

Imperial College London
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Essays on empirical asset pricing

by

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Abstract

In this thesis we look to advance our understanding of how asset prices fluctuate and why. In the first chapter we provide an extensive survey on the time-series and cross-sectional variation in average returns on currency carry trade strategies. We then identify a research niche that examines the relation between uncertainty, as measured by survey forecasts' dispersion, and the exchange rates. Subsequently, in the second chapter we find that forecast disagreements on key macro variables – economic activity growth, short-term interest rates and current account positions – help explain a considerable part of the time variation in FX volatility, and even allow FX volatility forecasts.

We continue exploring the FX market in the third chapter, which studies empirically the relation between macro uncertainty shocks and the cross-section of currency excess returns. We measure uncertainty over macro variables such as current account, inflation rate, short-term interest rate, real economic growth and foreign exchange rate using the cross-sectional dispersion of market participants' expectations from two international surveys of economic forecasts. We find evidence that typical investment currencies deliver low returns whereas funding currencies offer a hedge when current account uncertainty is unexpectedly high. In contrast, uncertainty over other macro indicators displays no significant relation with the cross-section of currency excess returns. We also find that current account uncertainty subsumes the information content of foreign exchange rate volatility risk.

The forth and final chapter looks at some claims made about the price acceleration giving an informative trading signal. We built several empirical measures of acceleration and compared them to the price signals from the previous academic literature on the equity market. We do find that acceleration signal leads to the construction of the long-short (LMH) trading strategies that deliver high profits. Moreover, those profits are not explained by the state-of-the-art equity factor models. However, all of the LMH profitability and cross-sectional variation in portfolios' mean returns are reconciled once we add our *la5* factor – a simple reversal strategy with a one trading week lookback horizon and one month holding period – to the off-the-shelf models. Taken together, our results cast doubt on acceleration being a separate phenomenon.

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Declaration of originality

I herewith certify that this thesis constitutes my own work and that all material, which is not my own work, has been properly acknowledged.

Aleksejs Krecetovs

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Валерию и Татьяне посвящается

Chapter 1

Introduction and FX literature review

1.1 Predictability: a survey

1.1.1 Introductory discussion

Conventional foreign exchange (FX) market carry trade is a trading strategy where the sum of money in one currency is converted into another currency with a relatively high risk free interest rate and invested at that rate.¹ At some defined point in the future the invested money is converted back. The received sum corresponds to the payoff on this investment strategy. Let us have $X_t/(1 + R_t^d)$ USD and convert it to e.g. GBP at a current spot exchange rate and invest in a sterling-denominated (default risk free) bond because of its higher interest rate R_t^f . After some time we sell the bond and convert all money back into USD, denoting by X_{t+1} the number of dollars we then hold. Alternatively, we could have invested in USD-denominated bond and received X_t at the end of the period. If X_t followed random walk ($E_t[X_{t+1}] = X_t$) then return on a carry trade Rx_{t+1} , adjusted for opportunity cost of capital R_t^d , would 1) not be predictable and 2) on average equal to zero even knowing information at time t :

$$\underbrace{\overbrace{(1 + Rx_{t+1})}^{\text{excess return}} (1 + R_t^d)}_{\text{total return}} X_t / (1 + R_t^d) = \underbrace{S_{t+1}/S_t (1 + R_t^f)}_{X_{t+1}} X_t / (1 + R_t^d) \quad (1.1)$$

¹The concept of “relatively high” will be explained on the next pages in more detail. What is important to emphasize straight away is that in time-series (TS) dimension of this section its meaning is different from that in the cross-sectional (XS) dimension.

where S is the spot exchange rate quoted in the units of domestic currency (USD) per unit of foreign currency (GBP). From here: $E_t(Rx_{t+1}) = 0$ easily follows under the assumption of random walk above. Rearranging, we get the expression we will refer later on to:

$$1 + Rx_{t+1} = S_{t+1}/S_t \frac{1 + R_t^f}{1 + R_t^d} \quad (1.2)$$

However, starting with [Hansen and Hodrick \(1980\)](#) and [Fama \(1984\)](#) the research on return predictability shifted from the stock and bond markets also to the FX market.²

Similar to the expectation hypothesis in the bond markets, the idea of uncovered interest rate parity (UIP), which dominates earlier traditional view, is that in log terms:³

$$E_t[\Delta s_{t+1}] = -(r_t^f - r_t^d) \quad (1.3)$$

That is, interest rate differential would predict future spot exchange rate. It follows directly from the assumption of random walk for $x_t \equiv \log X_t$: move x_t outside the expectation operator for x_{t+1} in Equation 1.1 and you immediately see the outcome. On the other hand, if it was the log exchange rate that followed random walk then the interest rate differential would utterly predict the return on a carry trade in excess of the domestic interest rate.

Note that the expectation is taken under the physical (i.e. real-world) probability measure. Since the UIP validity immediately means that expected excess returns are zero we see that the parity suggests investors are risk-neutral with respect to the FX risk. This theory also implicitly assumes all investors are rational (e.g. [Lustig and Verdelhan, 2007](#); [Della Corte, Sarno, and Tsiakas, 2011](#); [Fiotakis and Lund-Jensen, 2012](#), Appendix A).

The first results (in the first two lines of the Figure 1.1) taken from [Cochrane \(2005, ch. 20.1\)](#) do support the UIP view, which are analogous to the results received from the bond market (suggesting on average the long-term interest rate is equal to the short-term interest rate or,

²[Engel \(1996\)](#) is one of the most cited surveys on the earlier evidence about return predictability in the FX market. [Cochrane \(2005, ch. 20.1\)](#) provides a more recent one.

³Small letters denote the logs of respective levels. The expectation of logs instead of logs of expectation are used by convention due to the presence of [Siegel \(1972\)](#)'s paradox. See Appendix 1.B below.

alternatively, on average the yield curve is flat) implying:⁴

$$E[\Delta s_{t+1}] = -E[r_t^f - r_t^d] \quad (1.4)$$

Thus, the interest rate differential seems to explain the future currency spot rate, but not the carry trade return. Hence, on average you should neither make nor lose money by implementing a carry trade because exchange rate movement will net-off all the potential gain of the interest rate differential. Nonetheless, these results are misleading for the conclusion on whether UIP holds – since we are interested in predictability we need to study conditional moments.

FIGURE 1.1 ABOUT HERE

1.1.2 Regression evidence

If we now build forecasting regression over the whole time-series sample and look at what was the exchange rate reaction to “unusual” (above or below time-series sample average) difference in interest rates, we find negative coefficients – in the next two lines of Figure 1.1 – often statistically different from zero. This suggests the currency of the country with a relatively high interest rate tended, if anything, to appreciate over a carry period but not depreciate as implied by UIP. Figure 1.2 makes the same point for the particular pair USD/GBP. We see that although on average the interest rate differential is matched by depreciation in GBP, the variation through time hints that the relative increase in the UK interest rate is matched up by GBP appreciation, therefore, contradicting UIP. As for the bond market, the expectation hypothesis in the form of UIP appears rejected.

FIGURE 1.2 ABOUT HERE

As the interest rate differential does not predict future spot exchange rate or predicts with the sign not implied by UIP (i.e. in regression Equation 1.6 below $\beta \geq 0$ while UIP Equation 1.3 implies $\beta = -1$), it is natural to conclude it predicts the return on a carry trade because of its

⁴Note that in his book the author defines FX rates in foreign currency per unit of domestic currency (USD) while in this and most other papers FX rates are quoted in USD.

definition in log terms following Equation 1.2:

$$rx_{t+1} = r_t^f - r_t^d + \underbrace{s_{t+1} - s_t}_{\Delta s_{t+1}} \quad (1.5)$$

$$\Delta s_{t+1} = \alpha + \beta(r_t^f - r_t^d) + \epsilon_t \quad (1.6)$$

Or rearranging:

$$rx_{t+1} = \alpha + (1 + \beta)(r_t^f - r_t^d) + \epsilon_t \quad (1.7)$$

Thus, performing an analysis similar to that performed by Fama and Bliss (1987) for the predictability in the bond market, the results show that the interest rate differential predicts the return on the carry trade rather than the future spot currency exchange rate. Furthermore, the coefficients in front of the interest rate differentials in Equation 1.7 are sometimes significantly more than one. This is exactly because sometimes exchange rate tends to appreciate conditional on higher than usual interest rate differential in the period before.

Even in more than 30 years from the first reported evidence we still observe the same picture: the interest rate differential or equivalently, by no arbitrage assumption, the spread between the (log) FX forward and spot rates (for covered interest rate parity or CIP, see Appendix 1.A):

$$f_t - s_t = -(r_t^f - r_t^d) \quad (1.8)$$

does seem to forecast carry trade returns (see e.g. Jurek, 2009).⁵ The measure of model's explanatory power, R^2 , is very low in all individual currency pair forecasting regressions (see e.g. ch. 20.1 in Cochrane, 2005; Beber, Breedon, and Buraschi, 2010, for the latest evidence) because the right hand side variable is very slow-moving while the exchange rate changes are very volatile. As with the slow-moving D/P ratio in the stock markets, the forecasting ability of the interest rate differential seems to improve with horizon (Cochrane, 2005, ch. 20.1), although the more recent findings do not support this claim (Brunnermeier, Nagel, and Pedersen, 2009).

⁵Equation 1.5 then becomes $rx_{t+1} = s_{t+1} - f_t$ and Equation 1.7 transforms to $rx_{t+1} = \alpha - (1 + \beta)(f_t - s_t) + \epsilon_t$.

1.1.3 Portfolio formation evidence

TS strategies. The out-of-sample non-parametric evidence of predictability is provided by creating a clear-cut strategy of going long or short the foreign currency depending on an observed well-defined signal. [Burnside, Eichenbaum, and Rebelo \(2011\)](#) is one example which considers both individual currency carry and momentum strategies. Then they create two respective equally weighted portfolios of individual strategies. We note that the decision to go long or short is taken looking at an individual currency pair characteristic and not evaluating the respective characteristic relative to those of other currency pairs.

XS strategies. An alternative construction methodology for carry and momentum strategies is discussed and studied in [Lustig, Roussanov, and Verdelhan \(2011\)](#) and [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012b\)](#) – both works are described in detail in Section 1.2.3. The authors sort currencies into portfolios based on signals. They then long high signal portfolios and short low signal portfolios. Here, opposed to the strategies in the previous paragraph, the decision to go long does not depend purely on a foreign currency characteristic versus the USD but on its characteristic versus the rest of the foreign currencies.⁶

The next question should be why are the returns predictable? Is it due to market inefficiency (frictions, behavioural biases), non-zero and time-varying risk premium⁷, etc.? But in the latter case what systematic risk are we bearing? As [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012a\)](#) note about FX carry: “empirically, [...] the literature has had serious problems in convincingly identifying risk factors that drive these premia until now”. Below the most recent works are surveyed that seek the answers to these questions.

1.1.4 Unrepresentative samples / peso events

A popular early view is that crash events, when carry trades perform especially poor and make the cumulative performance less (although it can still be statistically different from zero if investors

⁶[Hassan and Mano \(2015\)](#) argue that in fact there is little relation between the regression-based and this type of portfolio-based evidence – they reflect different phenomena. More material on FX in the portfolio context see Appendix 1.C.

⁷Since the carry trade return is essentially in an excess return form it could be regarded as “premium”. Appendix A in [Fiotakis and Lund-Jensen \(2012\)](#) shows why one can interpret deviations from UIP as risk premium.

are risk averse and require a constant premium), are too rare and might not appear in sample as often as they (on average) should, if at all – see [Cochrane \(2005, ch. 20.1\)](#), [Burnside, Eichenbaum, Kleshchelski, and Rebelo \(2011\)](#), and [Jurek \(2014\)](#). Therefore, the price of risk estimates (in terms of Sharpe ratio) are overstated. These crashes make the return distribution on carry strategy very negatively skewed as on a general written insurance contract (e.g. financial out-of-the money put option). This is a famous peso problem hypothesis explained by [Cochrane \(2005, ch. 20.1\)](#): early research on the field might have received especially big estimates of carry trade return – because currency crashes were not realized in sample as frequently as they should have. This in turn “can skew forecasting regressions” as the latter author notes.

Turning now to the data for the support of the peso event idea, [Jurek \(2009\)](#) reports that over the recent financial crisis the maximum drawdown on a diversified carry trade was -20% with the Sharpe ratio decreasing to 0.57, while prior to the crisis the carry trade delivered the average Sharpe ratio in excess of 1 (roughly double that of the stock market) over 17 years.⁸ [Burnside, Eichenbaum, Kleshchelski, and Rebelo \(2011\)](#) conclude as well that the carry trade did not do particularly bad over the crisis, especially compared to the stock market. Nonetheless, the skewness of the carry trade returns is negative ([Burnside, Eichenbaum, Kleshchelski, and Rebelo, 2011](#); [Jurek, 2014](#); [Brunnermeier, Nagel, and Pedersen, 2009](#), who show that even risk-neutral future-looking distribution is negatively skewed) and in absolute value can be higher than that on the stock market portfolio ([Jurek, 2014](#)).

[Jurek \(2014\)](#)’s main finding is that hedging crash risk with out-of-the money currency options makes the excess premium lower, but it does not fully eliminate the carry mean return. He argues that currency crash risk explains at most a third of the average return on the strategy. Therefore, [Jurek \(2014\)](#) concludes that peso story cannot explain the carry premium.⁹

⁸Very high Sharpe ratios are also reported by many other works, among them [Brunnermeier, Nagel, and Pedersen \(2009\)](#) and [Burnside, Eichenbaum, Kleshchelski, and Rebelo \(2011\)](#).

⁹It should be noted that his article is part of an ongoing debate on the importance of crash (also known as rare disaster) risk, which is related to but different from the peso story. Some of the other notable articles include [Farhi and Gabaix \(forthcoming\)](#); [Farhi, Fraiburger, Gabaix, Ranci re, and Verdelhan \(2015\)](#); [Chernov, Graveline, and Zviadadze \(2015\)](#).

1.1.5 Risk-based explanations

There are two papers that promote the deviations from macroeconomic news (fundamentals) to explain FX and carry return dynamics in the risk-based framework.¹⁰ Brunnermeier, Nagel, and Pedersen (2009) argue that currency crash phenomenon does not depend on the news about fundamentals per se. They suggest it can happen as a result of overreaction when many investors unwind their positions (consistent with Lim, 2007) due to funding (liquidity) constraints, while small persistent carry trade premium is there because of news underreaction due to slow-moving capital. They also find that higher interest rate differential predicts negative skewness and, thus, the higher possibility of a crash of an investment currency (the opposite holds for the funding currency). Brunnermeier, Nagel, and Pedersen (2009) note that carry trade returns seem to be predicted by VIX¹¹ which often proxies for “global risk or risk aversion” (and simultaneously for liquidity risk) and that the predictive power of the interest rate differential is lost when it is controlled for. As authors argue, this helps to explain and understand the violations of UIP. Empirically, when VIX is high the returns on a carry trade are expected to be high, which makes sense – VIX is high in bad states of the world and returns are expected to be high to induce investors to participate in the market; this is consistent with the paper by Lustig, Roussanov, and Verdelhan (2014) which will be discussed later on. At the same time, increases in VIX were associated with losses on carry trades, because then liquidity problems arise.¹²

Beber, Breedon, and Buraschi (2010) is another example of work which also assumes the news about fundamentals and peso events do not reflect the whole picture of exchange rate dynamics. They perform the empirical analysis of FX market with carry trade return predictability among other covered topics. This is done within the context of the model with risk averse agents in incomplete information setting with heterogeneous beliefs about fundamentals (such as growth rate of the economy), but who are rational. The authors find backing for the neo-classical (risk-based) differences in beliefs explanation of exchange rate dynamics. In particular, they suggest

¹⁰For non-risk explanation of FX dynamics which still considers mechanisms of departure from fundamentals see e.g. the scapegoat theory by Bacchetta and van Wincoop (2013) with rational agents and incomplete information: investors switch over time as to which variables are important to determine FX prices; hence, correlations between fundamentals and exchange rates change over time.

¹¹Note that this is information obtained from the equity market.

¹²Through VIX one can also build a link between the carry trade and the cross-border capital flows (Rey, 2013).

disagreement proxy, which they term mean absolute deviation (MAD) and which is built from the analyst forecasts of the exchange rate, enters the stochastic discount factor (SDF), and they provide enough supporting evidence. [Beber, Breedon, and Buraschi \(2010\)](#) also learn that MAD is able to forecast both the first and second conditional moments of exchange rate changes, hence reporting also the time-varying variance risk premium. Moreover, the differences in beliefs proxy drives out the predictability power of the volatility measures for carry trade returns and seems to contain extra information to that implied by the forward-spot spread, predictive power of which was documented above. The link to the liquidity crisis, introduced in previous paragraph, is made to explain this extra information – conditional on illiquidity states of the world MAD drives out the interest rate differential in forecasting regressions.

[Lustig, Roussanov, and Verdelhan \(2014\)](#) approach predictability issue from another angle. Firstly, they discuss the forecasting power of the average forward-spot spread (termed AFD factor) for currency baskets and individual currencies versus the bilateral forward-spot spread as the return predictor. They receive R^2 twice larger when including the former in the regressions. Separately, individual forward discounts could not help forming a profitable trading strategy while AFD did (the authors call the corresponding trading strategy the base carry trade) providing non-parametric evidence on predictability. This made them to conclude that the whole sample average contains more information about future mean FX returns which is in line with [Cochrane and Piazzesi \(2005\)](#) results for bonds.¹³

Secondly, [Lustig, Roussanov, and Verdelhan \(2014\)](#) provide evidence that the expected return is associated with the US business cycle (they take USD as a base currency in main specification). They find AFD factor to be correlated with the business cycle variables such as industrial production growth, etc. That raises a natural question whether these US-specific macro variables could themselves be good predictors for carry trade returns.¹⁴ From the performed empirical work it turned out to be the case – US-specific industrial production (IP) growth and AFD together explain up to 25 percent of the variation in future excess returns on the strategy ([Lustig, Roussanov, and Verdelhan, 2014](#)). Note that the latter price-based factor was not able to drive out IP

¹³Nonetheless, [Lustig, Roussanov, and Verdelhan \(2014\)](#) do not claim that a factor, which is linear in forwards of different maturities, does a better job than a simple cross-sectional sample average.

¹⁴The authors project US IP growth onto the global IP growth and use the residuals in order to remove a common component and concentrate on a country-specific part of the business cycle.

growth; that is, macro variables contain even more additional information not contained in individual currency pair forward rates and AFD.¹⁵ This, as authors claim, is consistent with the bond and equity markets’ empirical findings. The predictive power of studied highly persistent variables (AFD and IP growth) does also seem to improve with horizon shifting from one month to twelve months which is consistent with [Cochrane \(2005, ch. 20.1\)](#) reported results.¹⁶ Moreover, [Lustig, Roussanov, and Verdelhan \(2014\)](#) factor is shown to predict exchange rate component of currency returns. Hence, exchange rates are also countercyclical and the dollar seems to appreciate during the US-specific recessions which is explained by “flight to quality” (expected returns required by US investor are higher in his or her bad times). This suggests carry premium being compensation for the exchange rate and not the interest rate risk (for more on the topic of what drives average carry returns see [Section 1.2](#) and [Appendix 1.D](#)). Finally, authors note that the base carry strategy only works for certain base currencies “whose forward discounts are informative about the local price of risk” (which seem to be neither traditional investing nor funding currencies).

To summarize, all empirical works discussed in the last two subsections are very different, but there is one common idea which goes through all of them – that of the potential risk investor is taking by being involved in various carry trades. Correspondingly, many in the academic world seem to agree that the return on the carry trade is a premium against a possible bad state realisation due to a large depreciation in the investment currency (alternatively, a large appreciation of the funded currency) – “exchange rates go up by stairs and down by the elevator” ([Brunnermeier, Nagel, and Pedersen, 2009](#)).¹⁷ The risk driver(s) of this premium is debatable as one can see from the few works surveyed. Time-variation in mean excess return and arising predictability is an even more controversial topic, and opinions differ on whether it is just a coincidence in the sample, there is true time-varying systematic risk premium demanded by investors, or it is some other non-risk story.¹⁸ Finally, it is interesting to note an increasing popularity of using aggregate

¹⁵This provides some motivation to study production models for FX dynamics explanation. Limited support was also found for the US non-durables consumption growth volatility as predictor.

¹⁶AFD autocorrelations also rise with lower data frequency.

¹⁷As is discussed below, [Burnside, Eichenbaum, Kleshchelski, and Rebelo \(2011\)](#) argue that alternatively bad states can be represented by the large value of the SDF, not the large negative returns.

¹⁸[Engel and West \(2005\)](#), [Engel and West \(2010\)](#), and [Burnside, Eichenbaum, and Rebelo \(2011\)](#) note several alternative interpretations to bear in mind such as e.g. a non-risk based liquidity (stories of price pressure and net illiquidity of foreign assets), deviations from rational expectations (behavioural stories like overconfidence), etc. Admittedly, if the price pressure explanation by [Burnside, Eichenbaum, and Rebelo \(2011\)](#) is true, it needs to hold for other asset markets as well since FX market, though decentralized, is the most liquid. This causes a challenge

level, not currency pair-specific, predicting variables (AFD, VIX, etc.). Such evidence implicitly suggests a strong factor structure in currency returns and allows to exploit the cross-sectional dimension of the data to test the models (Cochrane, 2011c).

1.1.6 Other FX strategies

Among popular FX signals studied in the predictability field are the past currency returns – this phenomenon is also known as momentum (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012b; Asness, Moskowitz, and Pedersen, 2013). Hong and Yogo (2012) seem to substantially weaken momentum (as well as interest rate differential) signal by their aggregate FX futures open interest factor. Their story is that increase in open interest, empirically being highly pro-cyclical, indicates domestic economic expansion and leads to higher inflation expectations which in turn makes the domestic currency to depreciate against all foreign currencies at the same time.

The additional set of predictors arises from the purchasing power parity (PPP) which is a strong theoretical concept in macroeconomics and which states that bilateral nominal exchange rates should depend on the respective price levels in the two countries. The factors based on PPP are used in both contemporaneous times-series analysis (Pojarliev and Levich, 2008) and forecasting (Asness, Moskowitz, and Pedersen, 2013; Ang and Chen, 2010; Menkhoff, Sarno, Schmeling, and Schrimpf, 2015). Nonetheless, their power in both cases seems to be rather weak (especially in the case of predictability regressions running “horse races” with other factors).

Finally, some other FX strategies also proved to have predictable returns. Motivated by the interest rate differential, Ang and Chen (2010) explore the information from the domestic and foreign yield curves and find that the change in the interest rate differential and term spread are also having incremental forecasting power, in addition to that of the forward-spot spread, for returns on term level-, spread-, momentum-based and other portfolios. Beber, Breedon, and Buraschi (2010) and Della Corte, Sarno, and Tsiakas (2011) find that implied volatility is predictable, and, hence, also returns on portfolios involving FX options. The latter work is interesting in a sense that authors find an analogue to the failure of UIP for the second moments, not just levels, of FX rates.

for their model which should be addressed in the future.

1.1.7 Additional evidence with emphasis on exchange rate predictability

An interesting extension of the UIP puzzle literature is provided by [Boudoukh, Richardson, and Whitelaw \(forthcoming\)](#) who use the forward interest rate differential as predictor instead of the (spot) interest rate differential. They show that as forward maturity increases the results become more consistent with the UIP theory. Moreover, the explanatory power of Δs_{t+1} predictability regression increases by one order of magnitude casting doubt on the claims by [Meese and Rogoff \(1983\)](#) (that the best modelling tool for bilateral exchange rates is a random walk model).

[Gourinchas and Rey \(2007\)](#) show the predictability of exchange rate for short (1 quarter) as well as long (8 quarters) horizons with their net asset variable. This variable is defined as a stationary deviation from the long term trend (taken as deterministic) of the external asset position of the US. Such robust result across horizons is motivated by the fact that FX plays a dual role contributing to valuation channel adjustment in the short run and to trade channel adjustment in the long run.

Another work on XS predictability is that by [Della Corte, Ramadorai, and Sarno \(2014\)](#), who show the volatility risk premium (VRP) being important for exchange rate predictability. They create an XS signal based on which LMH_{VOL} strategy – long low VRP currencies and short high VRP ones – is created. The profitability of the factor is shown to come from the exchange rate component of FX return and is motivated by limits to arbitrage story (which, admittedly, should also hold for other asset classes as well). On the other hand, the authors claim HML_{IR} by [Lustig, Roussanov, and Verdelhan \(2011\)](#), which is not much correlated with LMH_{VOL} , is not able to robustly predict Δs_{t+1} .

[Bakshi and Panayotov \(2013\)](#) study the predictability of HML_{IR} (XS carry) strategy.¹⁹ They find that three largely independent factors – changes to the commodities price index, VOL_{FX} , and aggregate liquidity – are having an incremental forecasting power. According to [Lustig, Roussanov, and Verdelhan \(2014\)](#) the premium for HML_{IR} should reflect the exposure to global shocks. Hence, the proposed factors should really capture the world and not the country-specific developments. Again, currency component seems to be the driving force. Thus, the cross-section

¹⁹TS carry strategy is shown to be forecastable which constitutes a puzzle given positive mean returns on this strategy.

contains relevant information which should not be ignored in Δs_{t+1} forecasting exercises. Finally, in a very interesting set of generalized method of moments (GMM) exercises authors argue that the predictability evidence is not reconciled with the asset pricing restrictions leaving the researchers with a puzzle.

Separately, there was a move into studying FX order flows for the predictability of exchange rates and exchange rate returns.²⁰ Menkhoff, Sarno, Schmeling, and Schrimpf (2013) looked at the information in the end-user orders differentiating across customer groups. They identified three potential channels behind the predictability – price discovery, price pressure and risk sharing motive – and analyzed which customer group is associated more with each channel.

As a final note, Equation 1.5 rearranged to express the expected change in the FX rate as a function of the interest rate differential and the residual has become one of the building blocks for structural and reduced-form models explaining exchange rate dynamics.²¹ Again, it is important to point out: the residual’s interpretation, known at least since Fama (1984), as a sole (systemic, undiversifiable) risk premium is not unilaterally acknowledged. Some alternatives are discussed in Footnote 18.

