In: James, J., Marsh, I., Sarno, L. (Eds.), Handbook of Exchange Rates, Wiley Publishing Inc., New Jersey, pp. 1–48.

Korajczyk, R., Sadka, R., 2004. Are momentum profits robust to trading costs? Journal of Finance 59, 1039–1082.

Lequeux, P., Acar, E., 1998. A dynamic benchmark model for managed currencies funds using cme currency contracts. European Journal of Finance 4, 311–330.

Lesmond, D., Schill, M., Zhou, C., 2004. The illusory nature of momentum profits. Journal of Financial Economics 43, 1121–1142.

Levich, R., Thomas III, L., 1993. The significance of technical trading-rule profits in the foreign exchange market: a bootstrap approach. Journal of International Money and Finance 12, 451–474.

Liu, L., Zhang, L., 2011. A model of momentum. NBER Working Paper No. 16747.

Lustig, H., Roussanov, N., Verdelhan, A., 2011. Common risk factors in currency markets. Review of Financial Studies 24, 3731–3777.

Lustig, H., Verdelhan, A., 2007. The cross section of foreign currency risk premia and consumption growth risk. American Economic Review 97, 89–117.

Lyons, R., 2001. The Microstructure Approach to Exchange Rates. MIT Press, Cambridge, MA.

Melvin, M., Shand, D., 2011. Active currency investing and performance benchmarks. Journal of Portfolio Management 37, 46–59.

Menkhoff, L., Sarno, L., Schmeling, M., Schrimpf, A., 2012. Carry trades and global foreign exchange volatility. Journal of Finance 67, 681–718.

Menkhoff, L., Taylor, M., 2007. The obstinate passion of foreign exchange professionals: technical analysis. Journal of Economic Literature 45, 936–972.

Mitchell, M., Pedersen, L., Pulvino, T., 2007. Slow moving capital. American Economic Review, Papers and Proceedings 97, 215–220.

Moskowitz, T., Ooi, Y., Pedersen, L., 2012. Time series momentum. Journal of Financial Economics 104, 228–250.

Neely, C., 1998. Technical Analysis and the Profitability of U.S. Foreign Exchange Intervention. Review, Federal Reserve Bank of St. Louis 80, 3–17.
Neely, C., 2002. The temporal pattern of trading rule returns and exchange rate intervention: intervention does not generate technical trading rule profits. Journal of International Economics 58, 211–232.
Neely, C., Weller, P., 1999. Technical trading rules in the European Monetary System. Journal of International Money and Finance 18, 429–458.
Neely, C., Weller, P., 2012. Technical analysis in the foreign exchange market. In: James, J., Marsh, I., Sarno, L. (Eds.), Handbook of Exchange Rates, Wiley Publishing Inc., New Jersey, pp. 369–402.
Neely, C., Weller, P., Dittmar, R., 1997. Is technical analysis in the foreign exchange market profitable? A genetic programming approach. Journal of Financial and Quantitative Analysis 32, 405–426.
Neely, C.J., Weller, P., Ulrich, J., 2009. The adaptive markets hypothesis: evidence from the foreign exchange market. Journal of Financial and Quantitative Analysis 44, 467–488.
Newey, W., West, K., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Okunev, J., White, D., 2003. Do momentum-based strategies still work in foreign currency markets? Journal of Financial and Quantitative Analysis 38, 425–447.
Olson, D., 2004. Have trading rule profits in the currency markets declined over time? Journal of Banking and Finance 28, 85–105.
Pastor, L., Stambaugh, R., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.
Patton, A., Ramadorai, T. On the high frequency dynamics of hedge fund risk exposures. Journal of Finance, in press.
Pojarliev, M., Levich, R., 2010. Trades of the living dead: style differences, style persistence and performance of currency fund managers. Journal of International Money and Finance 29, 1752–1775.
Pukthuanthong-Le, K., Levich, R., Thomas III, L., 2007. Do foreign exchange markets still trend? Journal of Portfolio Management 34, 114–118.
Pukthuanthong-Le, K., Thomas III, L., 2008. Weak-form efficiency in currency markets. Financial Analysts Journal 64, 31–52.
Rouwenhorst, K., 1998. International momentum strategies. Journal of Finance 53, 267–284.
Rouwenhorst, K., 1999. Local return factors and turnover in emerging stock markets. Journal of Finance 54, 1439–1464.
Sagi, J., Seascholes, M., 2007. Firm-specific attributes and the cross-section of momentum. Journal of Financial Economics 84, 389–434.
Sarno, L., Schneider, P., Wagner, C., 2012. Properties of Foreign Exchange Risk Premiums. Journal of Financial Economics 105, 279–310.
Sarno, L., Taylor, M., 2001. Official intervention in the foreign exchange market: Is it effective and, if so, how does it work? Journal of Economic Literature 39, 839–868.
Serban, A., 2010. Combining mean reversion and momentum trading strategies in foreign exchange markets. Journal of Banking and Finance 34, 2720–2727.
Shleifer, A., Vishny, R., 1997. The limits of arbitrage. Journal of Finance 52, 35–55.
Silber, W., 1994. Technical trading: when it works and when it doesn't. Journal of Derivatives 1, 39–44.
Sweeney, R., 1986. Beating the foreign exchange market. Journal of Finance 41, 163–182.
Verardo, M., 2009. Heterogeneous beliefs and momentum profits. Journal of Financial and Quantitative Analysis 44, 795–822.