1.2 Empirical asset pricing: a survey

1.2.1 Introductory discussion

After the empirical time-series results were first published, people started to talk about the embedded risk premium (Fama, 1984) and not only about its time-varying properties, but also how it might likely differ (on average, unconditionally) among individual currency carry trades. That is, the literature shifted to trying to explain the carry trade return variation in the cross-section. To understand this variation one could identify potential common risk factors on which all carry trade strategies are loaded. Since we are working with country-level data the common factors should truly be global risk factors. This leads us to the discussion below where the recent findings are surveyed.

²⁰For some early evidence on the (contemporaneous) relation between orders and currency spot prices, focused on the orders in the interdealer market, see Evans and Lyons (2002).

²¹See e.g. Engel and West (2005) for its application to Money Income (tested in Sarno and Schmeling, 2014) and Taylor Rule models, Bacchetta and van Wincoop (2013), etc.

We have previously noticed that returns on individual currency carry trades are skewed. Moreover, as more currencies with similar interest rate characteristic are added to the portfolio, skewness does not seem to get diversified away (see e.g. [Brunnermeier, Nagel, and Pedersen, 2009](#)). It means all crashes in similar currencies happen together, such as e.g. in periods of “flight to quality” (or “flight to liquidity”) as [Brunnermeier, Nagel, and Pedersen \(2009\)](#) suggested. Hence, there is a good story for a common (crash) risk factor, which, as they argue, could be a liquidity or other friction-related shock (stop-loss clauses, redemptions, etc.), prompting all traders simultaneously to unwind their positions. This also implies that the higher net speculator positions in the investment currency might lead to the higher likelihood of the crash risk in that currency. In their work these authors sorted the currencies based on the interest rate differential into three baskets and found that the higher differential currencies are associated with higher (in absolute terms, though with a negative sign) conditional skewness but at the same time higher mean returns. This in turn implies the probability of crashes conditional on currently available information is higher for the highest interest currencies. One could now provide a risk-based explanation for the average return earned on the corresponding carry trades: it is higher than that earned on the carry trades from the other two baskets because the former are more exposed to the liquidity factor (in the context of [Brunnermeier, Nagel, and Pedersen, 2009](#)) and, thus, the crash risk. The authors also noticed that currencies with similar interest rates, everything else controlled for, tend to positively covary among each other.

Even considering their limited data with only three currency pairs [Beber, Breedon, and Buraschi \(2010\)](#) were also able to demonstrate the explanatory power of their MAD factor in the cross-section. They estimated a difference-in-difference regression specification and found their claims, that the variation of MAD across currency options is able to explain variation in implied volatilities of those options, to be statistically robust. It is important to note that the authors have not performed the traditional cross-sectional asset pricing tests on the carry trade returns.

1.2.2 Unrepresentative samples / peso event risk

Another potential implication about SDF is made by [Burnside, Eichenbaum, Kleshchelski, and Rebelo \(2011\)](#). They show that the equally-weighted TS carry trade portfolio returns did not do particularly bad during the financial crisis and are not correlated with conventional common risk measures such as the marginal utility of consumption growth (as well as the stock market return and other [Fama and French, 1993](#), factors) within their sample.²² The authors' results are consistent with those of [Ang and Chen \(2010\)](#) who study portfolio returns on other FX strategies. Hence, the basic traditional asset pricing models are not able to explain the carry premium puzzle - some other risk is likely to be priced in or the prices of risk factors change considerably over time. The authors make an assumption that there are some states of the world (peso states) when huge currency crash happens and which have not appeared in sample. What if we eliminate the negative impact of such states of the world by insurance – buying currency options?²³ It turns out that the average hedged carry trade strategy return is very similar to that of the unhedged one (thus, not statistically different from it) and is statistically different from zero (such empirical finding is related to [Jurek, 2014](#)). The Sharpe ratios of the two strategies are equivalent. Moreover, when common risk is adjusted for, returns are still significantly positive under all SDF model specifications considered – the pricing errors in GMM tests are significant. Hence, the models significantly underestimate the returns on the carry strategy. That is, after controlling for potential source of risk (currency crash risk) the excess returns seem still not to be explained by traditional asset pricing models.

[Burnside, Eichenbaum, Kleshchelski, and Rebelo \(2011\)](#) also argue that it should be large values of the SDF rather than large negative pay-offs in the peso state that make average risk-adjusted pay-offs equal to zero. The rationale is that the unhedged (by currency options) carry trade and the hedged one²⁴ yield similar pay-offs in the non-peso states and, thus, should yield similar (negative) pay-offs in the peso states. It turns out that for the hedged carry trade the pay-

²²Note that here opposed to [Lustig, Roussanov, and Verdelhan \(2011\)](#) SDF models were chosen to contain information about the aggregate consumption figure (or similar variables) and the equity market.

²³They use close to at-the-money currency options to hedge the crash risk arguing that out-of-the money options are relatively expensive and not actively traded.

²⁴Note that the carry trade hedging currency crash risk is constructed to incur zero costs initially as does unhedged carry trade.

off is a relatively small negative value. Very high SDF in peso states means an investor attaches great importance to those losses (Burnside, Eichenbaum, Kleshchelski, and Rebelo, 2011). The authors alternatively estimate the value of the SDF through unhedged and hedged stock market portfolios and find support for their hypothesis about the huge SDF value in the peso states.

1.2.3 Factor extraction and its statistical interpretation

FX asset class-specific factor. Lustig, Roussanov, and Verdelhan (2011) sorted the countries' currencies on the interest rate differential, or more precisely on the forward discount (where forward is in a foreign currency per unit of domestic currency) which is an equivalent procedure under CIP, into six portfolios choosing USD as a domestic currency. The authors report that mean returns on the carry strategies for each basket rebalanced monthly seem to monotonically increase (from the "low interest" basket to the "high interest" basket). They then performed a principal component analysis (PCA) and identified that the first component is essentially an average of all foreign currency returns, RX ²⁵ (reported correlation of 0.99 between the two). The second component is a portfolio return of going long the "high interest" basket and short the "low interest" basket of currencies, HML_{IR} (reported correlation of 0.94 between the two).²⁶ Both components explained more than 80 percent of total portfolios' return variation. From PCA Lustig, Roussanov, and Verdelhan (2011) conclude that the first component, although explaining the bulk of time-series return variation in all portfolios, cannot explain the cross-sectional differences since all six carry trade portfolios seem to load equally on it. At the same time, the second component (which is essentially "high minus low" factor constructed from the data) loadings could indeed account for the cross-sectional differences as portfolios's loadings on it are monotonically changing. As one can notice, what authors did for the FX market is similar in spirit to the Fama and French (1993) analysis for the equity market. Lustig, Roussanov, and Verdelhan (2011) interpreted RX as a country-specific (in their case US-specific) risk factor, since if there is a shock in the domestic market for an investor, all foreign currency returns should be equally affected. HML_{IR} was given

²⁵One should not mix RX from Lustig, Roussanov, and Verdelhan (2011) with the base carry built on AFD from Lustig, Roussanov, and Verdelhan (2014) – the former goes unconditionally long in foreign currency equally-weighted portfolio while the latter can be long or short it depending on the AFD sign. Separately, RX and AFD are not the same – the former is the realized return and the latter is the signal.

²⁶Lustig, Roussanov, and Verdelhan (2014) show that their base carry strategy is uncorrelated with HML_{IR} . It seems like these capture different phenomena (risk premia).

an interpretation of the common or global risk factor, and because of different loadings on this common risk factor, the cross-section of carry trade returns is explained.²⁷

Lustig, Roussanov, and Verdelhan (2011) proposed a simple linear two-factor (RX and HML_{IR}) SDF model for pricing the portfolio payoffs. It is important to note that both the risk factors and the portfolios were constructed purely using FX market information. Their estimation using GMM did not find support for the joint significance of the pricing errors.

Analogously, Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) instead of the forward-spot spread used another signal – historical carry strategy return – and, under exactly the same methodology as in Lustig, Roussanov, and Verdelhan (2011), constructed time-series of monthly rebalanced XS momentum portfolios. After careful investigation they concluded that the mean return variation of XS momentum portfolios cannot be attributed to the loadings on any traditional risk factor, including HML_{IR} , consistent with the evidence from other asset classes: “carry and momentum are different phenomena that require different explanation” (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012b). There is some evidence that individual country and currency characteristics are important for the mean return explanation on the latter strategy. As in the case of carry, the exchange rate and not the interest rate component is found to play the main role.²⁸

Cross-asset class factor. Burnside (2012b), in line with his previous research, once again shows on the extended list of linear SDFs formed by taking the information from the equity markets and/or macroeconomic indicators²⁹ that they cannot price various FX strategies’ returns in the pool with Fama and French (1993) portfolios’ returns. The pricing errors are positive and significant for all the models.³⁰ It seems that these factors are not capturing enough crucial information. The author then proposes to consider SDFs incorporating the factors from the FX market, two of which are discussed in this survey – that by Lustig, Roussanov, and Verdelhan (2011) and that based on Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) volatility shocks

²⁷Verdelhan (2015) argues that there should really be at least two global factors to explain the currency premium. Separately, Lustig, Roussanov, and Verdelhan (2014) argue that the base carry trade loads on both global and base-currency specific risk.

²⁸The author of this survey also notes the fact that HML_{MOM} , constructed analogously to HML_{IR} , was able to price the cross-section of momentum portfolios very well. This causes a concern of HML-type factor mechanically pricing the small sample of assets from which it was extracted. Such concern is to be investigated in the future.

²⁹For instance, the changes in industrial production and durable consumption growth – which seem to do a decent job pricing equity returns.

³⁰Analysing time-series, betas are shown to be both statistically and economically insignificant.

which will be covered below (the third model uses a skewness factor instead of HML_{IR}).³¹ All were found to successfully price the [Lustig, Roussanov, and Verdelhan \(2011\)](#) portfolios’ payoffs (therefore, the conditional second and third moments seem to be important in explaining the first moment of carry returns), but failed to do a good job when equity portfolios considered above were added. [Burnside \(2012b\)](#) concludes that it is unlikely that systematic risk factors (i.e. negative pay-offs states) explain the carry trade premium, because there is no unifying SDF and, thus, systematic risk-based explanation of FX and Fama-French portfolios.

Addressing this issue, [Lettau, Maggiori, and Weber \(2014\)](#) use the downside risk CAPM (DR-CAPM) to show that, conditioning just on the negative market’s returns, a single factor seems to explain the average performance not just on the currency carry trade but also on the popular strategies in other asset classes. Hence, a unified (systemic) risk explanation is proposed and a strong factor structure among asset classes is suggested. As authors admit, some notable exceptions still remain a puzzle (in a sense that their single factor cannot explain the cross-sectional variation in mean returns on certain strategies) – e.g. momentum portfolios.³²

1.2.4 Economic interpretation of the factor

Volatility shocks. Admittedly, the puzzle then becomes to find the fundamental source of risk hiding behind HML_{IR} ([Burnside, 2012a](#)).³³ Since the second moment (volatility) based factor was able to predict carry trade returns (see [Section 1.1](#)), it is natural to ask if the volatility factors explain the cross-sectional variation in mean returns (see [Cochrane, 2005](#), p. 445 discussion). As discussed in the previous section, VIX also seems to be a good proxy for the global risk. In an earlier working paper version [Lustig, Roussanov, and Verdelhan \(2014\)](#) find support for the VIX explanation of the cross-section as well. Nonetheless, [Lustig, Roussanov, and Verdelhan \(2011\)](#) show the outperformance of HML_{IR} over the innovations to the constructed global volatility factor in a “horse race”.³⁴

³¹[Burnside, Eichenbaum, and Rebelo \(2011\)](#) and [Burnside \(2012a\)](#) acknowledge that markets’ segmentation could explain why the FX market might have its own systemic risk factor not present in other markets.

³²During the presentation at Imperial College in June 2013, Matteo Maggiori emphasized that their result does not imply anything on the notion of market completeness and the limits of diversification (across asset classes).

³³As recently as in [Cochrane \(2005, ch. 20.2\)](#) it is still reported that academics are struggling to find convincing interpretations for the [Fama and French \(1993\)](#) factors which are analogous to HML_{IR} in the equity market.

³⁴Importantly, the volatility factor is derived from the equity markets, not using interest rate and exchange rate information at all.

Referring to [Merton \(1973\)](#)’s ICAPM for the theoretical explanation, [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012a\)](#) investigate the relationship between unexpected aggregate FX volatility and carry trade returns. They suggest aggregate volatility innovation is a priced risk factor – high-interest differential portfolios load positively on it while low-interest differential portfolios load negatively, serving as a hedge in times of higher than expected currency market volatility. Therefore, carry premium seems to be a reward for bearing systematic risk (in the face of undiversifiable, at least within the FX market asset class, volatility exposure). Moreover, [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012a\)](#)’s factor was able to price other currency trading strategies and even international bonds. The authors also “kill” the liquidity factor proxies (such as the TED spread by [Brunnermeier, Nagel, and Pedersen, 2009](#)) in the pricing exercises in a “horse race”, but find mixing results for the [Lustig, Roussanov, and Verdelhan \(2011\)](#)’s HML_{IR} factor.³⁵ In addition, since the aggregate volatility factor is not traded, they consider a factor-mimicking portfolio based on [Balduzzi and Robotti \(2008\)](#) by coming up with a linear combination of five earlier constructed portfolios’ returns which closely replicate it.³⁶

Finally, as robustness checks, [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012a\)](#) provide the set of interesting findings. First, after sorting on the volatility beta rather than the interest rate differential (addressing the same point as [Lustig, Roussanov, and Verdelhan, 2011](#), about the interpretation of the proposed variable as a potential risk factor) they come up with portfolios which have different statistical patterns compared to interest-sorted ones – for instance, skewness is not monotonically lining up anymore. Hence, volatility does not seem to give the full story here for the interest rate sorts. There might be other factors involved. Second, the authors show that their estimates of the price of risk are robust to volatility outliers, thus, arguing against the entire peso explanation for carry premium – there is likely to be some systematic risk explanation also involved.³⁷

Liquidity shocks. [King, Osler, and Rime \(2012\)](#) suggest that dealers (or market makers) are

³⁵Both HML_{IR} and TED (and other liquidity proxies in this regard) were not found to correlate highly with the volatility factor developed by the authors.

³⁶The authors admit that there are OTC traded volatility contracts but these have not appeared until late in their time sample.

³⁷Among notable other explanations linking distributional characteristics of returns to their first moments is the work by [Mueller, Stathopoulos, and Vedolin \(2015\)](#). Instead of the second moments (volatility) risk, they find that correlation risk is priced in the same cross-section of assets.

providing immediate liquidity to market participants and need to be compensated for bearing the associated costs (e.g. inventory risk). When the funding liquidity of dealers dries up, the effect is passed to investors – this is e.g. a story behind [Mancini, Ranaldo, and Wrampelmeyer \(2013\)](#).³⁸ The latter authors, referring to the theoretical set up of [Brunnermeier and Pedersen \(2009\)](#), suggest (FX) market liquidity shocks are a “more fundamental explanation” of carry risk premium than volatility innovation shocks. They show the evidence for strong commonality in liquidity across asset classes (at least within their 2007-2009 time span) making it a global phenomenon. This fact lets them to conclude that cross-asset class diversification is limited, assuming that the liquidity factor is priced. The latter condition is confirmed in the data – authors find that the high interest currencies tend to be more illiquid and, at the same time, more sensitive to the liquidity factor, though they do not discuss why. [Mancini, Ranaldo, and Wrampelmeyer \(2013\)](#) promote the story of an investor who, being exposed to liquidity spirals which can doubtfully be diversified away, demands a risk premium.³⁹

The support for their results is found in [Engel and West \(2010\)](#) who suggest exchange rate dynamics during the financial crisis is not consistent with the usual UIP deviations. Hence, they propose financial risk or liquidity as a potential influential factor particularly for that period – the only period [Mancini, Ranaldo, and Wrampelmeyer \(2013\)](#) study.⁴⁰ However, the fact that liquidity is an important factor during the recent crisis does not imply it is important unconditionally. Research on the liquidity risk importance in normal market environments remains an open area. Some evidence from [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012a\)](#) implies it is not crucial – as they study a liquidity proxy pricing ability over time-series spanning three decades and, thus, over different market environments.⁴¹ Such explanation is very much consistent with [Acharya, Amihud, and Bharath \(2013\)](#) results from the corporate bond and equity markets and might be a cross-asset phenomenon.

³⁸Therefore, literature provides an interesting testable implication that in normal market periods the liquidity risk premium is demanded by dealers and in crisis periods – by end investors.

³⁹[Burnside \(2012a\)](#) also notes the liquidity spirals as a possible explanation of the UIP failure.

⁴⁰See [Karnaukh, Ranaldo, and Söderlind \(forthcoming\)](#) for the study of FX liquidity over the longer period of two decades.

⁴¹More precisely, [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012a\)](#) use the TED spread which according to [Mancini, Ranaldo, and Wrampelmeyer \(2013\)](#) is a funding liquidity proxy.

Consumption-based explanation. Contrary to [Burnside, Eichenbaum, Kleshchelski, and Rebelo \(2011\)](#) and [Burnside \(2012b\)](#), who as described above argued against a common risk factor in the FX market, [Lustig and Verdelhan \(2007\)](#) find support for the consumption-based explanation.⁴² In the heart of their analysis lies the model by [Yogo \(2006\)](#) which was originally developed to tie together consumption and the cross-section of stock returns. The core element of the model is the introduction of durable consumption growth as a priced risk factor (due to non-separable intra-temporal utility) in addition to non-durable consumption growth. The advantage of the former is its higher pro-cyclicality versus the latter.

The model turned out to explain the variation in expected returns on interest-sorted currency portfolios ([Lustig and Verdelhan, 2007](#)) as well as the time-varying property of expected returns. The introduction of durable consumption again is shown to be the key ingredient (opposed to the market return whose spread in betas was too little to account for the spread in mean returns). Low interest rate currencies are claimed to provide protection against the high marginal utility states of the carry investor. The significant positive relationship between consumption growth and HML_{IR} was suggested in [Lustig and Verdelhan \(2011\)](#).

Notably, the credibility of the [Lustig and Verdelhan \(2007\)](#)’s findings is questioned by some of the economists ([Burnside, 2011](#)). In defence, [Lustig and Verdelhan \(2011\)](#) argue that their main claim should still hold. For instance, the authors warn against looking at unconditional consumption betas, admittedly measured with high imprecision, as they understate the true risk inherited in the carry trades, since the price and quantity of risk are likely to co-move and be high during the crisis periods and recessions. Separately, betas seem to have generally increased with time, perhaps due to “financialisation” of FX markets. [Burnside \(2012b\)](#) argues that the time-variation in the amount of common risk (betas in time-series regressions) cannot account for the failure of traditional asset pricing models, because conditional betas on the risk factors seem to fluctuate in a very narrow region.⁴³ The debate leaves the area open for further exploration.

[Hassan \(2013\)](#) also works with the consumption model but allows the countries to differ in

⁴²While the original article focused on the US consumption growth, the follow up by [Lustig and Verdelhan \(2011\)](#) suggest evidence it is likely to be the world consumption growth risk which higher interest currencies load more on.

⁴³In other words, as [Burnside \(2012b\)](#) notes, it is unlikely that events such as the financial crisis, when as reported in some earlier works correlation between carry trade returns and those of the stock market have increased, can tell the full story.

(wealth) size. His model is able to explain the following empirical artifacts: larger economies have lower real rates, lower currency premium, and lower expected equity returns in the non-traded sector. The idea behind the mechanism is the following: the shock to the country's non-traded good sector triggers readjustment to the consumption of the traded good. In turn, the increased demand for the traded good in the country prompts real local currency appreciation. The larger the country, the more pronounced is the effect and the less country-specific consumption can be diversified internationally. At the same time the bonds of larger countries offer a better hedge against the domestic agent's consumption risk.⁴⁴

External imbalances. Yet another important empirical regularity is pointed out by [Della Corte, Riddiough, and Sarno \(2015\)](#). The authors find that the factor constructed as going long high deficit, high proportion of foreign FX liabilities currencies and short low deficit, low proportion of foreign FX liabilities currencies is closely matching HML_{IR} . Hence, unsurprisingly, their factor also prices the cross-section of carry trade strategies. The immediate question that comes to mind is why do the two characteristics – interest rates and global imbalances – provide related signals. Why if FX market transmits the risk premium should the nominal interest rates also carry similar information? The authors refer to the theoretical contributions of [Gabaix and Maggiori \(2015\)](#) and [Colacito, Croce, Gavazzoni, and Ready \(2015\)](#) as the possible explanations.

1.2.5 Outstanding debates

[Burnside and Graveline \(2014\)](#) argue that in incomplete asset markets the linear projection of SDFs on asset returns is in general not very informative about the underlying differences in the intertemporal rates of substitution of various (country) agents. The potential implication of this critique is that empirical asset pricing tests using the linear combination of the test assets as factors – [Lustig, Roussanov, and Verdelhan \(2011\)](#), ΔVOL_{FX} -mimicking factor by [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012a\)](#), and [Della Corte, Riddiough, and Sarno \(2015\)](#) – might not be very helpful to understand the fundamentals of the economy (e.g. the preferences of agents). [Lustig and Verdelhan \(2015\)](#) state, however, that assuming market incompleteness by

⁴⁴Nonetheless, it is unclear whether macro variables from countries like Switzerland can fit such an explanation – the country is relatively small, yet CHF typically appreciates in bad states of the world.

itself cannot resolve the exchange rate puzzles.

1.3 Research niche

From the conducted literature survey the following research niche is identified. One could see that the volatility-based factors are relatively successful in both the predictability (Brunnermeier, Nagel, and Pedersen, 2009) and the cross-sectional explanation of currency returns (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a).⁴⁵ Nonetheless, there is still one potential empirical research direction, taken e.g. by Beber, Breedon, and Buraschi (2010), and which has not yet to the knowledge of the author been extensively examined in the currency market asset pricing exercises.

There are several reasons to be cautiously optimistic about the potential of forecast dispersion to contribute to the FX literature.⁴⁶ Firstly, the support was found for FX disagreement explaining the cross-section of currency option returns (Beber, Breedon, and Buraschi, 2010). Hence, it is reasonable to expect that some forecast dispersion-based quantity would be as successful as volatility factor of Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) in explaining the cross-section of FX market carry portfolios. Secondly, FX disagreement was shown to drive out volatility measures in the predictive regressions (Beber, Breedon, and Buraschi, 2010). That is, forecast dispersion might simply contain more information than the latter variables. Thirdly, Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) themselves note that there might be some other page to the carry premium story than volatility since portfolios constructed by sorting on the volatility shock beta do not possess the same distributional characteristics as those constructed by sorting on the interest rate differential. Finally, disagreement allows for premium not to depend utterly on the risk in fundamentals which might partially explain the failure of traditional asset pricing models in Burnside (2012b)’s tests (such as Consumption CAPM).

To sum up, there is a clear scope to study empirically the impact of uncertainty through agents’ disagreement on currency strategies. In the next chapter we initially explore the relationship

⁴⁵Liquidity explanation on the other hand received less support – see the discussion of Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) work in Section 1.2.4. Consumption-based explanations are also debatable.

⁴⁶In this thesis, the following words and expressions are used interchangeably and mean the same: disagreement, forecast dispersion, difference in beliefs.

between forecast dispersion on the traditional macro variables and FX volatility. The direct link between macro forecast dispersion and asset pricing of currency carry portfolios is left to examine for the third chapter.

Table 20.11.

	DM	£	¥	SF
Mean appreciation	-1.8	3.6	-5.0	-3.0
Mean interest differential	-3.9	2.1	-3.7	-5.9
b , 1975-1989	-3.1	-2.0	-2.1	-2.6
R^2	.026	.033	.034	.033
b , 1976-1996	-0.7	-1.8	-2.4	-1.3

The first row gives the average appreciation of the dollar against the indicated currency, in percent per year. The second row gives the average interest differential—foreign interest rate less domestic interest rate, measured as the forward premium—the 30-day forward rate less the spot exchange rate. The third through fifth rows give the coefficients and R^2 in a regression of exchange rate changes on the interest differential = forward premium,

$$s_{t+1} - s_t = a + b(f_t - s_t) + \varepsilon_{t+1} = a + b(r_t^f - r_t^d) + \varepsilon_{t+1},$$

where s = log spot exchange rate, f = forward rate, r^f = foreign interest rate, r^d = domestic interest rate.

Source: Hodrick (forthcoming) and Engel (1996).

Figure 1.1: Uncovered interest rate parity – 1. Source: [Cochrane \(2005, ch. 20.1\)](#)

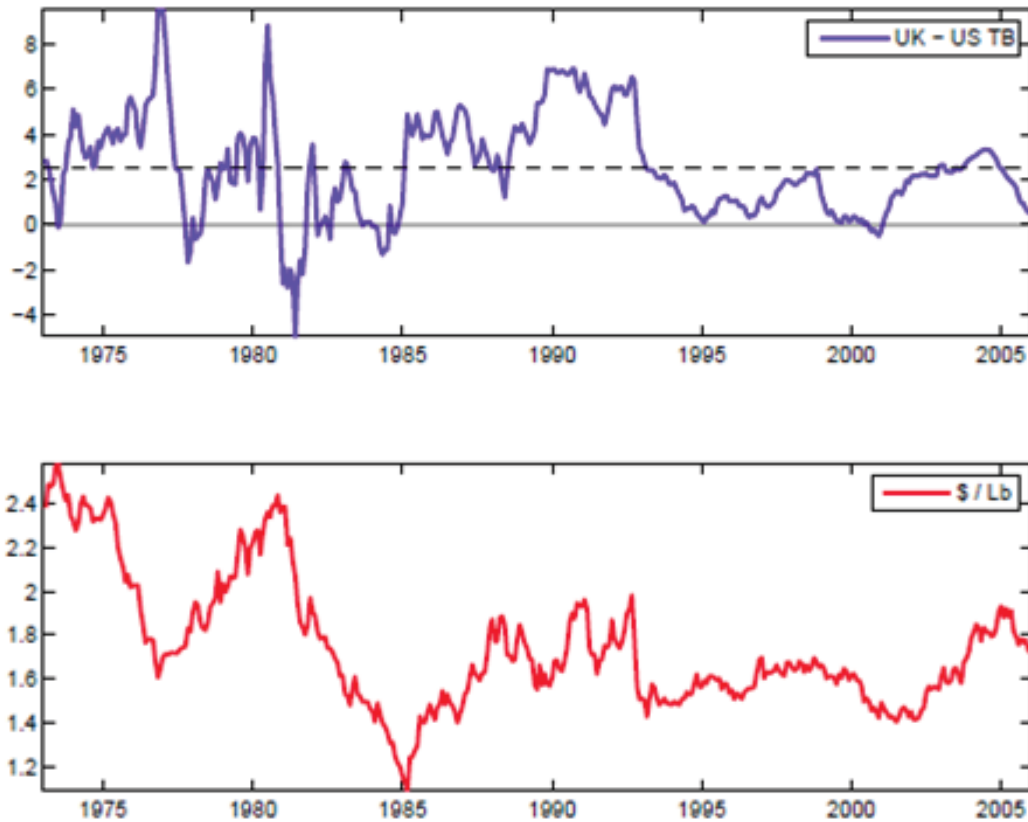


Figure 1.2: Uncovered interest rate parity – 2. Source: [Cochrane \(2011a\)](#) slides.

The upper chart presents the time-series of the short term interest rate differential between the United Kingdom and the United States. The lower chart presents the time-series of the USD/GBP exchange rate.

Appendices

1.A Covered interest rate parity

Under the assumption of no arbitrage opportunities the forward price satisfies:

$$F_t = \frac{1 + R_t^d}{1 + R_t^f} S_t$$

To see this, let us also assume it did not hold and in particular:

$$\underbrace{F_t}_{\text{'sell'}} > \underbrace{\frac{1 + R_t^d}{1 + R_t^f} S_t}_{\text{'buy'}}$$

To show that this is an arbitrage opportunity let us do the following.

At time t :

- Sell the forward contract at F_t : 0
- Sell short for $F_t/(1 + R_t^d)$ of domestic currency domestic bond: $+F_t/(1 + R_t^d)$
- Sell $S_t/(1 + R_t^f)$ of domestic currency at S_t : $-S_t/(1 + R_t^f)$
- Buy $1/(1 + R_t^f)$ of foreign currency at S_t : $+1/(1 + R_t^f)$
- Buy for $1/(1 + R_t^f)$ of foreign currency foreign bond: $-1/(1 + R_t^f)$
- **Net cashflow effect:** $\underbrace{+F_t/(1 + R_t^d) - S_t/(1 + R_t^f)}_{\text{greater than 0 by assumption}}$

At time $t + 1$:

- Sell for 1 of foreign currency foreign bond: +1
- Sell 1 of foreign currency at F_t : -1
- Buy F_t of domestic currency at F_t : $+F_t$
- Buy back for F_t of domestic currency domestic bond: $-F_t$
- **Net cashflow effect:** 0

Therefore, we locked in riskless profit at t which is an arbitrage opportunity. But by our first assumption there are none. Contradiction. Analogously:

$$\underbrace{F_t}_{\text{'buy'}} < \underbrace{\frac{1 + R_t^d}{1 + R_t^f} S_t}_{\text{'sell'}}$$

Nowadays it is not that interesting to test CIP as it is “essentially never violated at the daily and lower horizons” (Jurek, 2014).⁴⁷ Sometimes researchers do provide CIP test for their sample as a way to show the quality of the data collected (e.g. Burnside, Eichenbaum, Kleshchelski, and Rebelo, 2011). Lustig, Roussanov, and Verdelhan (2011) note that it is beneficial to take advantage of CIP because data on forwards (e.g. including bid-ask spreads), opposed to sovereign bonds, is available easily, and the risk of counterparty default (note that in case of using forwards the counterparty is not anymore a government rather an individual financial institution or a clearing house) is “minimal”. At the same time forward market is the most liquid for FX transactions (Brunnermeier, Nagel, and Pedersen, 2009).

Final notes. Firstly, if transaction costs are incorporated then no arbitrage relationships are (logic above applies)

- $F_t^b \leq \frac{1+R_t^{d,a}}{1+R_t^{f,b}} S_t^a$
- $\frac{1+R_t^{d,b}}{1+R_t^{f,a}} S_t^b \leq F_t^a$
- $F_t^b \leq F_t^a$

⁴⁷This was questioned by some authors in the latest financial crisis 2007-2008 (e.g. Baba and Packer, 2009) who explained CIP deviations by the counterparty (default) risk mismatch.

- $\frac{1+R_t^{d,b}}{1+R_t^{f,a}} S_t^b \leq \frac{1+R_t^{d,a}}{1+R_t^{f,b}} S_t^a$

Secondly, if forward rates are quoted in foreign currency per unit of domestic currency then CIP in log terms takes the following form (this is e.g. what [Cochrane \(2005, ch. 20.1\)](#) uses in his regressions):

$$f_t - s_t = r_t^f - r_t^d$$

1.B [Siegel \(1972\)](#)'s paradox

In a nutshell, [Siegel \(1972\)](#)'s paradox states that UIP cannot simultaneously hold for domestic (x) and foreign investor (y):

$$S_t^x \times S_t^y = 1 \tag{1.B.1}$$

$$F_t^x \times F_t^y = 1 \tag{1.B.2}$$

$$E_t[S_{t+1}^x] = F_t^x \tag{1.B.3}$$

$$E_t[S_{t+1}^y] = F_t^y \tag{1.B.4}$$

The first two equations hold by no arbitrage assumption, and the second two – by assumption that UIP (and CIP) holds for both investors. Then, if we substitute (1.B.1) into left hand side of (1.B.4) while (1.B.2) and (1.B.3) into right hand side of (1.B.4), we get:

$$E_t \left[\frac{1}{S_{t+1}^x} \right] = \frac{1}{E_t[S_{t+1}^x]} \tag{1.B.5}$$

which clearly cannot hold if S_t is a random variable due to Jensen's inequality. Hence, in practice people tend to estimate: $\frac{S_{t+1}^x}{S_t^x} = \frac{F_{t+1}^x}{S_t^x} \times e^{\epsilon_t}$ model instead of $\frac{S_{t+1}^x}{S_t^x} = \frac{F_{t+1}^x}{S_t^x} + \epsilon_t$ because taking logs of the former model (which admittedly is a bit different from the latter) and estimating conditional expectation of the log spot spread results in no controversial statements.

1.C FX from broad portfolio perspective

In practice it is better to form portfolios of carry trade pairs based on some weighting criteria⁴⁸ in order to get rid of any idiosyncratic risk (for diversification benefits). For instance, [Jurek \(2009\)](#) suggests the low volatility of the carry trade portfolio means exchange rate innovations are largely uncorrelated in the cross-section.⁴⁹ Many recent empirical works in FX predictability literature also use portfolio returns. Forming portfolios is not done with the purpose of potentially increasing R^2 of the forecasting regressions but can still increase the power of asset pricing tests ([Cochrane, 2011a,b](#); [Fama and French, 2012](#)).⁵⁰

[Barroso and Santa-Clara \(forthcoming\)](#) and [Pojarliev and Levich \(2012\)](#) study currency strategies from a broad portfolio perspective of a manager having invested in stocks and/or bonds. They find the former to be a valuable addition improving the risk-return characteristics of a pure stock-bond allocation. Related to this line of research is my own work with the chief currency strategist of an investment bank ([Krecetovs and Stolper, 2014](#)). We look at active currency management and in particular analyse how the currency hedging behaviour of the institutional players – asset managers and corporates – in the FX market differs and what consequences can the changes in such behaviour have on the exchange rates. Our work emphasizes three main results. First, there are considerable regional asymmetries in the average hedging behaviour. European investors tend to hedge their overseas FX risk to a larger extent than their United States (US) colleagues. European corporates also tend to hedge more than their US counterparts. Emerging markets’

⁴⁸The results by [DeMiguel, Garlappi, and Uppal \(2009\)](#) for stock market portfolios suggest the naive $1/N$ (i.e. equally-weighted) rule is not clearly dominated by other weighting schemes, although more complicated methods might be used, e.g. dependent on the first (and second) moments of interest rate differentials – see [Jurek \(2014\)](#) and [Cochrane \(2011a\)](#) for examples. Nevertheless, [Jurek \(2009\)](#) finds that equally weighted (as well as interest spread-weighted) portfolio is very efficient in a sense that it lies very close to the ex-post mean-variance frontier. Consistently, practitioners often construct indexes using both equal and “optimized” weights ([Bakshi and Panayotov, 2013](#)).

⁴⁹The same thought was expressed also by [Lustig, Roussanov, and Verdelhan \(2011\)](#), [Burnside, Eichenbaum, Kleshchelski, and Rebelo \(2011\)](#), and [Burnside, Eichenbaum, and Rebelo \(2011\)](#). The latter also showed diversification benefits for TS momentum portfolios – in both cases by observing that “Sharpe ratio of the average is twice higher than the average of individual Sharpe ratios”.

⁵⁰For more insights into the relative merits of working with portfolios versus individual securities as test assets see [Lustig, Roussanov, and Verdelhan \(2011\)](#). For advantages of the former see also [Cochrane \(2005, p. 199\)](#) – on the idea of stability of statistical properties of portfolios formed by certain characteristic(s) opposed to individual securities’ properties, [Lustig and Verdelhan \(2007\)](#), and [Ang and Chen \(2010\)](#).

exposure is rarely hedged by any investor.⁵¹ Second, if we look at the full distribution of responses, we find that most investors in the US and Euro area tend to have a preference either to fully hedge their foreign currency exposure or to keep the entire exposure unhedged. Japanese investors mostly apply partial hedge ratios. Overall, there is no evidence of a universally adopted FX hedging policy. This is consistent with the wide range of recommendations in the academic literature, suggesting that there is no unique accepted benchmark regarding the optimal hedge ratio. Even if there was, such an optimal hedging policy is likely to depend on the FX manager and on time-specific factors.⁵² Third, we look at the data on cross-border asset holdings between the Euro area and the US to gauge the magnitude of hedging-related FX flows. Our conclusion is that hedging-induced currency transactions are at least of the same order of magnitude as traditional cross-border portfolio or trade flows. To sum up, our survey results and related simulations suggest that currency hedging flows are certainly large enough to be an important driver of FX markets.⁵³

1.D Careful interpretation of some empirical results

More on UIP failure. Lustig, Roussanov, and Verdelhan (2011) divide the sample in two time subsamples and sort currencies into portfolios on the second subsample based on the time-series average interest rate differentials in the first one and find the recognisable monotonic pattern in mean returns to preserve. That made them to conclude that one can make money not even conditioning on time t information (i.e. instead invest in countries that have had higher interest rate on average than other countries).⁵⁴ They show that portfolios constructed in such a way have also a familiar monotonic pattern of loadings on the HML_{IR} factor. At the same time Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) show that constructing equally weighted

⁵¹The likely reason is that many currencies of the developing economies serve as investment currencies in a typical carry trade. As it is argued below, the carry trade (at least until the global financial crisis of the late 2000s) is a very profitable strategy. Hence, hedging certain FX exposure to emerging markets can be very costly as it essentially requires to implement the reverse carry strategy.

⁵²See Perold and Schulman (1988); Froot (1993); Glen and Jorion (1993); Campbell, Viceira, and White (2003); Campbell, Serfaty-De Medeiros, and Viceira (2010).

⁵³Our results are consistent with those by Botman, Filho, and Lam (2013) who concentrate on JPY – not traditional capital flows but hedging-related flows seem to explain Japan’s safe haven status.

⁵⁴Authors suggest that this result can be explained by the (ex-post) real interest rate differentials whose means also monotonically increase moving from low- to high-interest bucket.

portfolio of twenty currency pairs with USD as domestic currency results in a sample average significantly positive carry trade returns. Hence, taken together, the results suggest that UIP fails even unconditionally – direct evidence against [Cochrane \(2005, ch. 20.1\)](#) implicit result in Equation 1.4. As a final note, the spread in portfolios’ mean returns is relatively small compared to that of portfolios constructed based on current interest rate differential (40% of the latter; thus, accounting for 40% of mean return variation in the cross-section); therefore, conditioning on time t information might potentially lead to the explanation of the rest of the carry risk premium. There most likely is permanent variation in exposure to common risk (in the face of HML_{IR} factor) among individual currencies.

[Lustig, Roussanov, and Verdelhan \(2011\)](#) also argue that UIP fails not only in the time-series, but also in the cross-section because of the difference in mean returns across the portfolios – in contrast, UIP implies that average returns on each of the baskets of carry trades should be zero.⁵⁵ What this essentially means, as they point out, is that “investors earn large excess returns simply by holding bonds from currencies with interest rates that are currently high, i.e. currently higher than those of other countries, not only higher than usual, i.e. higher than usual for the same currency [in time-series]” – the opposite of what [Cochrane \(2005, ch. 20.1\)](#) suggested in his book. That explains why constructed strategies by [Burnside, Eichenbaum, Kleshchelski, and Rebelo \(2011\)](#), [Jurek \(2014\)](#) and others yielded consistent high return in their respective samples. [Lustig, Roussanov, and Verdelhan \(2011\)](#) provide the reduced-form framework to explain both – predictability with higher than usual and currently high interest rates.

Characteristic (interest rate) vs. risk-based explanation. Instead of sorting by interest rate, [Lustig, Roussanov, and Verdelhan \(2011\)](#) perform an analysis where they first regress carry returns on individual currencies against HML_{IR} factor and a constant; then currencies are sorted into portfolios by their betas. This procedure leads to portfolio profiles very similar to the original ones. Hence, the authors imply, since HML_{IR} can be interpreted as a (carry) risk factor, that current interest rates simply contain information on the “average” (or unconditional) exposure of individual currency carry strategies to the HML_{IR} factor. Thus, the risk-based explanation of carry premium cross-sectional variation is suggested. Moreover, the same results are received

⁵⁵This argument is consistent with [Hassan and Mano \(2015\)](#).

when sorting on global volatility factor beta constructed from individual country equity indexes, strengthening further carry return interpretation as premium for bearing global risk. Other robustness checks (e.g. subsample on which HML_{IR} is created is separated from the subsample of test assets on which portfolios are constructed) regarding this issue can be looked up in the authors' original paper.

Furthermore, conducting empirically asset pricing exercise on an individual currency level (rather than portfolio level) authors explicitly account for conditional covariation of returns with the risk factors by introducing betas as linear functions of the interest differential (forwards-spot spread in their case). They find support to the claim that there is time-varying component in the carry return exposure to the risk factor and this time variation seems to be exactly captured by the interest rate differential. To put it simply, interest rates contain information on time-varying betas. This could lead to the explanation of the additional mean return made conditioning on the currently available interest differential. There most likely is also temporary variation in exposure to common risk (in the face of HML_{IR} factor and indicated by time-varying betas) among individual currencies (accounting for remaining 60% of cross-sectional portfolio mean return variation), in addition to permanent one reported above.

Interest rate risk vs. exchange rate risk. Conditionally on time t information it is obvious that all covariation of returns with risk factors is driven entirely by exchange rate covariance:

$$Cov_t(rx_{t+1}^j, HML_{t+1}) = Cov_t(\Delta s_{t+1}^j, HML_{t+1}) \quad (1.D.1)$$

On the other hand, the betas from time-series regressions capture the estimate of unconditional covariance between interest rate differential and carry premium. That is why in time-series (contemporaneous) regressions which form part of the empirical asset pricing model tests in case of HML factor we have:

$$Cov(rx_{t+1}^j, HML_{t+1}) = Cov((r_t^f - r_t^d)^j, HML_{t+1}) + Cov(\Delta s_{t+1}^j, HML_{t+1}) \quad (1.D.2)$$

Running regression of log exchange rate changes on *HML* reveals that FX betas are almost identical to carry return betas. Thus, the following interpretation can be provided – “high-interest rate currencies expose investors to more carry risk, because they depreciate when the carry return is low” (Lustig, Roussanov, and Verdelhan, 2011). This higher risk is captured by higher loading on *HML* factor. Low-interest rate currencies on the other hand provide protection against carry risk.

In addition, performing PCA on portfolios’ exchange rate changes authors conclude that the same two factors RX and *HML* (as defined previously) seem to capture common variation in exchange rates (and, thus, accounted for cross-sectional explanation of changes of USD per foreign currency unit).

Chapter 2

Macro forecast dispersion and FX volatility¹

2.1 Introduction

Using different assumptions about fundamentals in an asset pricing model will often lead to different price implications. The further one assumption deviates from another, the more modelled prices will differ. Hence, it is intuitive to expect the variation in macro forecasts to be related to the volatility of asset returns. In FX market, one can motivate this relation, for example, in the context of [Bacchetta and Van Wincoop \(2006\)](#) if the dispersion in forecasts reflects the dispersion in agents' information sets.

We use forecast surveys for key macro variables. More specifically, we look at the disagreement between survey participants about future values of various macro variables and how this relates to the FX market volatility.² We motivate our choice by the fact that prices in financial markets, including FX, are often thought to be established at least partly by expectations about future economic conditions. That could be why models that focus purely on realised macro data may struggle to find close linkages between current fundamentals and exchange rates.³

¹This chapter is based on [Krcetovs and Stolper \(2013\)](#).

²Other recent works that study FX volatility are by [Berger, Chaboud, and Hjalmarsson \(2009\)](#) and [Djeutem and Kasa \(2013\)](#). The former studies volatility persistence at a fairly high frequency. The latter argues that the puzzlingly high exchange rate volatility level can be reconciled within the model that introduces ambiguity and agents' concern for model misspecification. Our results are potentially consistent with both works.

³Moreover, one benefit of working with survey-based macro disagreement measures, among other variables that track the state of the economy, is the timely availability of data and the lack of subsequent revisions: the initial releases of macroeconomic data can be quite different to the final revised numbers. This issue is especially important given that our work pays particular attention to the forecasting exercise. Survey data ensure that we do not have any look-ahead bias problems – in other words, we are confident that the information embedded in the survey forecasts is available at the corresponding release date.

Survey-based disagreement measures have been used previously in the literature; however, such studies have tended to focus on forecasts for prices (not real economy factors) for the asset class in question. For example, [Beber, Breedon, and Buraschi \(2010\)](#), who use forecast dispersion around future FX rates, help to explain the carry premium and the variance risk premium embedded in bilateral currency pairs. The logic of their exercise can be extended to investors' expectations about more fundamental variables of the economy, and this is the main contribution of our work.

Given the large number of exchange rates and their respective volatilities, as well as the many forecasts for macro variables, we concentrate here on explaining a global component of individual currency volatilities. Our decision is motivated by the fact that financial markets are highly integrated and, as a result, shocks in one asset price are often transmitted to other asset prices. The same turns out to be true for volatility. We have used a principal component analysis (PCA) to show the extent to which currency volatilities comove. We looked at the bilateral volatilities of liquid currencies against the US Dollar. The vast majority load positively on the first principal component, which explains around half the overall variation.

This strong factor structure suggests a big influence of global determinants.⁴ Linking variation in FX volatility to more fundamental global macro variables would therefore appear to be a natural and important path of research. In particular, we aim to identify the macro factors that can help explain why exchange rate volatility at times rises or falls globally.⁵

2.2 Data

All our constructed data series cover the 20-year period from 1993 to 2013. We collect daily exchange rates (mid quotes) from Datastream and for the results in the main text concentrate on the list of 28 liquid emerging and developed market currencies vis-à-vis the USD: Australia, Brazil, Canada, Chile, China, Czech Republic, Denmark, Euro area, Hungary, India, Indonesia, Israel, Japan, Malaysia, Mexico, New Zealand, Norway, Philippines, Poland, Russia, Singapore, South Africa, South Korea, Sweden, Switzerland, Taiwan, Turkey and United Kingdom.

⁴Since we work only with USD crosses, our results may be driven purely by macro information coming out of the US, rather than globally. We address this issue in Section 2.3.

⁵An example of the importance of the topic can be found in the work of [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012a\)](#), who show the relationship between global FX volatility shocks and the performance of the carry trade – the most popular currency trading strategy.

As we work with survey data at monthly frequency, we construct monthly non-overlapping realised volatility series from daily returns. It is important to reiterate that, as a starting point for our empirical work and given the high degree of correlation between different exchange rate volatilities, we focus on their global component. This motivated us to look at the cross-country average volatility, subsequently called $\overline{VOL}^{FX}$.⁶ One-month implied FX volatilities for the same sample of currencies are sourced from one investment bank traders' marks. We again take the cross-country average and call it $i\overline{VOL}^{FX}$ to be consistent with the analogue measure of aggregate realised volatility.

Survey data is from Consensus Economics. To match the global scale of our volatility variables we concentrate on the aggregate disagreement. The list includes⁷:

- $\overline{DiB}^Y$ – difference in beliefs on real GDP (% yoy)
- $\overline{DiB}^{i3m}$ – difference in beliefs on 3-month interest rate (%)
- $\overline{DiB}^{CA}$ – difference in beliefs on current account (% GDP)

Aggregate disagreement is taken as a cross-sectional average among individual country disagreements about a particular macro variable. Country-level differences in beliefs are constructed using

⁶The correlation of $\overline{VOL}^{FX}$ and the first principal component of individual volatilities is very high – more than 0.99 in our sample (at the same time, the former is lacking look-ahead bias). A case can also be made for studying aggregates applying non-equal country weights depending on, say, the size of the economy, its financial openness and exchange rate regime. We made a decision to work with an unweighted cross-sectional average. The choice has its disadvantages as well as advantages – for instance, the weighting scheme we used is very simple and intuitive, which arguably does not introduce additional estimation uncertainty. Economic activity-based weights are not precisely measurable, which may reflect on the results.

⁷We also considered aggregate disagreements on real consumption (% yoy), industrial production (% yoy), consumer prices (% yoy), wage growth (% yoy), money quantity in the economy (% yoy), unemployment rate (% of labour force), fiscal deficit (% GDP), and 10-year interest rates (%); nonetheless, we did not find any of those series to be additionally valuable to those discussed in the main text. Other variables, such as housing starts and foreign reserves, were only available for a limited set of countries, and, hence, we decided to omit them from the analysis as aggregates would not be representative of the entire cross-section.

the formula⁸:

$$DiB = \sqrt{TOP3 - BOT3}$$

where $TOP3$ and $BOT3$ are the top and bottom three averages of individual forecasts provided about a particular macro variable for a particular country at a particular point in time. The individual forecasts are themselves taken every month as a linear combination of the current and the next year-end forecasts to ensure an interpolated but stable 1-year forecasting horizon.

2.3 Empirical results

Preliminary analysis. The correlation between the disagreement on real GDP ($\overline{DiB}^Y$) and FX volatility (both series are averages across countries) is 0.6, pointing to a fairly strong relationship. The same result is visible if we fit $AR(1)$ and $AR(2)$ processes separately to the $\overline{VOL}^{FX}$ and $\overline{DiB}^Y$ series and take the residuals (“shocks”) – different autoregressive orders are taken to ensure both series of residuals have a low autocorrelation. A contemporaneous correlation of such shocks is 0.35 – far higher than with any other aggregate macro disagreement series. Hence, aggregate FX volatility and $\overline{DiB}^Y$ seem to be contemporaneously related.

In the same way, there is a significant, albeit weaker, relationship between aggregate current account disagreement ($\overline{DiB}^{CA}$) and $\overline{VOL}^{FX}$ and between aggregate short rate disagreement ($\overline{DiB}^{3m}$) and $\overline{VOL}^{FX}$ with correlations of 0.5 and 0.1, respectively. These linear relationships are confirmed in the multivariate regression analysis below, where we look at incremental information of each macro forecast dispersion series controlling for other variables. The correlation matrix in Table 2.1 provides evidence of the loose link between the three macro disagreement variables.

TABLE 2.1 ABOUT HERE

⁸The motivation for this definition stems from our aim to concentrate on the disagreement among more extreme forecasters. At the same time, there is a risk of coffee-break errors in the survey data (especially affecting extreme observations); thus, we downplay the higher dispersion numbers by taking the square root. In unreported results, we ensure that main conclusions are robust to country-level disagreement measure definition by using alternatively:

- $DiB = TOP3 - BOT3$ – a simpler version of the one used in the main text,
- $DiB = MAD(f_i)$ – a cross-sectional mean absolute deviation of forecasts, see e.g. [Beber, Breedon, and Buraschi \(2010\)](#),
- $DiB = STD(f_i)$ – a cross-sectional standard deviation of forecasts.

There could be linkages between the global business cycle and FX volatility. It is, therefore, important to further investigate the cyclical properties of our disagreement variables. For example, it is possible that macro forecast dispersions reflect the same information as $\overline{VOL}^{FX}$ about the global short-run economic fluctuations.

One simple way to test for this hypothesis is to include cyclical factors in our regressions (described below). However, this raises the question of which factors we should account for. We use a simple cross-sectional average of the consensus forecasts for growth, interest rates and the current account.

Using the proposed measures has the following advantages. First, forecast data is available at monthly frequency, as opposed to quarterly for realised growth or current account positions. Second, as mentioned above, survey polls have the benefit of providing unrevised timely information about the economy, whereas actual macro data is subject to major revisions over longer periods. This makes it harder to use economic releases in forecasting tests. Looking at the same point from another angle, consensus forecasts likely incorporate the latest perception about the state of the economies – such perception should fit closer with the price reactions in financial markets than the (lagging) economic data releases.

The correlation between forecast dispersion and simple cross-country average consensus growth, $\overline{Cons}^Y$, is very high (-0.8). This indicates that growth disagreement is indeed following a highly cyclical pattern. In unreported results we also compare $\overline{Cons}^Y$ to realised (GDP-weighted) world growth. Again, the relation looks fairly tight.

Analogously, there is high correlation between $\overline{DiB}^{i3m}$ and the aggregate consensus forecast of the 3-month rate, $\overline{Cons}^{i3m}$ (0.7). Both series appear to be trending down over the studied sample. This could reflect a stabilisation of inflation rates in the countries in question (in the earlier part of the sample) and the impact of unconventional policy measures (in the later part of the sample), such as forward guidance by policy makers to keep rates low.

Finally, we look at $\overline{DiB}^{CA}$ against the cross-country average of absolute consensus forecasts of the current account balance, $\overline{Cons}^Y$.⁹ The correlation between the two is fairly low: 0.5. The

⁹The absolute value of individual country consensus series is taken because, by accounting identity, the sum of all countries' current accounts is equal to zero. Indeed, when we do not take the absolute value, the correlation of $\overline{DiB}^{CA}$ and the aggregate consensus forecast measure drops to zero.

bottom line is that we note that some differences in beliefs about macro variables are highly cyclical. Nonetheless, the correlation with the aggregate mean forecasts is not perfect and there is a clear potential for an analysis of disagreement series to explain FX volatility.

Regression analysis: univariate tests. Our main numerical results are summarized in Table 2.2. We start by establishing a contemporaneous relationship between aggregate realised FX volatility and three aggregate disagreement series on real GDP, 3-month interest rates and the current account in Panel A column (1).¹⁰ As the results in Panel A indicate, there is often a strong link between the dependent and explanatory variables. The results are robust to controlling for the global business cycle (2-3), which in turn does not seem to contain extra information to that already embedded in the disagreement series. In fact, the fit with the business cycle proxies alone is nearly twice as bad. Generally, higher than average macro disagreement measures are associated with higher than usual $\overline{VOL}^{FX}$. As the R-squared suggests, roughly half of the variation in aggregate FX volatility can be explained with our regression model.

TABLE 2.2 ABOUT HERE

Similar results become visible with 1-month-ahead predictability – the major finding is that the coefficient on real growth disagreement decreases while those on the other two variables actually increase (4). Indeed, controlling for lagged FX volatility, we see that real GDP disagreement is no longer significant while the current account variable still is, although the coefficients on both $\overline{DiB}^{i3m}$ and $\overline{DiB}^{CA}$ are now halved (5). Tying such evidence to the discussion in the previous section, the results indicate that volatility is mainly attributable to the difference in beliefs about real growth, while some other macro variables contain incremental information. In fact, 12-month-ahead predictability reveals that current account disagreement captures a persistent component of aggregate FX volatility (6).¹¹

¹⁰To arrive at this specification, we use the full list of currencies and apply a general-to-specific regression methodology. We initially stack all aggregate macro disagreement series available – see Footnote 7 – as independent variables, while having $\overline{VOL}^{FX}$ as dependent variable, and remove those series with statistically and economically small coefficients. Checking various small alternations of this specification, we came to the conclusion that, if anything, those three variables – $\overline{DiB}^Y$, $\overline{DiB}^{i3m}$, $\overline{DiB}^{CA}$ – consistently stand out as the most important ones. Thus, we concentrate on the results that include only these variables.

¹¹Unreported results on the richer sample of 67 currencies, including some admittedly less liquid FX pairs, lead to unchanged main conclusions.

We replicate with implied volatility the same regressions used to analyse realised volatility (see Table 2.2 Panel B). Specifically, we use at-the-money option-implied volatility $\overline{iVOL}^{FX}$. $\overline{iVOL}^{FX}$ and $\overline{VOL}^{FX}$ move tightly together with a correlation of around 0.9. However, a closer look using unreported Granger causality tests reveals a leading property of implied volatility. Overall, the relationship with disagreement measures is similar to that of the realised volatility discussed above. Again, we find that dispersion on current account forecasts is a particularly significant model input that helps explain and predict $\overline{iVOL}^{FX}$. Interestingly, the overall explanatory power of macro disagreement variables seems higher in the case of implied volatility, as the R-squared values are generally higher than for comparable specifications of realised volatility.

TABLE 2.3 ABOUT HERE

Since our exchange rates are all based on USD crosses it is important to check that our results are not driven entirely by the US-specific factors. To do this, we reconstruct aggregate macro disagreement series removing the US component. Instead, we include the latter separately in the regressions (see Table 2.3). The results show that disagreement on the dynamics of the world's largest economy does matter for global FX volatility. Indeed, it would be a surprise to find no relevance at all, given the importance of the US for global financial markets. However, it is also clear that most of the explanatory power is linked to the forecast dispersion about the economy in the rest of the world. The significance levels and coefficients remain notably higher for cross-country aggregate variables than for US analogues. This is true for the contemporaneous (3) and forward-looking (6) specifications for both realised and implied volatility. Hence, we can genuinely assert that $\overline{VOL}^{FX}$ is driven by the perceptions of the global macroeconomic situation and not just the US.

Regression analysis: joint tests. The leading properties highlighted in the previous sections are based on the statistical inference on single coefficients, i.e. on a model with limited dynamic relationships. To complement this analysis, we also consider Granger-causality tests through estimating vector autoregression models, $VAR(k)$, which allow for richer dynamic structures among the studied variables, placing additional lags of dependent and independent variables on the right

hand side of regressions.¹² The results are broadly consistent with those established earlier – see Table 2.4.

TABLE 2.4 ABOUT HERE

For example, looking at 2-variable VAR s in Panel A we see that aggregate realised FX volatility does not Granger-cause current account disagreement (the six lags of the former are jointly not statistically significant in forecasting the latter) at a conventional 10% significance level, but $\overline{DiB}^{CA}$ does Granger-cause $\overline{VOL}^{FX}$. In other words – $\overline{DiB}^{CA}$ predicts $\overline{VOL}^{FX}$ but not vice versa. For differences in beliefs about other macro variables the results are not as strong: FX volatility predicts growth disagreement but not vice versa, while neither direction works for the short rate disagreement.

The results are confirmed in Panel B, which combines all four studied time-series and considers a 4-variable VAR . The marked p -values suggest the same conclusion on $\overline{DiB}^{CA}$ predictive abilities reached earlier. Other disagreement measures, based on the Granger technique, do not forecast FX volatility on an aggregate level; in fact, the latter predicts dispersion in beliefs about real growth (consistent with the discussion of univariate tests above). The results do not alter much if we instead concentrate on $\overline{iVOL}^{FX}$ (Table 2.4 Panel C). In addition, we again find that the disagreement on interest rate has some predictive power for implied volatility, although not for realised.

2.4 Conclusion

We find that forecast disagreements on key macro variables – economic activity growth, short-term interest rates and current account positions – help explain a considerable part of the variations in FX volatility, and even allow FX volatility forecasts. These variables also tend to be key inputs of exchange rate determination models. This matches our economic intuition and has increased our confidence in the results. We show that growth disagreement is not very helpful for predictability, even though it is closely related contemporaneously – lagged FX volatility

¹²We report results for $k = 6$ to include a sufficient number of lags. Playing with the reasonable values for the k parameter we notice that conclusions do not change drastically. For the sufficiently large k the null of no predictability is hard to reject.

incorporates the same amount of information, with the possible advantage of being less noisy. That said, current account and interest rate disagreement contain information that appears able to help predict future volatility. The results hold for both realised and implied volatility.

Forecast dispersions are related to the global business cycle. They tend to rise during economic and financial downturns, and are low in normal market times. Nonetheless, we show that aggregate FX volatility modelling can be improved by considering aggregate macro disagreement series. In addition, given the dominance of US data releases in global financial markets, it is plausible that our aggregate macro disagreement variables largely reflect US influences. However, our tests suggest that forecast dispersion for non-US economies is at least as relevant for FX volatility.

Finally, it is worth discussing a bit more the leading relationship we have identified empirically. It is more difficult to explain intuitively than a contemporaneous link proposed in Section 2.1: a high dispersion of assumptions about macro variables leads to larger differences among model-implied asset prices, which fundamentals traders fall back on. This creates higher volatility in financial markets at times when disagreement about the macro picture is high. However, we find that higher macro disagreement today leads to rising volatility in the future. In an earlier version of this paper¹³ we have suggested a mechanism, the intuition for which is based on growing offsetting speculative positions in the market with increasingly polarised views of agents. We can view a period of strong disagreement on future macro outcomes as the “calm before the storm”: while opposite speculative positions are built up by disagreeing agents, prices could stay unchanged. At the same time, tension builds in the market. If positions are large enough, even a relatively small macro surprise (news) can potentially lead to a big spike in volatility due to the unwinding of those positions accumulated in earlier periods as a result of diverging forecasts about fundamentals. In fact, later we became aware of the work by [Hong, Kubik, and Fishman \(2012\)](#), who study the equity market and “establish that the price of highly shorted stocks overshoots after good earnings news due to short covering compared with other stocks.” Leaving aside the issue that there is no natural “short” position in the FX market, our mechanism is very much consistent with their theoretical and empirical results.

¹³Appeared as [Kretetovs and Stolper \(2013\)](#).

Table 2.1: Correlations among macro disagreements

This table presents the time-series correlations between constructed macro forecast dispersion series. All quantities are calculated on a monthly frequency. The forecast data is taken from Consensus Economics database. Daily exchange rates (mid quotes) are collected from Datastream. One-month implied FX volatilities are sourced from one investment bank traders' marks. The period of study is from 1993 to 2013.

	$\overline{DiB}^Y$	$\overline{DiB}^{i3m}$	$\overline{DiB}^{CA}$
$\overline{DiB}^Y$			
$\overline{DiB}^{i3m}$	0.30		
$\overline{DiB}^{CA}$	0.27	-0.33	

Table 2.2: Regression results – base case

This table presents the time-series regression results of aggregate FX volatility measures on the constructed macro forecast dispersion and consensus series (all variables are defined in main text). In Panel A realised aggregate FX volatility ($\overline{VOL}^{FX}$) is used, while in Panel B aggregate implied FX volatility is utilised ($i\overline{VOL}^{FX}$). Depending on the volatility measure, each panel presents the results for the following six regression specifications:

- (1) $VOL_t = \beta_0 + \beta_1 \overline{DiB}_t^Y + \beta_2 \overline{DiB}_t^{i3m} + \beta_3 \overline{DiB}_t^{CA} + \epsilon_t$
- (2) $VOL_t = \beta_0 + \beta_1 \overline{Cons}_t^Y + \beta_2 \overline{Cons}_t^{i3m} + \beta_3 \overline{Cons}_t^{CA} + \epsilon_t$
- (3) $VOL_t = \beta_0 + \beta_1 \overline{DiB}_t^Y + \beta_2 \overline{DiB}_t^{i3m} + \beta_3 \overline{DiB}_t^{CA} + \beta_4 \overline{Cons}_t^Y + \beta_5 \overline{Cons}_t^{i3m} + \beta_6 \overline{Cons}_t^{CA} + \epsilon_t$
- (4) $VOL_t = \beta_0 + \beta_1 \overline{DiB}_{t-1}^Y + \beta_2 \overline{DiB}_{t-1}^{i3m} + \beta_3 \overline{DiB}_{t-1}^{CA} + \epsilon_t$
- (5) $VOL_t = \beta_0 + \beta_1 \overline{DiB}_{t-1}^Y + \beta_2 \overline{DiB}_{t-1}^{i3m} + \beta_3 \overline{DiB}_{t-1}^{CA} + \beta_4 VOL_{t-1} + \epsilon_t$
- (6) $VOL_t = \beta_0 + \beta_1 \overline{DiB}_{t-12}^Y + \beta_2 \overline{DiB}_{t-12}^{i3m} + \beta_3 \overline{DiB}_{t-12}^{CA} + \beta_4 VOL_{t-12} + \epsilon_t$

Constant is included in all regressions but not reported. [Newey and West \(1987\)](#) standard errors are shown in parentheses and statistical significance at the 10, 5 and 1% level is marked respectively with *, ** and ***. All quantities are calculated on a monthly frequency. The forecast data is taken from Consensus Economics database. Daily exchange rates (mid quotes) are collected from Datastream. One-month implied FX volatilities are sourced from one investment bank traders' marks. The period of study is from 1993 to 2013.

Panel A: Realised FX volatility				Panel B: Option-implied FX volatility			
	(1)	(2)	(3)		(1)	(2)	(3)
$\overline{DiB}^Y$	0.064*** (0.011)		0.031* (0.018)	$\overline{DiB}^Y$	0.052*** (0.008)		0.020* (0.012)
$\overline{DiB}^{i3m}$	0.024 (0.018)		0.025 (0.016)	$\overline{DiB}^{i3m}$	0.025** (0.012)		0.032** (0.013)
$\overline{DiB}^{CA}$	0.065*** (0.018)		0.061*** (0.015)	$\overline{DiB}^{CA}$	0.052*** (0.017)		0.047*** (0.013)
$\overline{Cons}^Y$		-0.073*** (0.021)	-0.019 (0.016)	$\overline{Cons}^Y$		-0.062*** (0.018)	-0.018 (0.012)
$\overline{Cons}^{i3m}$		0.005 (0.018)	-0.011 (0.017)	$\overline{Cons}^{i3m}$		0.011 (0.012)	-0.013 (0.010)
$\overline{Cons}^{CA}$		0.034 (0.026)	-0.010 (0.013)	$\overline{Cons}^{CA}$		0.029 (0.020)	-0.005 (0.010)
R-squared	0.46	0.26	0.46	R-squared	0.55	0.32	0.56
# obs	236	236	236	# obs	236	236	236

	(4)	(5)	(6)		(4)	(5)	(6)
$\overline{DiB}^Y$	0.044*** (0.011)	0.001 (0.009)	-0.023* (0.013)	$\overline{DiB}^Y$	0.038*** (0.008)	-0.005 (0.007)	0.002 (0.010)
$\overline{DiB}^{i3m}$	0.029 (0.020)	0.013 (0.008)	-0.013 (0.015)	$\overline{DiB}^{i3m}$	0.028* (0.014)	0.008 (0.006)	0.006 (0.011)
$\overline{DiB}^{CA}$	0.072*** (0.022)	0.028*** (0.011)	0.042** (0.020)	$\overline{DiB}^{CA}$	0.057*** (0.021)	0.014* (0.008)	0.049*** (0.017)
$\overline{VOL}^{FX}$ lagged		0.681*** (0.079)	0.111 (0.072)	$i\overline{VOL}^{FX}$ lagged		0.820*** (0.071)	-0.116 (0.081)
R-squared	0.38	0.62	0.11	R-squared	0.45	0.74	0.11
# obs	235	235	224	# obs	235	235	224

Table 2.3: Regression results – isolating US-specific information

This table presents the time-series regression results of aggregate FX volatility measures on the constructed macro forecast dispersion and consensus series (all variables are defined in main text). $\overline{DiB}^X$ corresponds to cross-country average disagreement about the macro variable X , but importantly it excludes the disagreement component related to the United States. In Panel A realised aggregate FX volatility ($\overline{VOL}^{FX}$) is used, while in Panel B aggregate implied FX volatility is utilised ($\overline{iVOL}^{FX}$). Depending on the volatility measure, each panel presents the results for the following six regression specifications:

- (1) $VOL_t = \beta_0 + \beta_1 \overline{DiB}_t^Y + \beta_2 \overline{DiB}_t^{i3m} + \beta_3 \overline{DiB}_t^{CA} + \epsilon_t$
- (2) $VOL_t = \beta_0 + \beta_1 DiB_{US,t}^Y + \beta_2 DiB_{US,t}^{i3m} + \beta_3 DiB_{US,t}^{CA} + \epsilon_t$
- (3) $VOL_t = \beta_0 + \beta_1 \overline{DiB}_t^Y + \beta_2 \overline{DiB}_t^{i3m} + \beta_3 \overline{DiB}_t^{CA} + \beta_4 DiB_{US,t}^Y + \beta_5 DiB_{US,t}^{i3m} + \beta_6 DiB_{US,t}^{CA} + \epsilon_t$
- (4) $VOL_t = \beta_0 + \beta_1 \overline{DiB}_{t-1}^Y + \beta_2 \overline{DiB}_{t-1}^{i3m} + \beta_3 \overline{DiB}_{t-1}^{CA} + \epsilon_t$
- (5) $VOL_t = \beta_0 + \beta_1 DiB_{US,t-1}^Y + \beta_2 DiB_{US,t-1}^{i3m} + \beta_3 DiB_{US,t-1}^{CA} + \epsilon_t$
- (6) $VOL_t = \beta_0 + \beta_1 \overline{DiB}_{t-1}^Y + \beta_2 \overline{DiB}_{t-1}^{i3m} + \beta_3 \overline{DiB}_{t-1}^{CA} + \beta_4 DiB_{US,t-1}^Y + \beta_5 DiB_{US,t-1}^{i3m} + \beta_6 DiB_{US,t-1}^{CA} + \epsilon_t$

Constant is included in all regressions but not reported. [Newey and West \(1987\)](#) standard errors are shown in parentheses and statistical significance at the 10, 5 and 1% level is marked respectively with *, ** and ***. All quantities are calculated on a monthly frequency. The forecast data is taken from Consensus Economics database. Daily exchange rates (mid quotes) are collected from Datastream. One-month implied FX volatilities are sourced from one investment bank traders' marks. The period of study is from 1993 to 2013.

Panel A: Realised FX volatility				Panel B: Option-implied FX volatility			
	(1)	(2)	(3)		(1)	(2)	(3)
$\overline{DiB}^Y$	0.064*** (0.011)		0.044*** (0.012)	$\overline{DiB}^Y$	0.052*** (0.008)		0.030*** (0.007)
$\overline{DiB}^{i3m}$	0.024 (0.018)		0.024 (0.015)	$\overline{DiB}^{i3m}$	0.025** (0.012)		0.024** (0.010)
$\overline{DiB}^{CA}$	0.065*** (0.018)		0.046*** (0.015)	$\overline{DiB}^{CA}$	0.052*** (0.017)		0.033*** (0.013)
DiB_{US}^Y		0.038*** (0.012)	0.006 (0.010)	DiB_{US}^Y		0.038*** (0.012)	0.015** (0.007)
DiB_{US}^{i3m}		-0.007 (0.005)	-0.011** (0.006)	DiB_{US}^{i3m}		-0.001 (0.004)	-0.006 (0.004)
DiB_{US}^{CA}		0.025* (0.013)	0.013** (0.006)	DiB_{US}^{CA}		0.016 (0.010)	0.009* (0.005)
R-squared	0.46	0.25	0.46	R-squared	0.55	0.35	0.56
# obs	236	236	236	# obs	236	236	236

	(4)	(5)	(6)		(4)	(5)	(6)
$\overline{DiB}^Y$	0.044*** (0.011)		0.027** (0.013)	$\overline{DiB}^Y$	0.038*** (0.008)		0.017** (0.007)
$\overline{DiB}^{i3m}$	0.029 (0.020)		0.029 (0.018)	$\overline{DiB}^{i3m}$	0.028* (0.014)		0.025** (0.011)
$\overline{DiB}^{CA}$	0.072*** (0.022)		0.051*** (0.018)	$\overline{DiB}^{CA}$	0.057*** (0.021)		0.035** (0.015)
DiB_{US}^Y		0.034*** (0.013)	0.008 (0.012)	DiB_{US}^Y		0.035*** (0.012)	0.018** (0.008)
DiB_{US}^{i3m}		-0.005 (0.005)	-0.011** (0.006)	DiB_{US}^{i3m}		0.000 (0.004)	-0.005 (0.004)
DiB_{US}^{CA}		0.024* (0.013)	0.012 (0.008)	DiB_{US}^{CA}		0.016 (0.010)	0.009* (0.005)
R-squared	0.38	0.21	0.38	R-squared	0.45	0.25	0.48
# obs	235	235	235	# obs	235	235	235

Table 2.4: Regression results – Granger causality tests

This table presents the p -values for the Granger causality tests – particular predictability tests for the vector autoregressive system, $VAR(k)$. More specifically, the cell in the i -th row and the j -th column provides the test of a null that k lags of the j -th factor are jointly not statistically significant in forecasting the i -th factor. Throughout the table the results are reported for the case $k = 6$. In Panel A a vector consists of two elements – realised aggregate FX volatility (VOL^{FX}) and one of the three aggregate macro forecast dispersion series (all variables are defined in main text). The results are reported separately for each of the disagreement measures. In Panel B all four variables are stuck in a vector. Panel C replicates the results of the previous panel but utilising aggregate implied FX volatility ($iVOL^{FX}$) instead of VOL^{FX} . Constant is included in all regressions. All quantities are calculated on a monthly frequency. The forecast data is taken from Consensus Economics database. Daily exchange rates (mid quotes) are collected from Datastream. One-month implied FX volatilities are sourced from one investment bank traders' marks. The period of study is from 1993 to 2013.

Panel A: Bivariate Granger causality tests for realised FX volatility										
$\overline{DiB}^Y$ VOL^{FX}	$\overline{DiB}^Y$ lags		VOL^{FX} lags		$\overline{DiB}^{i3m}$ lags		VOL^{FX} lags		$\overline{DiB}^{CA}$ lags	
	0%	0%								
								</		

Chapter 3

Macro uncertainty and currency premia¹

“Current account [...] deficits appear not to matter until, well, they suddenly do!”

[Wadhwani \(1999\)](#), Bank of England Monetary Policy Committee.

3.1 Introduction

Currency returns are in theory anchored through several channels to macro fundamentals such as short-term interest rate, inflation rate, real output, and external imbalances (e.g., [Engel and West, 2005](#); [Gabaix and Maggiori, 2015](#); [Lustig, Roussanov, and Verdelhan, 2011](#)). If these macroeconomic variables affect the investment opportunities that investors face, then excess returns should comove with unexpected changes in these state variables ([Merton, 1973](#)). If investors have little information about the dynamics of the true data generating process dictating the evolution of both asset returns and state variables, then uncertainty over future macroeconomic conditions should be priced in the cross-section of excess returns (e.g., [Anderson, Ghysels, and Juergens, 2009](#); [Bali, Brown, and Caglayan, 2014](#)). Motivated by these insights, we investigate empirically whether macro uncertainty matters in the cross-section of currency excess returns.

While the concept of uncertainty is well grounded – an event is uncertain when both the outcome and its distribution are unknown – in practice it remains difficult to measure as individuals’ subjective beliefs are not directly observable (e.g., [Bloom, 2014](#)).² Despite being in its early stage,

¹This chapter is based on [Della Corte and Krcetovs \(2016\)](#).

²While measures of option-implied volatility are often used as indicators of uncertainty, their information content may also reflect other components and, thus, provide a biased measure of economic uncertainty. [Bekaert, Hoerova, and Lo Duca \(2013\)](#) find that a large component of the VIX index is driven by factors associated with

a growing literature quantifies macro uncertainty using the cross-sectional dispersion in economic forecasts as they are likely to reflect changing economic circumstances agents are exposed to (e.g., [Beber, Breedon, and Buraschi, 2010](#); [Bloom, 2009](#); [Bomberger, 1996](#); [Zarnowitz and Lambros, 1987](#)). It can also be viewed as a model-free measure as forecasts are observable and, thus, its construction does not require estimating any specific models. Using a standard decomposition of forecast errors into a common and idiosyncratic shocks, [Lahiri and Sheng \(2010\)](#) show that uncertainty is simply the disagreement among forecasters plus the variability of future aggregate shocks that accumulate over forecast horizons.

We quantify macro uncertainty using measures of cross-sectional dispersion of economic forecasts collected from *Blue Chip Economic Indicators* and *Consensus Forecasts* – to our knowledge, the most comprehensive and long-dated international surveys of monthly expectations for both developed and emerging market countries. Armed with these economic forecasts, we first construct cross-sectional dispersions for each country, and then average across all available countries to measure the systematic component. Ultimately, we obtain five indicators of global uncertainty for current account, inflation rate, short-term interest rate, real economic growth, and foreign exchange rate from each survey of market participants’ expectations. In our exercise, we work with one-year ahead economic forecasts collected every month. This implicit overlapping structure generates a strong predictable component in our monthly measures of macro uncertainty which we remove by computing unexpected changes (or innovations) via a simple autoregressive model. The resulting standardized residuals can be viewed as measures of macro uncertainty shocks. We further consider a broad index of global economic uncertainty shocks that captures the common variation across our measures of global macro uncertainty. We construct this index for each survey as in [Bali, Brown, and Caglayan \(2014\)](#) by means of principal component analysis.

We evaluate the sensitivity of currency excess returns to our measures of macro uncertainty using a standard linear asset pricing framework. The link between excess returns and macro uncertainty can be rationalized using the intertemporal capital asset pricing model of [Merton \(1973\)](#) as in [Bali, Brown, and Caglayan \(2014\)](#) who investigate hedge fund and mutual fund exposure to measures of macro uncertainty, and [Bali, Brown, and Tang \(2015\)](#) who examine individual stock

time-varying risk aversion whereas [Della Corte, Ramadorai, and Sarno \(2014\)](#) report evidence that volatility risk premia in foreign exchange markets reflects the costs of insuring against currency volatility fluctuations.

return exposure to a broad measure of economic uncertainty. Moreover, [Anderson, Ghysels, and Juergens \(2009\)](#) expand the general equilibrium model of [Merton \(1973\)](#) and decompose excess returns into risk and uncertainty, thus augmenting the traditional risk-return relation with the uncertainty-return tradeoff. Risk is identified with the asset return volatility whereas uncertainty is based on aggregate disagreement amongst professional forecasters. In this model, uncertainty arise from the fact that investors have little knowledge about both the mean of the asset return and the mean of the state variable. Intuitively, when forecasters provide very different predictions about future economic fundamentals, we should then expect that market participants are unsure about the mean of asset prices and state variables dynamics, and thus uncertainty is high. In contrast, when forecast dispersion is low, it is likely that forecasters tend to agree about future economic fundamentals and hence uncertainty is low. Consistent with this literature, we examine the exposure of currency excess returns to both uncertainty arising from the mean of the exchange rate return process and uncertainty stemming from the evolution of the economic state variables, i.e. current account, inflation rate, short-term interest rate and real economic growth.³ We then use standard asset pricing methods to assess whether currency excess returns can be understood as compensation for macro uncertainty, and if so, whether uncertainty originates from the exchange rate return process or the evolution of the economic state variable, or both.

To preview our results, we find strong empirical evidence that high-yielding currencies are negatively correlated to innovations in current account uncertainty, and thus offer low returns when uncertainty on future current account positions is unexpectedly high. In contrast, currencies with low interest rates display a positive relationship with our measure of current account uncertainty, and hence provide a hedge by yielding positive excess returns when current account uncertainty is unexpectedly high. Our results hold for a broad sample of currencies for the period from 1993 to 2013, and are consistent for both *Blue Chip Economic Indicators* and *Consensus Forecasts* data. In contrast, the broad measure of uncertainty as well as uncertainty over short-term interest rate, inflation rate, real economic growth, and exchange rate display no significant relation with the cross-section of currency excess returns. In short, we document that our proxy of global current

³In the empirical analysis, [Anderson, Ghysels, and Juergens \(2009\)](#) consider a restricted version of their model and focus only on uncertainty in mean returns. In contrast, our dataset allows us to consider both sources of uncertainty.

account uncertainty is the more powerful macro uncertainty factor in explaining the cross-section of currency excess returns, and it subsumes the information contained in both foreign exchange global volatility factor and other measures of global macro uncertainty.⁴

Our empirical results support the recent theoretical contributions of [Gourinchas and Rey \(2007\)](#) and [Gabaix and Maggiori \(2015\)](#). [Gourinchas and Rey \(2007\)](#) show that a deterioration in the external account of a country is unsustainable over time unless counterbalanced by future trade surpluses and/or positive returns on the net foreign asset position. Currency fluctuations are key to this process of external adjustment as a domestic currency depreciation affects the country's international competitiveness in goods and services, as well as the value of its foreign assets and liabilities. [Gabaix and Maggiori \(2015\)](#) build on this literature and suggest a novel theory of exchange rate determination based on capital flows in imperfect financial markets. They propose a two-country model in which currency excess returns are jointly determined by global imbalances and financiers' risk-bearing capacity. Countries run trade imbalances and financiers absorb the resultant currency risk, i.e. they are long the debtor country and short the creditor country. Financiers, however, are financially constrained, and this affects their ability to take positions. Intuitively, when there is little risk-bearing capacity they are unwilling to intermediate currency mismatches regardless of the excess return on offer. In contrast, when financiers have unlimited risk-bearing capacity they are willing to take positions in currencies whenever a positive excess return is available, and hence uncovered interest rate parity holds.

Our paper builds on a recent literature seeking for a risk-based explanation of currency carry trade in a cross-sectional asset pricing setting. [Lustig, Roussanov, and Verdelhan \(2011\)](#) and [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012a\)](#) report evidence that currency excess returns can be thought of as compensation for exposure to a global risk factor. [Lustig, Roussanov, and Verdelhan \(2011\)](#) rationalize returns to carry trade using a data-driven approach in line with the Arbitrage Pricing Theory of [Ross \(1976\)](#). They identify two risk factors: the average excess return on a basket of currencies against the US dollar and the excess return to the carry trade portfolio itself. [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012a\)](#) replace the carry factor with innovations

⁴In a related paper, [Beber, Breedon, and Buraschi \(2010\)](#) construct measures of exchange rate disagreement for three currency pairs and use them to explain the level of implied volatility of currency options as well as the underlying exchange rate returns.

to global foreign exchange volatility and find that in times of high unexpected volatility, high-interest currencies deliver low returns, whereas low-interest currencies perform well. While these global risk factors provide valuable information on the properties of currency returns, they leave unanswered the question on what economic fundamental forces drive the factors and, hence, currency risk premia. This paper can be considered as attempt to shed light empirically on the primitive economic determinants of currency excess returns.⁵

In our empirical analysis, we follow much for the existing literature and construct currency excess returns sorted on forward discounts as test assets (Lustig and Verdelhan, 2007; Lustig, Roussanov, and Verdelhan, 2011). We start our asset pricing exercise using individual currency excess returns as test assets before moving to traditional currency-sorted portfolios. Working with country-level excess returns brings the advantage of having a large cross-section. This is important as the linear asset pricing framework used in this paper implies a pricing kernel with multiple factors. Meanwhile, we can address at the outset any concerns stemming from the practice of grouping assets into portfolios as pointed out by a recent literature (e.g., Lewellen, Nagel, and Shanken, 2010; Ang, Liu, and Schwarz, 2010). In our setup, we first define a two-factor pricing kernel with the dollar factor and in turn each global measure of macro uncertainty shocks. Note that the dollar factor displays no cross-sectional relation with currency returns, and it works as a constant that captures the common mispricing in the cross-section of currency returns (Lustig, Roussanov, and Verdelhan, 2011). This exercise is performed to check whether macro uncertainty bears a premium in the cross-section of currency excess returns. Second, we control for volatility risk by adding the foreign exchange volatility innovations of Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) to our pricing kernel. With this exercise, we attempt to understand whether there is a macro uncertainty premium that is distinct with respect to the traditional volatility risk premium or whether the latter subsumes the information content embedded in the various measures of macro uncertainty. Thirdly, we run a horse race analysis that involves having all measures of macro uncertainty shocks stacked together in our pricing kernel. We execute this exercise to discriminate among our measures of uncertainty and, thus,

⁵Other papers studying carry trade returns include Brunnermeier, Nagel, and Pedersen (2009), Colacito and Croce (2013), Farhi, Fraiberger, Gabaix, Ranci re, and Verdelhan (2015), Hassan and Mano (2015), Jurek (2014), Lettau, Maggiori, and Weber (2014), Mueller, Stathopoulos, and Vedolin (2015), and Mancini, Ranaldo, and Wrampelmeyer (2013).

understand whether the uncertainty premium can be attributed to a specific macroeconomic force, or whether it is common to all macroeconomic indicators. Finally, we move to sorting currencies into six portfolios according to their forward discounts as pioneered by [Lustig and Verdelhan \(2007\)](#). The first portfolio contains the funding currencies of a carry trade strategy (low-yielding currencies relative to the US dollar) while the last portfolio contains the investment currencies in a carry trade strategy (high-yielding currencies relative to the US dollar). This exercise, which we run as a robustness check, confirms that carry trade returns can be understood as compensation for exposure to current account uncertainty.

To summarize, the main contribution of this paper relative to existing research is twofold. First, we show that current account uncertainty is an important determinant of risk premia in the cross section of carry trade returns. Second, among a set of competing economic indicators, we provide empirical evidence on the key economic channel through which uncertainty affects currency premia. Our results corroborate the recent empirical evidence of [Della Corte, Riddiough, and Sarno \(2015\)](#) who show that global imbalances are an important driver of currency risk premia. Our findings are also in line with [Bachmann, Elstner, and Sims \(2013\)](#) and [Gilchrist, Sim, and Zakrajsek \(2014\)](#) who point that the impact of uncertainty shocks on the economy is likely to come not through the real options channel but more likely through the financial frictions channel.

The remainder of the paper is organized as follows. Section [3.2](#) provides in detail motivation for the empirical analysis of the paper in relation to the current literature. Section [3.3](#) describes the surveys of market participants' expectations on macro indicators, whereas Section [3.4](#) provides details on the construction of our measures of forecast dispersions and shows that they can be thought of as proxy for uncertainty. We then present asset pricing tests in Section [3.5](#) using country-level excess returns and in Section [3.6](#) using portfolio-level excess returns. Section [3.7](#) presents a number of extensions and robustness exercises, before concluding in Section [3.8](#). A separate Internet Appendix provides further robustness tests and additional results.

3.2 Motivations and testable hypothesis

In a recent paper, [Gabaix and Maggiori \(2015\)](#) present a modern micro-founded version of the portfolio balance model that incorporates the interaction between global capital flows and the

risk-bearing capacity of financiers in a setting with financial markets imperfections. In their two-period model, each country borrows or lends in local currency but financiers face constraints that affect their ability to absorb the exchange rate risk arising from globally imbalanced capital flows.

In this model, the carry trade strategy is profitable as financiers demand a risk premium to intermediate global financial flows. In their two-period two-country version of the model, [Gabaix and Maggiori \(2015\)](#) show that [see Proposition 6, p. 1398]:

$$E(RX_1) = \Gamma_0 \frac{\frac{R^*}{R} E(\iota_1) - \iota_0}{(R^* + \Gamma)\iota_0 + \frac{R^*}{R} E(\iota_1)}$$

where $E(RX_1)$ is the expected return to carry trade; Γ_0 controls the ability of financiers to bear risk and is referred to as financiers' risk-bearing capacity; R and R^* are the gross domestic and foreign interest rates, respectively; ι_t denotes the value of imports in domestic currency at time t , and $E(\iota_1) - \iota_0$ determines the expected evolution of external imbalances (with exports normalized to unity).

The risk-bearing capacity of financiers plays an important role in this model since it causes carry trade returns to unwind. Γ_0 depends on the variance of future exchange rates. As capital flows drive both the size and the composition of financiers' balance sheets, in equilibrium capital flows affect both the level and the variance of exchange rates. It follows that the risk-bearing capacity worsens when the variance of future external imbalances increases as

$$\Gamma_0 = \gamma \text{var}(\iota_1)^\alpha, \tag{3.1}$$

where γ captures the global risk aversion and $\text{var}(\iota_1)$ is the variance of future external imbalances, with $\alpha \geq 0$ and $\gamma \geq 0$. Here, an increase in the perceived uncertainty about future external imbalances is associated with an immediate currency depreciation and an expected future currency appreciation such that constrained financiers have greater incentives to absorb the capital imbalance of the external debtor country.

Motivated by the prediction in Equation 3.1, we test whether the uncertainty about future imbalances matters in the cross-section of currency excess returns using a linear asset pricing framework. We source market participants' expectations from two different surveys of interna-

tional economic forecasts – namely *Blue Chip Economic Indicators* and *Consensus Forecasts* – and use the cross-country average of dispersions in current account forecasts as proxy for the uncertainty about future external imbalances on a global dimension.⁶ We find empirically that investment currencies yield low returns whereas funding currencies act as an insurance when current account forecast dispersion is unexpectedly high. In contrast, forecast dispersion over other macro indicators widely used in the exchange rate determination literature such as inflation rate, short-term interest rate, real economic growth and foreign exchange rate display no significant relation with the cross-section of currency excess returns.

In sum, we use the theory of [Gabaix and Maggiori \(2015\)](#) as a modern example of the portfolio balance approach to exchange rate determination in order to construct a testable and economically plausible empirical hypothesis. We provide robust empirical evidence in favour of this hypothesis and show that the uncertainty about future external imbalances proxied by the cross-sectional dispersion of current account forecasts matters in the cross-section of currency excess returns. Our results, however, can be also read in light of the recent literature on the link between macro uncertainty and asset returns. Throughout the rest of the paper, we will refer to the cross-sectional dispersion of macro forecasts simply as macro uncertainty. It is beyond the goal of this paper to discriminate among alternative theories that ultimately can rationalize our findings.

3.3 Data description

This section describes two cross-country surveys – *Blue Chip Economic Indicators* and *Consensus Forecasts* – of market participants’ expectations on economic indicators and prices which we refer to as macro variables. We also describe data on exchange rates as well as other data used in our empirical analysis.

Data on macro forecasts. We have assembled a unique dataset of monthly forecasts running from July 1993 to July 2013 on five international economic indicators and prices: current account (*ca*), inflation rate (*if*), short-term interest rate (*ir*), real economic growth (*rg*), and foreign

⁶Using the standard debt accumulation equation $na_t = na_{t-1} + ca_t$, where na_t is the stock of net foreign assets at time t and ca_t is the current account balance between times t and $t - 1$ (while abstracting from any valuation effects), it is easy to show that the conditional volatility of na_t depends on the conditional volatility of ca_t .

exchange rate (fx). We have obtained these forecasts from two distinct surveys of market participants' expectations, namely *Blue Chip Economic Indicators* published by Aspen Publishers and *Consensus Forecasts* compiled by Consensus Economics. We have collected manually most of these data using the original paper archives made available by Wolters Kluwert and Consensus Economics, respectively. The resulting dataset of digitized forecasts represents an important source of information to examine whether macro uncertainty matters in the cross-section of currency excess returns. Below we describe the surveys used in our empirical analysis.

The *Blue Chip Economic Indicators* survey is conducted among economists working at financial institutions, corporations, professional forecast firms, and academic institutions.⁷ It contains international macro forecasts for up to 20 major trading partners of the United States, that are, Australia, Belgium, Brazil, Canada, China, Euro area, France, Germany, Hong Kong, India, Italy, Japan, Mexico, Netherlands, Russia, Singapore, South Korea, Switzerland, Taiwan, and United Kingdom. We remove the data on an individual Eurozone country after its introduction of the Euro. The survey participants submit their forecasts on the first or the second business day of each month. While forecasts are collected at individual level, the published data are for the top (3 average) and the bottom (3 average) forecasts. From July 1993, when the survey started, and until May 1995, data are only available for the top (high) and bottom (low) forecasts.

The second international survey is *Consensus Forecasts* which is carried out monthly among experts from a large number of financial and economic institutions.⁸ We use forecasts for up to 46 countries organized in regional volumes (G7-Western Europe, Asia Pacific, Latin America and Eastern Europe) and comprising Argentina, Australia, Brazil, Bulgaria, Canada, Chile, China, Colombia, Croatia, Czech Republic, Estonia, Euro area, France, Germany, Hong Kong, Hungary, India, Indonesia, Italy, Japan, Latvia, Lithuania, Malaysia, Mexico, Netherlands, New Zealand, Norway, Peru, Philippines, Poland, Romania, Russia, Singapore, Slovakia, Slovenia, South Ko-

⁷The fact that forecasters are not restricted to banks' research teams is very likely to be beneficial – [Anderson, Ghysels, and Juergens \(2005\)](#) and [Kim and Zapatero \(2011\)](#) caution that financial analysts might not represent a random sample from the population of investors. If that is the case, macro uncertainty proxies, and more importantly their dynamics, through forecast dispersions could be distorted. By using a broader set of economists coming from various institutions we can alleviate this problem.

⁸This data covers a wide range of international macroeconomic indicators. In our empirical analysis, we only consider the cross-sectional dispersion of forecasts on the five indicators described at the beginning of this section in order to match the sample of data collected from *Blue Chip Economic Indicators*. The Internet Appendix shows that additional variables do not change the conclusion of our study.

rea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, Ukraine, United Kingdom, United States, and Venezuela. Again, we remove the data on an individual Eurozone country after its introduction of the Euro. We exclude an additional number of 39 countries as the survey only reports the consensus (mean) forecasts and not the cross-sectional distribution of forecasts. For the G7-Western Europe and Asia Pacific countries, the survey is conducted on the second Monday of the month whereas for Latin American and Eastern European economies forecasts are collected on the third Monday of the month and then sent to the subscribers the following Thursday. In contrast to *Blue Chip Economic Indicators*, *Consensus Forecasts* reports international forecasts at individual level.⁹

Before running the empirical analysis, we have cleaned and transformed the data as follows. For *Blue Chip Economic Indicators* we have removed few data points when the bottom forecast was larger than the top forecast whereas for *Consensus Forecasts* we have excluded few individual forecasts that were substantially different from other forecasts.¹⁰ Moreover, while forecasts on *if*, *ir* and *rg* are reported as year-on-year percentage change, forecasts on *ca* and *fx* are measured in levels. We make them comparable across countries by scaling the forecasts on *ca* with respect to the end of previous year annual gross domestic product (IMF estimates) and the forecasts on *fx* with respect to the end of previous year spot exchange rate.

Constant maturity forecasts. Every month *Blue Chip Economic Indicators* and *Consensus Forecasts* collect from respondents expectations for the end of the current calendar year and expectations for the end of the next calendar year. For instance, in April 2001 Ford Motor Company submitted a real economic growth forecast for the end of 2001 (9 months ahead) and the end of 2002 (21 months ahead). Since these forecasts are formed on a moving forecast horizon, their cross-sectional dispersion is strongly seasonal (uncertainty about the realization of the underlying variable is resolved through time as the forecasting horizon decreases). Instead of using these fixed-event forecasts, we utilize a simple linear interpolation method to compute fixed-horizon forecasts (e.g., [Dovern, Fritsche, and Slacalek, 2012](#); [Buraschi and Whelan, 2012](#)). In every month

⁹Foreign exchange rate forecasts are only available for top (high) and bottom (low) forecasts starting from January 1995.

¹⁰In a number of cases, the data provider kindly helped us identify and fix outliers likely due to typing errors by respondents. We have also experimented with a 99% winsorization but results remain qualitatively identical.

t , we construct a one-year constant maturity forecast f_t as a weighted average of year-end forecasts as follows

$$f_t = \frac{n}{12}f_{t+n|t} + \frac{12-n}{12}f_{t+12+n|t}$$

where $f_{t+n|t}$ is the forecast for the end of the current calendar year (n months ahead) available at time t , $f_{t+12+n|t}$ is the forecast for the end of the next calendar year ($12 + n$ months ahead) available in month t , and $1 \leq n \leq 12$. For instance, the one-year constant maturity forecast in April 2001 is constructed as a weighted average of a 9-month ahead forecast and 21-month forecast where $n = 9$. We will employ these one-year constant maturity forecasts to construct measures of forecast dispersion which are then related to the cross-section of currency excess returns.

Forecast formation dates. We largely know the submission dates of forecasts, but we do not know when they are formed. Due to potential forecast staleness problem, we assume that forecasts are formed on the day prior to the submission date, i.e. on the business day prior to the first business day of each month for *Blue Chip Economic Indicators*, and on the business day prior to the second Monday of each month for *Consensus Forecasts*. For instance, the forecasts submitted to *Blue Chip Economic Indicators* at the beginning of April 2001 are thought as of forecasts formed at the end of March 2001. Similarly, the forecasts submitted to the *Consensus Forecasts* survey on the 9th of April 2001 are used as macro forecasts formed on the 6th of April 2001.¹¹

Exchange rates and excess returns. We collect daily data from July 1993 to July 2013 on spot and 1-month forward exchange rates vis-à-vis the US dollar (USD) from Barclays and Reuters via Datastream. Our sample comprises 48 countries as in [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012a\)](#): Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, 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, and

¹¹Latin American and Eastern European countries' forecasts are submitted on the third Monday of the month. We will treat them as the G7-Western Europe and Asia Pacific countries' forecasts (i.e. we assume that they are formed on the business day prior to the second Monday of each month).

United Kingdom. We remove the data on an individual Eurozone country after its introduction of the Euro. As in [Lustig, Roussanov, and Verdelhan \(2011\)](#), we remove data when we observe large deviations from the covered interest rate parity condition.

We define spot and forward exchange rates at time t as S_t and F_t , respectively, and sample them on the forecast formation dates described in the previous section. As robustness, however, we will also sample exchange rates on different dates – up to a 5 business days before and 5 business days after the default formation dates – and show that results remain qualitatively identical. Exchange rates are defined as units of US dollars per unit of foreign currency such that an increase in S_t indicates an appreciation of the foreign currency. We construct currency excess returns adjusted for transaction costs using bid-ask quotes.

Other data. Our analysis employs a variety of additional data which we summarize below. First, we obtain from JP Morgan daily 1-month implied volatilities from at-the-money currency options traded over-the-counter from July 1993 to July 2013.¹² Second, we collect from Bloomberg the 3-month interbank (LIBOR) and overnight index swap (OIS) rates for the Euro area (Germany before 1999), Japan, Switzerland, United Kingdom, and United States. Note that the OIS rates are available from the end of 1990s at the earliest – we extend the series back with the 3-month government bond yields. We interpret the average of the LIBOR-OIS spread across major countries as a proxy of global funding liquidity. Third, we gather daily 1-month interbank or deposit rates for all countries included in our analysis from Datastream, and use them to proxy for global monetary policy uncertainty (described later in the empirical analysis). Finally, we also collect monthly data on exports and imports of goods and services from the IMF Direction of Trade Statistics for all countries included in our analysis until July 2014. We will use this data later in the analysis to fit a stochastic volatility model and proxy for the conditional volatility of external imbalances.

¹²See e.g. [Della Corte, Ramadorai, and Sarno \(2014\)](#) for the description of the currency options data.

3.4 Macro uncertainty and forecast dispersion

This section describes first the construction of the cross-sectional dispersion in economic forecasts and then shows, that forecast dispersion and uncertainty are tightly linked, both analytically and empirically.

Dispersion in macro forecasts. We proxy uncertainty over macroeconomic indicators using the dispersion of market participants' expectations. To formalize our notation, let $f_{m,t}^{i,k}$ be the one-year forecast on the macro variable m for the country k formed by the agent i at time t . Every month t , we construct the cross-sectional standard deviation for each country k and each macro variable m as follows

$$u_{m,t}^k = \sqrt{\frac{1}{N_t} \sum_{i=1}^{N_t} \left[f_{m,t}^{i,k} - \bar{f}_{m,t}^k \right]^2} \quad (3.1)$$

where N_t is the number of forecasts on the macro variable m available at time t for the country k , and $\bar{f}_{m,t}^k$ is the cross-sectional average of $f_{m,t}^{i,k}$. When data are only available for top and bottom forecasts for a particular series, we replace Equation (3.1) with a simple range-based measure in line with [Bali, Brown, and Caglayan \(2014\)](#). Denoting as $f_{m,t}^{h,k}$ and $f_{m,t}^{l,k}$ the top and bottom forecasts, respectively, we compute the range-based standard deviation of the forecasts at time t for each country k as

$$u_{m,t}^k = \sqrt{\ln \left[\frac{1 + f_{m,t}^{h,k}}{1 + f_{m,t}^{l,k}} \right]}. \quad (3.2)$$

Armed with these country-specific measures of macro forecast dispersion, we construct the global component in the spirit of [Buraschi, Trojani, and Vedolin \(2014\)](#) and [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012a\)](#) by simply averaging across all countries K_t available at time t

$$u_{m,t} = \frac{1}{K_t} \sum_{k=1}^{K_t} u_{m,t}^k,$$

thus, measuring global uncertainty stemming from a variety of macroeconomic fundamentals such as current account, inflation rate, short-term interest rate, real economic growth and foreign exchange rate.

FIGURE 3.1 ABOUT HERE

We display our macro forecast dispersions, standardized to have zero means and unit variances for ease of comparison, in Figure 3.1 for both *Blue Chip Economic Indicators* and *Consensus Forecasts*. The visual inspection reveals that our proxies of uncertainty on the same macro variable tend to move together despite our surveys (i.e. *Blue Chip Economic Indicators* versus *Consensus Forecasts*) do not cover the same set of countries, do not poll the same cohort of contributors, and have different submission dates with a difference of few weeks apart.¹³ Moreover, our series are highly persistent as the first order serial correlation ranges from 0.64 for global foreign exchange uncertainty (based on *Blue Chip Economic Indicators* data) to 0.95 for global real economic growth uncertainty (using *Consensus Forecasts* data). This strong level of persistence is expected since we use forecasts with overlapping horizons (i.e. one-year forecast estimates sampled monthly).

Finally, we observe different time-series behavior when moving across indicators. Uncertainty on monetary variables – inflation and interest rates – tends to trend down. This may reflect an increase in the credibility and transparency of central banks’ monetary policy actions (e.g., the adoption of an explicit policy target) as well as an improvement in the policy communication (e.g., [Bernanke and Mishkin, 1997](#); [Dovern, Fritsche, and Slacalek, 2012](#)). Real economic activity growth uncertainty, in contrast, displays a clear counter-cyclical pattern as it is low in normal times but high in periods of global economic recessions. Current account uncertainty instead tends to be low in first half of the sample and high in the second part of the sample. This may manifest market participants’ concerns regarding external imbalances sustainability that has been central to the economic debate over the last decade. Overall, the pattern reveals that current account uncertainty is likely to summarize information that is not contained in the global uncertainty measures on other macro variables. The dynamics of exchange rate uncertainty turns out to be mixed as we observe a spike during the Asian crisis and a persistent increase during the recent financial crisis.

¹³For *Consensus Forecasts* we find very similar results when we compare standard deviation-based and range-based measures of macro uncertainty: the sample correlation is about 96% for the current account, 89% for the inflation rate, 75% for the interest rate, and 98% for the real economic growth. Recall that for foreign exchange rate forecasts, we only have top (high) and bottom (low) forecasts, and hence, our measure of uncertainty is computed using a range-based dispersion measure.

Relation between forecast dispersion and uncertainty. To understand the relationship between forecast dispersion and uncertainty, consider the actual value m_{t+1} of a variable of interest. This realized value can be written as the sum of a forecast and an error

$$m_{t+1} = f_t^i + \eta_{t+1} + e_{t+1}^i$$

where f_t^i is the forecast made by agent i at time t ($f_t^i \equiv E_t^i[m_{t+1}]$). The forecast error comprises a component η_{t+1} that is common to all forecasters and a component e_{t+1}^i that is specific to the forecaster i . The error components are conditionally mean zero so each agent's forecast is unbiased. All right hand side elements are also assumed to be conditionally orthogonal to each other (e.g., [Lahiri and Sheng, 2010](#)).

Uncertainty is measured as the average of agents' forecast errors variances.¹⁴ If forecasters share the same perceived variance of their forecast error components, then uncertainty can be expressed as

$$u_t = \frac{1}{N_t} \sum_{i=1}^{N_t} (var_t^i(\eta_{t+1}) + var_t^i(e_{t+1}^i)) = \sigma_{\eta t}^2 + \sigma_{et}^2.$$

Forecast dispersion instead is based on the expected variance of agents' point forecasts. Under mild additional regulatory conditions it converges to σ_{et}^2 when we allow for the number of forecasters to approach infinity:

$$d_t \equiv \frac{1}{N_t} \sum_{i=1}^{N_t} [f_t^i - \bar{f}_t]^2 = \frac{1}{N_t} \sum_{i=1}^{N_t} [e_{t+1}^i - \bar{e}_{t+1}]^2 \xrightarrow{p} \sigma_{et}^2$$

where $\bar{f}_t$ and $\bar{e}_{t+1}$ are the cross-sectional averages of f_t^i and e_{t+1}^i , respectively.

These equations reveal that forecast dispersion converges to uncertainty when there is no common component in forecast errors ($\eta = 0$). When the condition is not satisfied but $\sigma_{\eta t}^2$ is constant, then dispersion will be perfectly correlated with uncertainty. While this assumption may sound strong, [Bachmann, Elstner, and Sims \(2013\)](#) and [Nimark \(2014\)](#) provide evidence that forecast dispersion and uncertainty are strongly correlated, thus suggesting that forecast

¹⁴Commonly used theoretical notion of uncertainty for agent i is her perceived conditional variance of the forecast error: $u_t^i \equiv E_t^i[(m_{t+1} - E_t^i[m_{t+1}])^2] = E_t^i[(\eta_{t+1} + e_{t+1}^i)^2] = var_t^i(\eta_{t+1}) + var_t^i(e_{t+1}^i)$ (see e.g. [Lahiri and Sheng, 2010](#); [Jurado, Ludvigson, and Ng, 2015](#)). Aggregate uncertainty is then defined as $u_t \equiv \frac{1}{N_t} \sum_{i=1}^{N_t} u_t^i$ (motivated by [Lahiri and Sheng, 2010](#)).

dispersion is a natural metric to proxy uncertainty.

Forecast dispersion as a proxy for uncertainty. A recent literature suggests that higher information uncertainty leads to higher expected returns following good news and lower expected returns following bad news. This happens as information is slowly incorporated into prices. [Zhang \(2006\)](#) investigates this hypothesis using price momentum to distinguish good news from bad news, and a number of indicators such as dispersion in analyst earnings forecasts and stock market volatility to proxy for information uncertainty. Ultimately, greater information uncertainty should predict relatively lower future returns for past losers and relatively higher future returns for past winners. In his empirical evidence, he finds that the profitability of the momentum strategy that buys past winners and sells past losers is enhanced in periods of high uncertainty as opposed to periods of low uncertainty.

Similarly to [Zhang \(2006\)](#), we study the interaction between price momentum and information uncertainty in foreign exchange markets. We view this exercise as a preliminary check to understand whether our measures of macro forecast dispersion can be understood as proxies of information uncertainty. Each month, we sort currencies into three baskets using the past exchange rate returns from $t - 1$ to t as in [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012b\)](#). For each basket, we then sort currencies into two groups by means of information uncertainty level. To proxy for information uncertainty, we use country-specific measures of forecast dispersion on current account, inflation rate, short-term interest rate, real economic growth and foreign exchange rate as defined in Equations (3.1)-(3.2). As additional measures of information uncertainty, we also use 1-month foreign exchange implied volatilities from at-the-money currency options traded over-the-counter (*iv*).

TABLE 3.1 ABOUT HERE

Table 3.1 presents the performance of currency momentum strategies when investors face periods of high and low uncertainty, which we denote as u_h and u_l , respectively. Panel A shows the interaction between price momentum and information uncertainty. Consider, for instance, the double sorted strategy when we measure uncertainty by means of current account dispersion. The excess return from a trading strategy with a long position in past winners and a short

position in past losers is as high as 3.83% (3.72%) per annum in periods of high uncertainty and as low as 1.15% (1.51%) per annum in periods of low uncertainty when we use *Blue Chip Economic Indicators* (*Consensus Forecasts*) data. The return differential $u_h - u_l$ between these momentum strategies is 2.68% per annum for *Blue Chip Economic Indicators*, and 2.21% per annum for *Consensus Forecasts*. The return differential is generally positive but less pronounced when uncertainty is proxied by the additional macroeconomic forecast dispersions, and negative when implied volatilities act as a proxy of uncertainty. Overall, we find that there is consistent evidence for the link between price momentum and information uncertainty when the latter is proxied by macroeconomic forecast dispersions as opposed to volatility measures.¹⁵

In Panel B, we test the null hypothesis of equal return differentials $u_h - u_l$ for different proxies of uncertainty. The first column, for instance, reports the t -statistics for the null hypotheses that $u_h - u_l$ for current account uncertainty is the same as $u_h - u_l$ based on other proxies of uncertainty. We reject the null hypothesis with a t -statistic of 2.86 (1.99) when we compare current account uncertainty to implied volatility for *Blue Chip Economic Indicators* (*Consensus Forecasts*) data. In general, we fail to reject the null when we compare macro forecast dispersions, whereas we tend to reject the null when we compare macro forecast dispersions to foreign exchange implied volatility.

Our results seem to suggest that our measures of macro forecast dispersion are likely to proxy for information uncertainty whereas implied volatility largely reflects other phenomena. This is consistent with [Bekaert, Hoerova, and Lo Duca \(2013\)](#) who find that option implied volatility is partly driven by factors associated with time-varying risk-aversion rather than economic uncertainty. In a similar vein, [Della Corte, Ramadorai, and Sarno \(2014\)](#) find that volatility risk premia computed as difference between realized volatilities and currency option implied volatilities indicate the costs of insuring against currency volatility fluctuations. In sum, we construct currency portfolios sorted on past price momentum and different proxies of information uncertainty, and find empirically that macro forecast dispersions can be thought as proxies of information uncertainty.

¹⁵Our results remain virtually unchanged if one uses 12-month currency option implied volatilities as well as model-free implied volatilities as in [Della Corte, Ramadorai, and Sarno \(2014\)](#).

3.5 Country-level asset pricing

We start our cross-sectional asset pricing tests using individual currency excess returns as test assets and macro uncertainty shocks (or innovations) as non-traded pricing factors. While working with assets grouped into portfolios is popular in the literature as it improves the estimates of the time-series slope coefficients, it can dramatically influence the asset pricing results. [Lo and MacKinlay \(1990\)](#) show that forming portfolios of assets can potentially create data-snooping biases whereas [Lewellen, Nagel, and Shanken \(2010\)](#) show that grouping assets into portfolios creates a strong factor structure whose consequence is that any factors weakly correlated with the characteristics used to sort the test portfolios will be able to explain the differences in average returns across them. More recently, [Ang, Liu, and Schwarz \(2010\)](#) advocate the use of individual assets suggesting that the greater dispersion in the cross-section of factor loadings reduces the variability of the risk-premium estimator, i.e. forming portfolios can potentially destroy information by shrinking the dispersion of betas. By using individual returns, we will address at the outset the concerns highlighted by these recent literature. We will run traditional portfolio-level cross-sectional regressions in the next section.

Macro uncertainty shocks. We use macro uncertainty shocks as non-traded pricing factors and denote them as Δu_m . Since the first differences of our forecast dispersion measures are significantly autocorrelated – the first-order autocorrelation ranges from -0.44 to -0.24 for *Blue Chip Economic Indicators*, and from -0.30 to 0.33 for *Consensus Forecasts* – we estimate a univariate autoregressive process (AR) as in [Mancini, Rinaldo, and Wrampelmeyer \(2013\)](#) and [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012a\)](#), and then use the resulting innovations (with zero mean and unit standard deviation) as unexpected shocks to macro uncertainty. We include a constant and two lags in the AR model as determined by the Box-Jenkins methodology.¹⁶ We report the correlation matrix of Δu_m for both *Blue Chip Economic Indicators* and *Consensus Forecasts* in Table 3.2. We find that Δu_{ca} is generally the least correlated with the other macro uncertainty shocks, thus suggesting that Δu_{ca} is likely to reflect information that is not fully

¹⁶We also estimate a vector autoregressive process (VAR) with two lags but results remain qualitatively identical. Results are reported in the Internet Appendix

captured by other candidate pricing factors. In contrast, the highest level of correlation is observed for Δu_{if} and Δu_{rg} in both surveys.

TABLE 3.2 ABOUT HERE

Information uncertainty, however, may arise broadly from all macro forecast dispersions as opposed to be related to a specific economic force. We capture this common variation as in [Bali, Brown, and Tang \(2015\)](#) by taking the first principal component of Δu_m which we refer to as Δu_{pc} . Moreover, in the spirit of [Petkova \(2006\)](#), we also orthogonalize our macro uncertainty shocks by projecting each Δu_m onto the competing group of pricing factors

$$\Delta u_{m,t} = a + \sum_{j \neq m} b_j \Delta u_{j,t} + \sigma_m \varepsilon_{m,t}. \quad (3.1)$$

and then taking the standardized projection residuals, $\varepsilon_{m,t}$. By construction, the vector of residuals is uncorrelated with the right-hand side variables and contains information that cannot be explained by these group of candidate pricing measures. To keep the notation simple, we will continue to refer to orthogonalized shocks as $\Delta u_{m,t}$.

Cross-sectional asset pricing tests. For each currency i , we compute the excess return as $RX_t^i = \gamma_{t-1}^i \times (S_t^i - F_{t-1}^i) / S_{t-1}^i$, where S_t^i and F_t^i are the spot and 1-month forward exchange rate, respectively, defined as units of US dollars per unit of foreign currency i , respectively, and γ_t^i is an indicator function. We set $\gamma_t^i = 1$ when the forward discount $(S_t^i - F_t^i) / S_t^i$ in deviation from its cross-sectional median is positive (the excess return originates from buying the foreign currency and selling the US dollar), and $\gamma_t^i = -1$ when the forward discount $(S_t^i - F_t^i) / S_t^i$ in deviation from its cross-sectional median is negative (the excess return arises from selling the foreign currency and buying the US dollar). We thus obtain individual excess returns that are consistent with the popular dollar-neutral carry trade strategy (e.g., [Lustig, Roussanov, and Verdelhan, 2011](#)). We adjust the excess returns for the bid-ask spread as described in the data section, and express them in percentage per month.

The literature in international finance typically employs a two-factor pricing kernel. The first factor is the expected market excess return approximated by the average excess return on

a portfolio strategy that invest in foreign money markets with equal weights while borrowing in the US money market, generally referred to as *dol* factor. As the second factor, we use the macro uncertainty shocks defined above. Since the set of currencies is unbalanced, we only report estimates of the factor prices and the cross-sectional R^2 obtained via [Fama and MacBeth \(1973\)](#)-type procedure. In the first step, we run time-series regressions of each country's i excess return on a constant, and the factors *dol* and Δu_m as follows:

$$RX_t^i = a^i + \beta_{dol}^i dol_t + \beta_m^i \Delta u_{m,t} + \varepsilon_t^i. \quad (3.2)$$

In the second step, we perform cross-sectional regressions of all currency excess returns on betas as

$$RX_t^i = \beta_{dol}^i \lambda_{dol,t} + \beta_m^i \lambda_{m,t} + \alpha_t^i, \quad (3.3)$$

and estimate λ and α^i as the average of the cross-sectional regression estimates, i.e. $\hat{\lambda}_c = T^{-1} \sum_{t=1}^T \hat{\lambda}_{c,t}$ and $\hat{\alpha}^i = T^{-1} \sum_{t=1}^T \hat{\alpha}_t^i$. We add no constant in the second stage of [Fama and MacBeth \(1973\)](#) regression as the *dol* factor has no cross-sectional relation with currency returns, and it works as a constant that allows for a common mispricing (e.g., [Lustig, Roussanov, and Verdelhan, 2011](#); [Burnside, 2011](#)).

TABLE 3.3 ABOUT HERE

Panel A of Table 3.3 presents cross-sectional asset pricing results for both *Blue Chip Economic Indicators* and *Consensus Forecasts*. The dollar factor price, λ_{dol} , as expected, is never statistically different from zero. Turning to macro uncertainty shocks, the price is negative and highly statistically significant only for current account uncertainty shocks: λ_{ca} ranges from -0.64 (with a robust t -statistic of -3.16) for *Blue Chip Economic Indicators* to -0.51 (with a robust t -statistic of -3.03) for *Consensus Forecasts*. The prices of additional macro uncertainty shocks – inflation rate, short-term interest rate, real economic growth and foreign exchange rate – show no sign of statistical significance. The cross-sectional R^2 for Δu_{ca} tends to be reasonably high, 34% for *Blue Chip Economic Indicators* and 36% for *Consensus Forecasts*, but lower than the R^2 typically uncovered for portfolio-based asset pricing tests. This is expected as individual excess returns are far more noisy than portfolio returns.

Despite being intuitive and appealing, the Fama-MacBeth procedure employs pre-estimated betas in the second stage regression, and this requires an adjustment to the cross-sectional standard errors of the factor price estimates. [Shanken \(1992\)](#), for instance, provides such a correction under the assumption of normally distributed errors. Since the residuals may exhibit heteroscedasticity and autocorrelation, we construct standard errors (and confidence regions) via the stationary bootstrap of [Politis and Romano \(1994\)](#). The exercise consists of 1,000 replications in which blocks with random length of individual currency excess returns and risk factor realizations are simulated with replacement from the original sample without imposing the model’s restrictions. We provide full details on the bootstrap algorithm in the [Appendix 3.A](#). We report bolded factor prices when we detect statistical significance at 5% (or lower) using our bootstrapped standard errors and confidence intervals. The estimates of λ maintain their statistical significance for Δu_{ca} across both surveys, thus confirming that currency excess returns can be thought of as compensation for exposure to current account uncertainty shocks.

Formation dates. As described in [Section 3.3](#), we assume that forecasts are formed on the day prior to the submission date to mitigate the effect of stale forecasts. This means that RX_t^i – the monthly excess return for currency i at time t defined above – is computed at the end of the month when we use *Blue Chip Economic Indicators*’s forecasts, and on the business day prior to the second Monday of the month when we employ *Consensus Forecasts*’s forecasts.

FIGURES [3.2](#) AND [3.3](#) ABOUT HERE

We now perform a simple exercise to show that our choice is not affecting the key results presented earlier. We sample individual excess returns up to five business days before (after) the default formation date and re-estimate the Fama-MacBeth regressions in [Equations \(3.2\) and \(3.3\)](#). In [Figure 3.2](#), we report the estimates of the factor price and the 95% confidence interval based on Newey-West standard errors for *Blue Chip Economic Indicators*’ forecasts. The first panel displays the estimates of λ_{ca} which remain negative and statistically significant up to four (two) days before (after) the default formation date. For the other macro uncertainty measures, we find no evidence that changing the formation date would enhance their statistical significance. In [Figure 3.3](#), we repeat the exercise for *Consensus Forecasts*’ data and conclusions remain largely

the same. In particular, the estimates of λ_{ca} remain negative and statistically significant up to four (five) days before (after) the default formation date.¹⁷ In contrast, we find no evidence of statistical significance for the competing macro uncertainty shocks. In brief, this exercise seems to suggest that our choice to define a monthly forecast formation date is not driving our key results.

Horse race analysis. The dispersion of analyst forecasts on current account may simply contain information already incorporated in other macro uncertainty indicators. *Panel B* of Table 3.3 presents asset pricing tests with orthogonalized shocks as defined in Equation (3.1) and find qualitatively identical results. We report some evidence for real economic growth, but the sign of λ is positive, is not in line with a risk-based explanation of currency excess returns, and is not robust to changes in empirical modelling. *Panel C* of Table 3.3 runs a horse race exercise between current account and the competing pricing factors. Here we use orthogonalized uncertainty shocks as described in Equation (3.1) only for current account. We find that information in Δu_{ca} is different with respect to the information scattered in other macro uncertainty measures. The estimates of λ_{ca} remain always negative and statistically significant ranging from -0.78 (with a t -statistic of -3.62) to -0.65 (with a t -statistic of -3.08) for *Blue Chip Economic Indicators*, and from -0.78 (with a t -statistic of -3.91) to -0.68 (with a t -statistic of -4.18) for *Consensus Forecasts*. Moreover, results remain consistent when we perform our bootstrap exercise.

We also consider all measures of macro uncertainty shocks as pricing factors (with current account uncertainty shocks orthogonalized with respect to all other macro uncertainty shocks), and uncover the following Fama-MacBeth estimates:

$$\widehat{E}[RX^i] = 0.12\beta_{dol}^i - \mathbf{0.49}\beta_{ca}^i + 0.20\beta_{if}^i - 0.25\beta_{ir}^i + 0.21\beta_{rg}^i + 0.41\beta_{fx}^i \quad (3.4)$$

[0.86] [-2.16] [1.14] [-1.26] [0.96] [1.72]

$$\widehat{E}[RX^i] = 0.13\beta_{dol}^i - \mathbf{0.84}\beta_{ca}^i + 0.03\beta_{if}^i + 0.20\beta_{ir}^i + 0.10\beta_{rg}^i + 0.04\beta_{fx}^i. \quad (3.5)$$

[0.94] [-4.64] [0.18] [1.75] [0.53] [0.14]

where $\widehat{E}[RX^i]$ denotes the average excess return for currency i predicted by the model whereas the β s are the slope estimates from the first-stage Fama-MacBeth regressions. We display t -statistics

¹⁷Recall that *Consensus Forecasts'* data for Latin American and Eastern European countries are submitted on the third Monday of the month, but we treat them for convenience as the G7-Western Europe and Asia Pacific countries' forecasts (submitted on the second Monday of the month). This could explain why λ_{ca} remains statistical significant up to a week after the default formation date.

based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection in brackets. In addition, we bold the factor prices when we find statistical significance at 5% (or lower) using our bootstrap exercise. Equation (3.4) refers to *Blue Chip Economic Indicators* whereas Equation (3.5) pertains to *Consensus Forecasts* data. The estimate of λ_{ca} is -0.49 on the former (with a t -statistic of -2.16) and -0.84 on the latter survey (with a t -statistic of -4.64), and confirms our findings on current account uncertainty.

FIGURE 3.4 ABOUT HERE

We present the fit of the asset pricing models defined in Equations (3.4) and (3.5) in Figure 3.4. We plot the actual average excess returns along the vertical axis, and the average predicted excess returns along the horizontal axis. The symbols refer to the developed nations' currencies (solid circle), most liquid emerging market currencies (solid plus), and other countries's currencies (diamond).¹⁸ The model-predicted excess returns lie very close to the 45 degree line, suggesting that current account uncertainty shocks explain the spread in average excess returns reasonably well for most of the countries. The largest pricing errors are found for currencies that are pegged or subject to capital controls as for Brazil (BRL), Egypt (EGP), Indonesia (IDR), Ireland (IEP), Israel (ILS), and Slovenia (SIT). We also compute the average pricing error across all currencies α that turns out to be equal to 0.13% per annum for *Blue Chip Economic Indicators*, and to 0.46% per annum for *Consensus Forecasts*.

Developed countries. We construct our proxy of current account uncertainty using a large cross-section of developed and emerging market countries. Because of large international capital flows, it can be argued that emerging market economies run volatile capital account positions and as a result are more likely to suffer from current account instability than developed countries. Hence, one might be concerned that our proxy of current account uncertainty is mainly capturing information that stems from emerging market countries.

TABLE 3.4 ABOUT HERE

¹⁸The developed countries include Australia, Belgium, Canada, Denmark, Euro Area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom, whereas Brazil, Czech Republic, Hungary, South Korea, Mexico, Poland, Singapore, Turkey, Taiwan and South Africa denote the most liquid emerging market countries (see, for instance, the Deutsche Bank Global Currency Harvest Index).

To address this question, we reconstruct our measures of macro uncertainty using only forecasts for developed (or “G-10”) economies, and report the new asset pricing tests in Table 3.4. As test assets, we keep the same set of country-level excess returns used in the previous table. Overall, our results remain qualitatively identical to the previous table as λ_{ca} remains statistically significant using either robust standard errors or bootstrapped confidence intervals. We thus reject the hypothesis that our measure of current account uncertainty is mainly driven by emerging market countries.

Currency sub-samples. Do illiquid or non-traded currencies drive our key result? We address this question by considering two subsets of currencies. In the first subset, we use the financial openness index of Chinn and Ito (2006) and remove from the test assets those countries that impose capital account restrictions and thus affect severely the actual trading of their currencies.¹⁹ In the second subset, we employ the exchange rate classification index of Ilzetzi, Reinhart, and Rogoff (2011) and retain only floating and quasi-floating currencies as test assets.²⁰

TABLE 3.5 ABOUT HERE

We report these asset pricing tests in Table 3.5. In *Panel A*, we keep time- t country-level excess return when the openness index is greater than or equal to zero. In *Panel B*, we keep time- t country-level returns when the classification code ranges from 9 to 13. These regimes comprise currencies which are in a pre-announced crawling band that is wider than or equal to $+/-2\%$, a de facto crawling band that is narrower than or equal to $+/-2\%$, a moving band that is narrower than or equal to $+/-2\%$, a managed float, or a free float. As pricing factors, we use the same factors used in *Panel B* of Table 3.3. Overall, we find no qualitative change in our key empirical results as λ_{ca} remains negative and highly statistically significant using either robust standard errors or bootstrapped confidence regions. The evidence brings to the same conclusion, that is, current account uncertainty is an important determinant of excess returns in foreign exchange markets.

¹⁹The data are available on Hiro Ito’s website at yearly frequency. We construct monthly observations by forward filling, i.e. we keep end-of-period data constant until a new observation becomes available. Note that the Chinn-Ito index is not available for Taiwan. In this case, we rely on the capital account liberalization index of Kaminsky and Schmukler (2008), available on Graciela Kaminsky’s website.

²⁰The data are available on Ethan Ilzetzi’s website at monthly frequency until the end of 2010. We extend the sample to July 2013 by forward filling.

Additional robustness checks with country-level returns. We examine our main results using a variety of additional specifications and find no qualitative changes of our findings. We report these additional results in the Internet Appendix: (i) we use the first difference of the macro uncertainty series rather than their AR-estimated innovations as pricing factors in Table 3.C.1; (ii) we estimate a VAR with two lags to compute macro uncertainty innovations in Table 3.C.2; (iii) (iv) we replace foreign exchange volatility innovations with VIX innovations and equity market uncertainty shocks in Table 3.C.3; (iv) we employ simple long-short individual excess returns constructed by setting $\gamma_t^i = 1(-1)$ when the forward discount is positive (negative) in Table 3.C.4; (v) we proxy cross-sectional dispersion using a range-based estimator for *Consensus Forecasts*’s data in Table 3.C.5; and (vi) we run country-level asset pricing tests for additional economic indicators covered by *Consensus Forecasts* in Table 3.C.7.

3.6 Asset pricing with portfolios

In this section, we run cross-sectional asset pricing tests using portfolio-level excess returns. The empirical results confirm that currency excess returns can be seen as a reward for bearing unexpected uncertainty shocks to external imbalances.

Portfolio-level excess returns. A number of recent papers construct portfolios excess returns by grouping currencies into baskets on the basis of their forward discounts (or equivalently, using the interest rate differential relative to the US dollar). We follow this literature and form six portfolios as in Lustig, Roussanov, and Verdelhan (2011) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) using $t - 1$ information such that the first portfolio (P_1) contains low-yielding currencies and the sixth and last portfolio (P_6) comprises high-yielding currencies. We refer to them as carry trade portfolios. Portfolios sorted on forward discounts, however, may not provide an exhaustive description of currency excess returns as the latter may depend not only on interest rate differentials but also on countries’ external imbalances as Gabaix and Maggiori (2015) show in a novel theory of exchange rate determination based on capital flows and imperfect financial markets. The authors show that currency excess returns are higher when interest rate differentials are larger and the investment (funding) currency’s country is a net foreign debtor

(creditor) economy. The model developed by [Gabaix and Maggiori \(2015\)](#) assumes for tractability that each country borrows or lends in its own currency. In practice, a number of economies – typically emerging market countries – cannot issue all their external liabilities in domestic currency. [Gourinchas and Rey \(2007\)](#), [Gourinchas \(2008\)](#) and [Lane and Shambaugh \(2010\)](#) consider the role of currency denomination of external liabilities in the process of re-equilibration of external imbalances showing that countries with a propensity to issue liabilities in foreign currencies should experience larger currency depreciations.

[Della Corte, Riddiough, and Sarno \(2015\)](#) take these predictions to the data and construct portfolios sorted on $t - 1$ information about countries' net foreign asset positions as percentage of the gross domestic product, and the percentage share of external liabilities denominated in foreign currency such that the first portfolio (P_1) contains the currency of the largest net creditor economies with the highest share of foreign liabilities denominated in domestic currency whereas the sixth and last portfolio (P_6) comprises the currency of the largest net debtor countries with the largest share of foreign liabilities denominated in foreign currency.²¹ More recently, [Colacito, Croce, Gavazzoni, and Ready \(2015\)](#) provide a unified theoretical framework using a frictionless risk-sharing model with recursive preferences that replicates the properties of the carry trade portfolios and the global imbalance portfolios.

Consistent with this recent literature, we complement the carry trade portfolios with the global imbalance portfolios in order to fully characterize the cross-section of portfolio-based currency excess returns. We use RX_t^j to denote the equally-weighted average of the individual currency excess returns falling within each portfolio j in period t . We adjust excess returns for bid-ask spreads as described in the data section and express them in percentage per month. In particular, we assume that investors go short foreign currencies in the first portfolio and long foreign currencies in the remaining portfolios of each strategy.

Asset pricing methods. In the absence of arbitrage opportunities, the risk-adjusted expected excess return on each portfolio j is zero, i.e. Euler equation holds:

$$E[RX_t^j M_t] = 0, \tag{3.1}$$

²¹We refer to their work for the underlying data description and the construction methodology.

with a linear stochastic discount factor (SDF) given by $M_t = 1 - (h_t - \mu)'b$, where h_t denotes the vector of pricing factors, b is the vector of factor loadings and μ denotes the factor means (e.g., [Cochrane, 2005](#)). This specification implies the following beta pricing model:

$$E[RX_t^j] = \lambda' \beta^j \quad (3.2)$$

where expected excess returns depend on factor prices λ and risk quantities β^j , the regression coefficients of each portfolio j excess returns on the risk factors. The relationship between the factor prices in Equation (3.2) and the factor loadings in equation (3.1) is given by $\lambda = \Sigma_h b$ with Σ_h denoting the covariance matrix of the factors. We estimate the parameters of Equation (3.1) via the generalized method of moments (GMM) of [Hansen \(1982\)](#) with a prespecified weighting matrix. The factor means μ and the individual elements of Σ_h are estimated jointly with the factor loadings b by adding the corresponding moment conditions to those implied by the Euler equation. In this way we incorporate the potential uncertainty induced by the estimation of the means and the covariance matrix elements of the factors (e.g., [Burnside, 2011](#); [Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a](#)). For more details on the estimation procedure consult the Appendix 3.B.

Asset pricing models only provide an approximation of reality, and their respective SDFs are misspecified proxies for the true unknown SDF. [Hansen and Jagannathan \(1997\)](#) propose the minimum distance between the stochastic discount factor of an asset pricing model and the set of admissible SDFs as a natural measure of model misspecification, generally interpreted as the normalized maximum pricing error of the set of test assets. We construct the distance metric of [Hansen and Jagannathan \(1997\)](#) by choosing the model's parameters b such that $d_T(b) = \sqrt{\min g_T'(b) G_T^{-1} g_T(b)}$, where $g_T(b)$ is the vector of sample average of pricing errors and G_T is the second moment matrix of the test asset returns.

Asset pricing results. Table 3.6 reports GMM estimates of b and implied λ , the cross-sectional R^2 and the Hansen-Jagannathan (HJ) distance measure. We report t -statistics based on [Newey and West \(1987\)](#) standard errors with optimal lag length selection according [Andrews \(1991\)](#). Note that standard errors for λ are obtained via delta method. We also report simulated p -values to test whether the HJ distance is equal to zero using a weighted sum of χ^2 -distributed random

variables as in [Jagannathan and Wang \(1996\)](#). As described above, we use portfolio-level excess returns adjusted for bid-ask spreads for *carry trade* and *global imbalance* portfolios as test assets. As pricing factors, we use the *dol* and the orthogonalized macro uncertainty shocks Δu_m .

TABLE 3.6 ABOUT HERE

We focus on the sign and the statistical significance of the factor price λ . We find negative and statistically significant estimates of the prices attached to current account uncertainty shocks: λ_{ca} ranges from -1.58 (with a t -statistic of -2.60) for *Blue Chip Economic Indicators* to -1.29 (with a t -statistic of -4.36) for *Consensus Forecasts*. Here, a negative estimate of the factor price means higher currency premia for portfolios whose returns co-move negatively with current account uncertainty shocks, and lower currency premia for portfolios exhibiting a positive covariance with current account uncertainty shocks (i.e. uncertainty hedges). We also find that the model with current account uncertainty shocks produces a strong cross-sectional fit with R^2 s of more than 80%. We are unable to reject the null that the HJ distance is equal to zero with large p -values. Moreover, the values of the HJ distance for current account uncertainty shocks are smaller than the ones generated by the competing macro uncertainty shocks. For the latter, we find some evidence of statistical significance for λ , but we always reject the null that the HJ distance is equal to zero. Thus, we conclude that these models suffer from severe model misspecification.

As pointed out by a growing literature, ignoring model misspecification can lead to the erroneous conclusion that a risk factor is priced, despite it not contributing to the pricing ability of the model (e.g., [Kan and Robotti, 2009](#); [Gospodinov, Kan, and Robotti, 2014](#); [Bryzgalova, 2015](#)). This happens as standard estimation and inference techniques become unreliable when factors are only weakly correlated (or uncorrelated) with test asset returns.

FIGURE 3.5 ABOUT HERE

Figure 3.5 reports the sample correlations between our macro uncertainty shocks and the excess returns on the long-short strategies (i.e. P_6 minus P_1) arising from the *carry trade* and *global imbalance* portfolios. We refer to them as *CAR* and *IMB* factors, respectively. The sample correlation between Δu_{ca} and *CAR* evolves around 14% whereas the sample correlation between

Δu_{ca} and IMB ranges between 13% and 20%. In contrast, the competing macro uncertainty shocks display a somewhat lower sample correlation, on average, below 5%.

Model comparison. The Hansen-Jagannathan metric is often used to rank the performance of asset pricing models. Despite being a powerful tool, it provides no method for a statistical comparison. Suppose for instance that the value of model A's HJ is less than the value of model B's HJ, are they also statistically different from each other once we account for the sampling error? [Chen and Ludvigson \(2009\)](#) have addressed this question by proposing a procedure to compare statistically HJ distances of K competing models using the reality check method of [White \(2000\)](#). Let $j = 1, \dots, K$ index the asset pricing models reported in [Table 3.6](#), with $j = 1$ being the model delivering the smallest HJ distance among the K competing models, i.e. the model based on current account uncertainty shocks. The null hypothesis is

$$H_0 : \max_{j=2, \dots, K} (d_{T,1}^2 - d_{T,j}^2) \leq 0,$$

where $d_{T,j}^2$ denotes the squared HJ distance associated with model j . This hypothesis translates into saying that model 1 (the one based on current account uncertainty shocks) has the smallest pricing error among the K competing models according to the HJ distance. The alternative hypothesis

$$H_1 : \max_{j=2, \dots, K} (d_{T,1}^2 - d_{T,j}^2) > 0,$$

implies that at least one of the competing models has a smaller pricing error than model 1 in terms of HJ distance. We use the White's reality check test statistic $\mathcal{T}^W$ based on [White \(2000\)](#), and the Hansen's modified reality check test statistic $\mathcal{T}^H$ based on [Hansen \(2005\)](#), which are defined as

$$\mathcal{T}^W = \max_{j=2, \dots, K} \sqrt{T}(d_{T,1}^2 - d_{T,j}^2), \quad \mathcal{T}^H = \max(\mathcal{T}^W, 0).$$

We compute bootstrap estimates of the p -values via the stationary bootstrap (i.e. resampling blocks of random lengths) of [Politis and Romano \(1994\)](#) as

$$p_W = \frac{1}{R} \sum_{r=1}^R \#(\mathcal{T}_r^W > \mathcal{T}^W), \quad p_H = \frac{1}{R} \sum_{r=1}^R \#(\mathcal{T}_r^H > \mathcal{T}^H),$$

where R is the number of bootstrap replications, and $\#$ denotes the number of times the bootstrapped statistics is larger than the sample one. Since this is a one-sided test, the critical value is the equal to the 95th percentile of the bootstrap test statistic when we use a 5% level of significance. Therefore, we reject the null hypothesis if p_W or p_H are less than 0.05, otherwise we do not reject the null. Table 3.6 shows that we are unable to reject the null hypothesis – the model based on Δu_{ca} has the smallest pricing errors among the universe of models based on Δu_m – with large p -values: p_W ranges from 0.92 to 0.95 whereas p_H from 0.62 to 0.31 when moving across surveys.²²

We also run a simple horse race exercise as an alternative statistical procedure to check whether current account uncertainty shocks survive in the presence of other macro uncertainty shocks. While we use orthogonalized shocks for current account uncertainty, we leave the competing pricing factor unorthogonalized.

TABLE 3.7 ABOUT HERE

We report these results in Table 3.7 and find strong evidence that Δu_{ca} is not driven out by the competing Δu_m . We uncover statistical significance in favor of Δu_{ca} for both b and implied λ estimates. While λ asks whether the factor j is priced, b asks whether factor j helps price assets given the other factors. Overall, the empirical evidence reported in Tables 3.6-3.7 coupled with the sample correlations in Figure 3.5 confirm our key results on the pricing performance of the current account uncertainty shocks.

3.7 Robustness and extensions

This section presents additional empirical evidence in support of our key results presented earlier.

Controlling for volatility risk. One may expect that market participants disagree more when volatility is high. This gives rise to larger forecast dispersions which in turn may be reflected in our measures of macro uncertainty. We control for volatility risk by augmenting our set of pricing factors with the global foreign exchange volatility innovations of [Menkhoff, Sarno, Schmeling, and](#)

²²Results remain qualitatively similar if we use either *carry trade* or *global imbalance* portfolios separately as test assets. See Tables 3.C.12-3.C.13 in the Internet Appendix.

Schrimpf (2012a). We calculate the absolute daily exchange rate return for each currency in our sample, average across them, and then average daily values up to the monthly frequency such that $\sigma_{fx,t} = T_t^{-1} \sum_{\tau \in T_t} (\sum_{k \in K_\tau} |\Delta s_\tau^k| / K_\tau)$, where Δs_τ^k is the daily log exchange rate return for currency k , K_τ denotes the number of available currencies on day τ , and T_t denotes the total number of trading days over the month prior to day t (i.e. monthly observations are calculated on the forecast formation dates described in the data section). Finally, we fit an AR(1) process and use the resulting residuals (with zero mean and unit standard deviation) as volatility innovations $\Delta\sigma_{fx}$.

TABLE 3.8 ABOUT HERE

We report asset pricing tests in Table 3.8 where the test assets are the portfolio-based excess returns described in the previous section. We find that current account uncertainty shocks remain priced even after controlling for volatility risk: b_{ca} ranges from -1.91 (with a robust t -statistic of -2.53) for *Blue Chip Economic Indicators* to -1.030 (with a robust t -statistic of -4.07) for *Consensus Forecasts*. In contrast, the factor loading attached to volatility risk b_σ turns out to be statistically insignificant for both surveys, thus suggesting that volatility risk does not help price the cross-section of currency excess returns over current account uncertainty shocks.²³ Nonetheless, $\Delta\sigma_{fx}$ helps price currency excess returns when we use the alternative measures of macro uncertainty shocks.

Controlling for policy uncertainty. In addition to controlling for volatility risk, we also check for policy uncertainty as another potential driver of our results. When monetary and economic policies become more credible, macro indicators are easier to forecasts and market participants may disagree less about their future outcomes. In Table 3.C.14 in the Internet Appendix, we proxy for monetary policy uncertainty using the cross-country variations in policy interest rates. Following Dovern, Fritsche, and Slacalek (2012) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), we average the absolute daily changes in the 1-month interest rate across all currencies in our sample, and then average daily values up to the monthly frequency such that

²³Results remain largely comparable when macro uncertainty shocks are orthogonalized against volatility risk innovations as the sample correlations tend to be low. For instance, across surveys, we find that $Corr(\Delta u_{ca}, \Delta\sigma_{fx})$ ranges between 5% and 8%.

$u_{mp,t} = T_t^{-1} \sum_{\tau \in T_t} (\sum_{k \in K_\tau} |\Delta i_\tau^k| / K_\tau)$, where Δi_τ^k is the daily change in the 1-month interest rate for currency k . In Table 3.C.15, we employ the news-based economic policy uncertainty measure of Baker, Bloom, and Davis (2013). We average daily values up to the monthly frequency such that $u_{ep,t} = T_t^{-1} \sum_{\tau \in T_t} u_\tau$, where u_τ is the economic policy uncertainty on day τ . We construct shocks by fitting univariate autoregressive processes and then taking the resulting (standardized) residuals. Overall, we find no change in our core results for both *Blue Chip Economic Indicators* and *Consensus Forecasts*.

Liquidity as an alternative explanation. A considerable amount of the recent literature investigates the link between uncertainty and market liquidity. Routledge and Zin (2009) and Easley and O'Hara (2010), for instance, show in theory that market liquidity (and in turn trading activity) dries up when traders face periods of high uncertainty as in the recent 2007-2009 financial crisis. Battalio and Schultz (2011) examine the September 2008 short sale restrictions and find empirically a negative relationship between regulatory uncertainty and market liquidity in the equity options market. More recently, Chung and Chuwonganant (2014) provide evidence that aggregate market uncertainty, proxied by the VIX, explains the dynamics of market liquidity of individual stocks.

A related literature studies the effect of funding liquidity conditions on international trade following the severe shocks to the banking and financial sector during the recent financial crisis. Chor and Manova (2012) find that countries with higher interbank rates and hence tighter credit conditions experienced a large decline in their exports during the peak of the crisis, and the effect was larger for industries that are more sensitive to the cost of external capital or have limited access to buyer-supplier trade credit. Amiti and Weinstein (2011) show that banks engaged in trade finance are key to understand the collapse of exports during crises. Since higher credit default risks and working-capital loans due to longer time lags associated with international trade make exporting firms more dependent on banks for their exports, shocks to the supply of trade finance can affect firm-level exports during banking crises. In addition, Niepmann and Schmidt-Eisenlohr (2014) find evidence that the decline in the supply of trade finance is more pronounced when economic uncertainty is high and firms export to riskier markets. Intuitively, in response

to a deterioration in trade finance, exporting firms could either reduce their exports or switch to non-intermediated international trade through cash-in-advance and open-account transactions. As any outcomes between these extremes – detrimental impact on cross-border trade or completely unaffected trade – is possible, uncertainty about international trade is likely to rise and our current account forecast dispersion could simply reflect changes in trade finance conditions. Put it differently, current account forecast dispersion could result from funding conditions that tighten simultaneously for both international firms and international investors involved in carry trade.²⁴

Motivated by these lines of research, we examine the extent to which our key result is robust to controlling for liquidity risk. While funding liquidity and market liquidity are endogenously related (see, for instance, [Brunnermeier and Pedersen, 2009](#)), we provide evidence using proxies for both concepts of liquidity. In [Table 3.9](#), we construct the market liquidity factor of [Karnaukh, Ranaldo, and Söderlind \(forthcoming\)](#) and then run portfolio-level asset pricing tests using its innovations $\Delta mliq$ as an additional pricing factor.²⁵

TABLE 3.9 ABOUT HERE

We find for both surveys that market liquidity shocks are unable drive out the pricing power of current account uncertainty shocks. While the coefficients b associated with current account uncertainty remain statistically significant with a negative sign, they turns out to be insignificant for market liquidity shocks. We find that b_{ca} ranges from -1.70 (with a t -statistic of -2.39) for *Blue Chip Economic Indicators* to -1.07 (with a t -statistic of -4.06) for *Consensus Forecasts* while b_{mliq} ranges from 0.05 (with a t -statistic of 0.16) for *Blue Chip Economic Indicators* to -0.19 (with a t -statistic of -0.93) for *Consensus Forecasts*. In contrast, innovations to market liquidity tend to price the cross-section of currency excess returns when compared to the other measures of macro uncertainty shocks.

²⁴This story, however, would be consistent with countries' uniform exposure to changes in trade finance conditions. In contrast, causality might run in the opposite direction and be in line with the model of [Gabaix and Maggiori \(2015\)](#). When global uncertainty about current account sustainability is high, banks engaged in trade finance might reduce their supply of trade finance to firms exporting to countries with large international exposure. This would make more costly for those country to maintain negative external positions thus facing higher risk premia for holding their currencies.

²⁵We follow the authors' methodology using daily bid and ask quotes from Bloomberg and daily mid, low and high quotes from Thomson Reuters via Datastream for 30 floating currency pairs. We refer to their paper for additional details.

In Table 3.C.16 in the Internet Appendix, we proxy global funding liquidity using the cross-country average of the LIBOR-OIS spread – a barometer of distress in the money market and an indicator of the overall wellbeing of the banking system – for major economies. We then run portfolio-level asset pricing tests using its innovations $\Delta fliq$ as an additional pricing factor. Results remain largely comparable to those reported in Table 3.9.

Does current account uncertainty reflect fundamental volatility? A natural question to ask is whether the dispersion in current account forecasts truly captures the conditional volatility of future external imbalances. To answer this question, we fit for each country i in our test asset space the following stochastic volatility model:

$$\begin{aligned} y_{i,t} &= \kappa_{i,t} + v_{i,t}\varepsilon_{i,t} \\ v_{i,t} &= \exp\{h_{i,t}/2\} \\ h_{i,t} &= \mu_i + \phi_i(h_{i,t-1} - \mu_i) + \nu_i\eta_{i,t}, \end{aligned}$$

where $y_{i,t}$ is the observed net exports of goods and services normalized by GDP at time t , $\kappa_{i,t}$ is the conditional mean modeled using a constant and an autoregressive process of order p determined by the Bayesian information criterion, $h_{i,t}$ is the unobserved log-volatility with unconditional mean μ_i , persistence parameter ϕ_i , and volatility ν_i . We use data on net exports as proxy for current account positions as the former are available at monthly frequency whereas the latter are only available at quarterly frequency. Similarly to Jurado, Ludvigson, and Ng (2015), we first estimate the conditional mean $\kappa_{i,t}$ via least squares, and then obtain the stochastic volatility parameters μ_i , ϕ_i and ν_i from the least square residuals via the simulated maximum likelihood approach of Malik and Pitt (2011).²⁶

We then proxy the global volatility of external imbalances by simply taking the cross-sectional average of country-level volatilities as $v_t = K_t^{-1} \sum_{i \in K_t} \hat{v}_{i,t}$, where the “hat” indicates the estimated value of $v_{i,t}$ and K_t denotes the number of available currencies at time t . Finally, we link the volatility of external imbalances to current account uncertainty by running the following predictive

²⁶Alternatively, we use a Bayesian algorithm as in Della Corte, Sarno, and Tsiakas (2009) but results remain qualitatively identical. This method, however, may be sensitive to prior distributions when the data sample is small.

regression

$$v_{t+12} = \alpha_v + \beta_v u_{ca,t} + \sum_{i=-j}^j b_{v,i} \Delta u_{ca,t-i} + \epsilon_{t+12} \quad (3.1)$$

where Δ denotes the first difference operator and the 12-month lag is dictated by the fact that $u_{ca,t}$ is constructed using one-year ahead forecasts. Since both v_t and $u_{ca,t}$ are highly persistent and we fail to reject the null of unit root using conventional unit root tests, we estimate the coefficients α_v and β_v using the dynamic least squares technique of [Stock and Watson \(1993\)](#). This method generates optimal estimates of the cointegrating parameters in a multivariate setting by adding leads and lags of the first difference of the right-hand side variables to a standard least squares regression to eliminate the effects of regressor endogeneity on the distribution of the least squares estimator. Note that cointegration is associated with long-run comovements and the above predictive regression should not be regarded as providing information about short-term unbiasedness of current account uncertainty as predictor of future volatility of external imbalances. Instead, this regression provides information about the nature of the long-run relation between the two volatility measures.

We implement the regression in Equation (3.1) using monthly data from July 1994 (July 1993) to July 2014 (July 2013) for v_t ($u_{ca,t}$) and obtain the following point estimates (ignoring coefficient estimates on leads and lags whose number is determined according to the Bayesian information criterion) for the parameters α_v and β_v :

$$v_t = \underset{[35.56]}{0.67} + \underset{[5.25]}{0.92} u_{ca,t-12} + \epsilon_t \quad R^2 = 11\% \quad (3.2)$$

$$v_t = \underset{[34.69]}{0.52} + \underset{[15.93]}{0.23} u_{ca,t-12} + \epsilon_t \quad R^2 = 67\%, \quad (3.3)$$

where Equation (3.2) reports results *Blue Chip Economic Indicators* and Equation (3.3) for *Consensus Forecasts* data, and heteroscedasticity corrected t -statistics appear in brackets below the coefficient estimates. The sign and statistical significance of β_v suggest that current account uncertainty is strongly related the future volatility of external imbalances for both surveys. We also examine a number of additional specifications and find no qualitative changes of our findings: (i) we apply HP-filter with a smoothing parameter equal to 1600 to each series $y_{i,t}$ before fitting the

stochastic volatility model, (ii) we control Equation (3.1) for the 12-month lagged v_t , and (iii) we control Equation (3.1) for the 12-month lagged global volatility of exchange rates constructed as the cross-sectional average of country-level volatilities computed using either stochastic volatility or realized volatility.

3.8 Conclusion

A recent literature shows that carry trade investors are compensated for bearing global risk (Lustig, Roussanov, and Verdelhan, 2011; Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a). This paper contributes to this literature and provides novel empirical evidence on the fundamental driver of this long-standing phenomenon. Using a unique dataset of agents' expectations from the two independent surveys of international macro forecasts, we construct cross-sectional forecast dispersions on current account, short-term interest rate, inflation rate, real economic growth and foreign exchange rate which we interpret as proxies of macro uncertainty. We then test empirically whether these measures of uncertainty play a role in the cross-section of currency excess returns using a linear asset pricing framework. We find that investment currencies deliver low returns whereas funding currencies offer a hedge when current account uncertainty suddenly spikes. Our results support the recent theoretical contribution of Gabaix and Maggiori (2015) who provide a novel theory of exchange rate determination based on capital flows with imperfect financial markets. Overall, we show that currency excess returns can be rationalized as compensation for unexpected shocks to current account uncertainty.

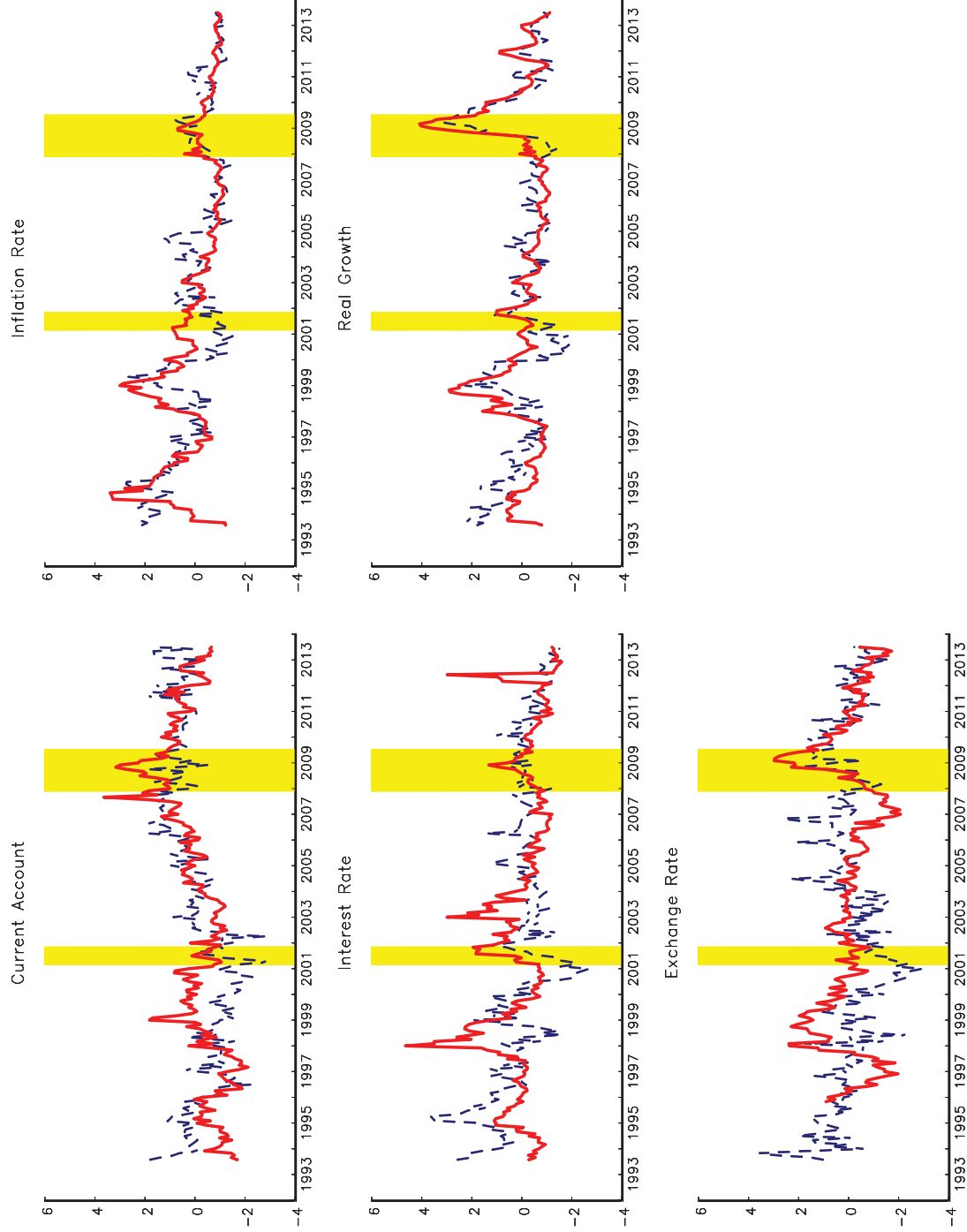


Figure 3.1: Measures of macro uncertainty

The figure presents measures of macro uncertainty constructed as cross-country averages of forecast dispersions. We use international macro forecasts collected from *Blue Chip Economic Indicators* survey (dashed line) and *Consensus Forecasts* survey (solid line). Shaded areas denote United States NBER-dated recession periods. We display standardized measures with zero means and unit variances for ease of comparison. The sample runs from July 1993 to July 2013.

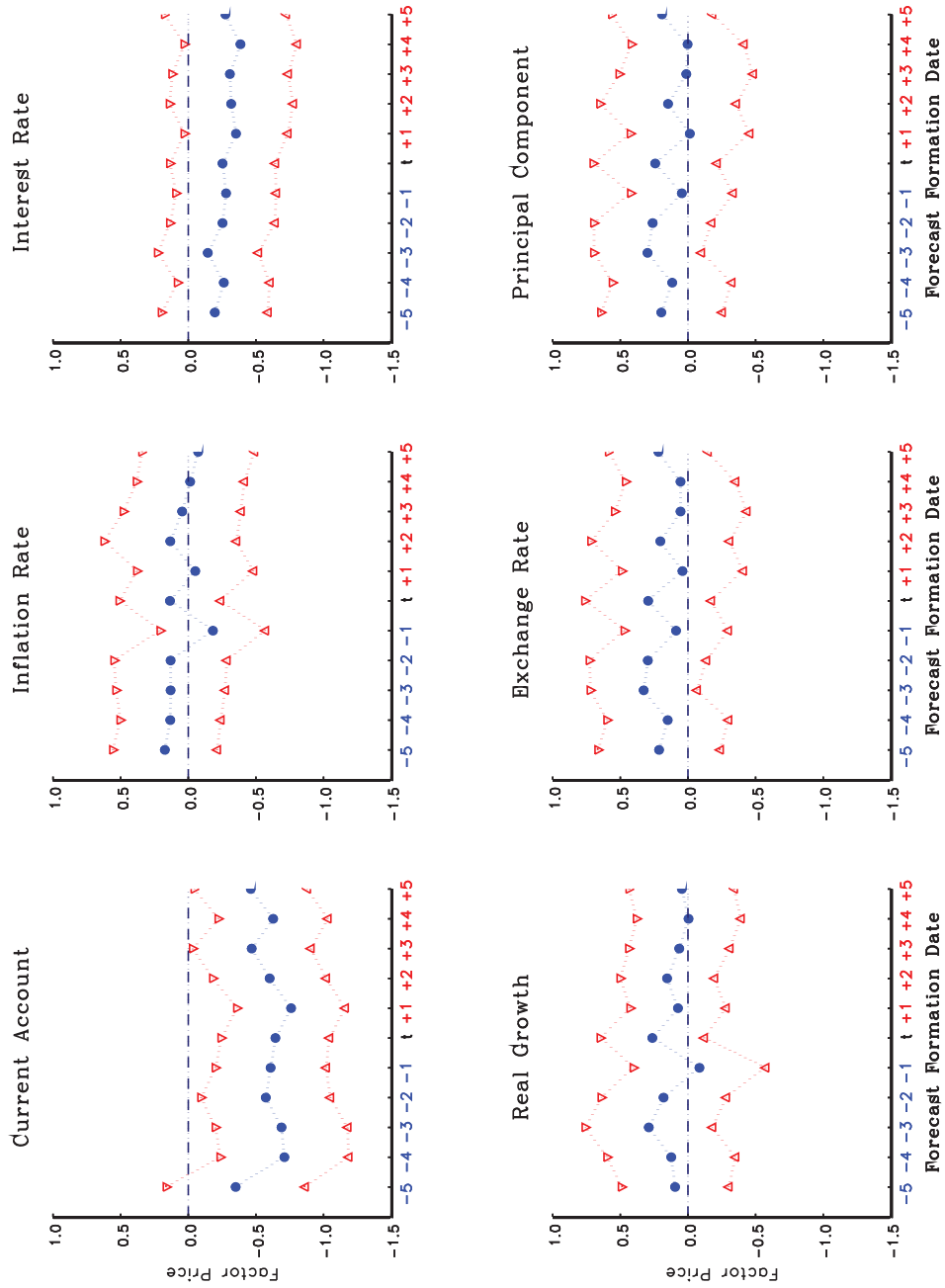


Figure 3.2: Forecasts formation dates: Blue Chip Economic Indicators

The figure presents estimates of the prices attached to macro uncertainty shocks (λ_m) when we use different forecast formation dates for *Blue Chip Economic Indicators* expectations. The test assets are individual excess returns computed on the business day prior to submission date in t (the default case used throughout this paper), five business days before in $t - 5$, and five business days after in $t + 5$. The dashed-dotted (blue) line denotes factor prices obtained via Fama-MacBeth procedure. The dashed-triangle (red) lines denote the 95% confidence interval based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length. Excess returns are monthly and net of bid-ask spreads. The sample runs from July 1993 to July 2013.

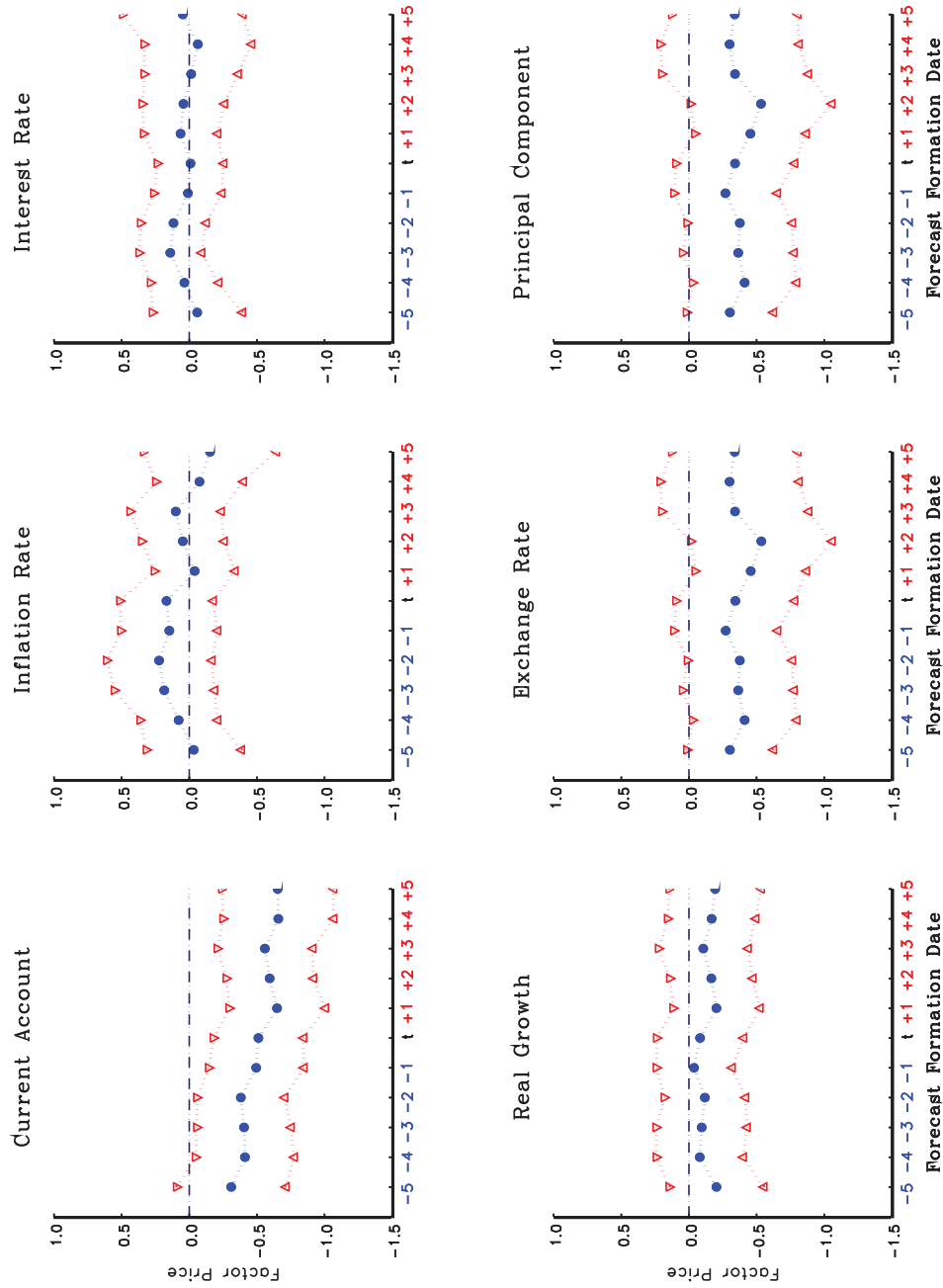


Figure 3.3: Forecasts formation dates: Consensus Forecasts

The figure presents estimates of the prices attached to macro uncertainty shocks (λ_m) when we use different forecast formation dates for *Consensus Forecasts* expectations. The test assets are individual excess returns computed on the business day prior to submission date in t (the default case used throughout this paper), five business days before in $t - 5$, and five business days after in $t + 5$. The dashed-dotted (blue) line denotes factor prices obtained via Fama-MacBeth procedure. The dashed-triangle (red) lines denote the 95% confidence interval based on [Newey and West \(1987\)](#) standard errors with [Andrews \(1991\)](#) optimal lag length. Excess returns are monthly and net of bid-ask spreads. The sample runs from July 1993 to July 2013.

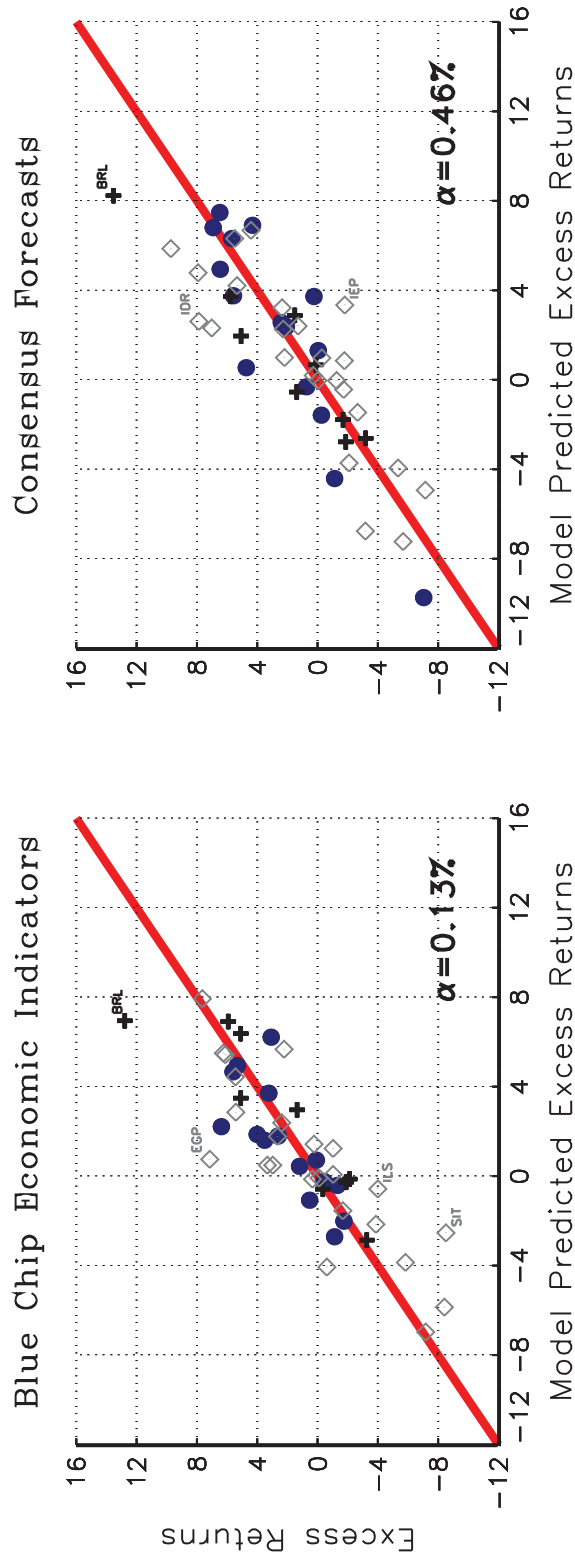


Figure 3.4: Pricing errors: individual excess returns

The figure presents cross-sectional pricing errors for the linear factor model based on the dollar (dol), and current account (Δu_{ca}), inflation rate (Δu_{if}), short-term interest rate (Δ_{ir}), real economic growth (Δ_{rg}), and foreign exchange rate (Δ_{fx}) uncertainty shocks. The test assets are country-level excess returns. The symbols denote the pricing errors of developed countries (solid circle), emerging countries (solid plus), and other countries (diamond). Excess returns are expressed in percentage per annum, and are net of bid-ask spreads. α denotes the average pricing error in percentage per annum. The sample runs from July 1993 to July 2013. Exchange rates are from *DataStream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*.

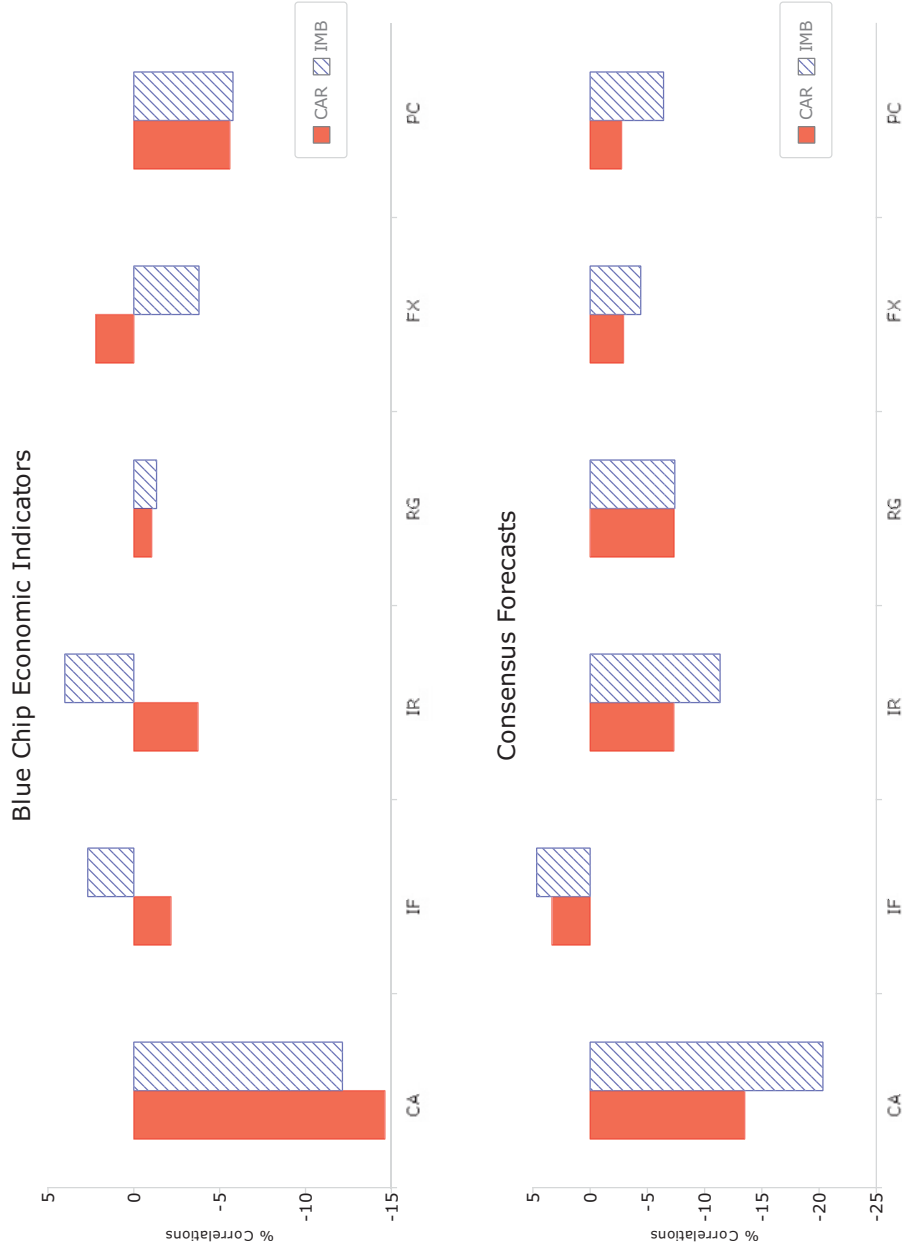


Figure 3.5: Portfolio-level excess returns and macro uncertainty shocks

The figure presents the sample correlations between macro uncertainty shocks and excess returns on the long-short strategies (i.e. P_6 minus P_1) arising from the *carry trade* and *global imbalance portfolios*. We refer to them as *CAR* and *IMB*, respectively. Macro uncertainties are constructed as cross-country averages of forecast dispersions on current account (*ca*), inflation rate (*if*), short-term interest rate (*ir*), real economic growth (*rg*), and foreign exchange rate (*fx*). Excess returns are net of bid-ask spreads. The sample runs from July 1993 to July 2013. Exchange rates are from *Datstream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*.

Table 3.1: Portfolio sorted on past returns and proxies of uncertainty

This table presents currency portfolios sorted first into three buckets using past 1-month spot currency percentage changes, and then into two groups by information uncertainty level. To proxy for uncertainty, we use country-specific measures of forecast dispersion on current account (ca), inflation rate (if), short-term interest rate (ir), real economic growth (rg), and foreign exchange rate (fx), and 1-month implied volatilities (iv) from at-the-money currency options. *Panel A* reports the average return from a strategy that buys past winners and sells past losers in periods of high uncertainty u_h and in periods of low uncertainty u_l . The mean return differential is denoted as $u_h - u_l$. Excess returns are reported annualized in percentage. *Panel B* presents t -statistics for the null hypothesis of equal return differentials $u_h - u_l$ between any two different proxies of information uncertainty. We compute t -statistics using [Newey and West \(1987\)](#) standard errors with [Andrews \(1991\)](#) optimal lag length. The sample runs from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*. Implied volatility data are from JP Morgan.

	Blue Chip Economic Indicators						Consensus Forecasts					
	ca	if	ir	rg	fx	iv	ca	if	ir	rg	fx	iv
Panel A: Momentum returns under high and low uncertainty												
u_l	1.15	1.33	2.67	0.76	1.55	5.23	1.51	1.56	2.38	2.30	2.85	3.60
u_h	3.83	3.23	1.24	3.33	3.78	-1.43	3.72	4.95	3.53	3.98	4.07	-2.06
$u_h - u_l$	2.68	1.90	-1.43	2.58	2.22	-6.65	2.21	3.39	1.15	1.68	1.22	-5.66
Panel B: Testing for equal return differentials $u_h - u_l$												
if	0.23						-0.76					
ir	1.20	0.97					0.32	0.87				
rg	0.03	-0.20	-1.18				0.03	0.72	-0.17			
fx	0.11	-0.10	-0.90	0.10			0.34	0.77	0.02	0.12		
iv	2.86	2.64	1.61	2.76	2.66		1.99	2.77	2.25	2.15	1.67	

Table 3.2: Sample correlation: macro uncertainty

This table presents the sample correlations of macro uncertainty shocks on current account (*ca*), inflation rate (*if*), short-term interest rate (*ir*), real economic growth (*rg*), and foreign exchange rate (*fx*). The sample runs from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*.

	Blue Chip Economic Indicators				Consensus Forecasts			
	<i>ca</i>	<i>if</i>	<i>ir</i>	<i>rg</i>	<i>ca</i>	<i>if</i>	<i>ir</i>	<i>rg</i>
<i>if</i>	0.19				0.13			
<i>ir</i>	0.30	0.37			0.08	0.11		
<i>rg</i>	0.15	0.55	0.37		0.14	0.50	0.24	
<i>fx</i>	0.23	0.34	0.36	0.41	0.02	0.09	0.12	0.18

Table 3.3: Country-level asset pricing tests: macro uncertainty

This table presents country-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (*dol*) and macro uncertainty shocks (Δu_m) computed as innovations to the cross-country average of forecast dispersions on current account (*ca*), inflation rate (*if*), short-term interest rate (*ir*), real economic growth (*rg*), and foreign exchange rate (*fx*). The first principal component of these innovations is referred to as *pc*. Orthogonalized macro uncertainty shocks are computed by projecting each Δu_m on the remaining uncertainty shocks. The table reports estimates of the factor price λ obtained via Fama-MacBeth procedure, the cross-sectional R^2 , and the *t*-statistic – based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length – in brackets. A bolded λ denotes statistical significance at 5% (or lower) obtained via 1,000 stationary bootstrap repetitions. All excess returns are net of bid-ask spreads. The sample runs from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*.

Blue Chip Economic Indicators					Consensus Forecasts		
<i>m</i>	λ_{dol}	λ_m	λ_{ca}	R^2	λ_m	λ_{ca}	R^2
Panel A: macro uncertainty							
<i>ca</i>	0.13 [1.06]	-0.64 [-3.16]		34% [1.25]	-0.51 [-3.03]		36%
<i>if</i>	0.12 [0.91]	0.14 [0.71]		26% [0.72]	0.17 [0.97]		21%
<i>ir</i>	0.13 [1.04]	-0.25 [-1.28]		28% [0.77]	-0.01 [-0.07]		20%
<i>rg</i>	0.12 [0.93]	0.26 [1.35]		42% [0.82]	-0.08 [-0.51]		12%
<i>fx</i>	0.13 [1.01]	0.29 [1.24]		39% [0.83]	-0.34 [-1.54]		34%
Panel B: (orthogonalized) macro uncertainty							
<i>ca</i>	0.12 [0.95]	-0.74 [-3.44]		32% [1.39]	-0.67 [-3.76]		48%
<i>if</i>	0.14 [1.13]	-0.06 [-0.26]		33% [0.71]	0.42 [2.13]		26%
<i>ir</i>	0.14 [1.09]	-0.41 [-1.91]		33% [0.76]	-0.01 [-0.06]		19%
<i>rg</i>	0.13 [1.06]	0.31 [1.56]		36% [0.74]	-0.20 [-1.05]		17%
<i>fx</i>	0.15 [1.16]	0.49 [1.91]		47% [0.86]	-0.48 [-1.71]		41%
<i>pc</i>	0.13 [0.99]	0.24 [1.04]		36% [0.77]	-0.28 [-1.21]		22%
Panel C: macro vs. (orthogonalized) current account uncertainty							
<i>if</i>	0.10 [0.77]	0.18 [0.92]	-0.78 [-3.62]	40% [1.37]	0.36 [2.16]	-0.78 [-4.47]	52%
<i>ir</i>	0.12 [0.90]	-0.17 [-0.86]	-0.65 [-3.08]	35% [1.39]	0.19 [1.46]	-0.78 [-3.91]	47%
<i>rg</i>	0.10 [0.80]	0.27 [1.40]	-0.68 [-3.36]	47% [1.49]	0.18 [0.97]	-0.78 [-3.97]	49%
<i>fx</i>	0.12 [0.92]	0.23 [0.97]	-0.65 [-3.13]	45% [1.09]	0.01 [0.04]	-0.68 [-4.18]	60%
<i>pc</i>	0.12 [0.90]	0.17 [0.74]	-0.65 [-3.17]	42% [1.35]	0.05 [0.23]	-0.69 [-4.23]	54%

Table 3.4: Country-level asset pricing tests: macro uncertainty for developed countries

This table presents country-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (*dol*) and macro uncertainty shocks (Δu_m) computed as innovations to the cross-country average of forecast dispersions on current account (*ca*), inflation rate (*if*), short-term interest rate (*ir*), real economic growth (*rg*), and foreign exchange rate (*fx*) for developed countries. The first principal component of these innovations is referred to as *pc*. Orthogonalized macro uncertainty shocks are computed by projecting each Δu_m against the remaining ones. The table reports estimates of the factor price λ obtained via Fama-MacBeth procedure, the cross-sectional R^2 , and the *t*-statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length in brackets. A bolded λ denotes statistical significance at 5% (or lower) obtained via 1,000 stationary bootstrap repetitions. All excess returns are net of bid-ask spreads. The sample runs from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*, respectively.

Blue Chip Economic Indicators					Consensus Forecasts			
<i>m</i>	λ_{dol}	λ_m	λ_{ca}	R^2	λ_{dol}	λ_m	λ_{ca}	R^2
Panel A: macro uncertainty								
<i>ca</i>	0.13 [0.98]	-0.67 [-2.54]		32%	0.12 [0.89]	-0.75 [-2.77]		27%
<i>if</i>	0.11 [0.88]	0.10 [0.43]		39%	0.11 [0.86]	-0.07 [-0.41]		20%
<i>ir</i>	0.13 [0.96]	-0.10 [-0.50]		33%	0.12 [0.94]	0.09 [0.51]		24%
<i>rg</i>	0.15 [1.13]	0.29 [1.10]		39%	0.10 [0.78]	-0.25 [-1.19]		24%
<i>fx</i>	0.13 [1.04]	0.30 [1.33]		52%	0.10 [0.73]	-0.16 [-0.84]		38%
Panel B: (orthogonalized) macro uncertainty								
<i>ca</i>	0.13 [0.98]	-0.70 [-2.88]		39%	0.12 [0.93]	-0.84 [-3.23]		50%
<i>if</i>	0.14 [1.08]	-0.05 [-0.23]		34%	0.11 [0.83]	0.02 [0.10]		27%
<i>ir</i>	0.14 [1.04]	-0.21 [-1.05]		33%	0.11 [0.86]	0.09 [0.55]		35%
<i>rg</i>	0.16 [1.22]	0.26 [1.12]		32%	0.09 [0.70]	-0.23 [-1.28]		31%
<i>fx</i>	0.14 [1.08]	0.35 [1.61]		56%	0.10 [0.75]	-0.15 [-0.80]		43%
<i>pc</i>	0.13 [1.04]	0.29 [1.29]		52%	0.10 [0.73]	-0.16 [-0.83]		38%
Panel C: macro vs. (orthogonalized) current account uncertainty								
<i>if</i>	0.10 [0.79]	0.15 [0.59]	-0.74 [-3.05]	51%	0.18 [1.37]	0.36 [2.16]	-0.78 [-4.47]	52%
<i>ir</i>	0.12 [0.92]	-0.15 [-0.83]	-0.63 [-2.86]	41%	0.18 [1.39]	0.19 [1.46]	-0.78 [-3.91]	47%
<i>rg</i>	0.15 [1.11]	0.30 [1.29]	-0.73 [-3.40]	51%	0.20 [1.49]	0.18 [0.97]	-0.78 [-3.97]	49%
<i>fx</i>	0.13 [1.00]	0.16 [0.80]	-0.55 [-2.43]	55%	0.14 [1.09]	0.01 [0.04]	-0.68 [-4.18]	60%
<i>pc</i>	0.13 [0.99]	0.15 [0.72]	-0.55 [-2.45]	54%	0.18 [1.35]	0.05 [0.23]	-0.69 [-4.23]	54%

Table 3.5: Country-level asset pricing tests: sub-samples of currencies

This table presents country-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (*dol*) and macro uncertainty shocks (Δu_m) computed as innovations to the cross-country average of forecast dispersions on current account (*ca*), inflation rate (*if*), short-term interest rate (*ir*), real economic growth (*rg*), and foreign exchange rate (*fx*). The first principal component of these innovations is referred to as *pc*. Current account uncertainty shocks are orthogonalized against the remaining uncertainty shocks. In *Panel A*, we remove the currencies subject to capital controls using the financial openness index of [Chinn and Ito \(2006\)](#), i.e. we remove a currency when the index has a negative value. In *Panel B*, we retain floating and quasi-floating currencies using the exchange rate classification index of [Ilzetzi, Reinhart, and Rogoff \(2011\)](#), i.e. we retain a currency with a classification code ranging from 9 to 13. The table reports estimates of the factor price λ obtained via Fama-MacBeth procedure, the cross-sectional R^2 , and the *t*-statistic based on [Newey and West \(1987\)](#) standard errors with [Andrews \(1991\)](#) optimal lag length in brackets. A bolded λ denotes statistical significance at 5% (or lower) obtained via 1,000 stationary bootstrap repetitions. All excess returns are net of bid-ask spreads. The sample runs from July 1993 to July 2013. Exchange rates are from *DataStream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*.

<i>m</i>	Blue Chip Economic Indicators				Consensus Forecasts			
	λ_{dol}	λ_m	λ_{ca}	R^2	λ_{dol}	λ_m	λ_{ca}	R^2
	Panel A: without currencies subject to capital controls							
<i>if</i>	0.13 [0.97]	0.09 [0.48]	-0.72 [0.48]	26% [-2.84]	0.12 [0.91]	0.22 [1.11]	-0.75 [-3.62]	58%
<i>ir</i>	0.12 [0.86]	-0.19 [-0.93]	-0.56 [-0.93]	10% [-2.40]	0.14 [1.08]	0.14 [0.99]	-0.87 [-4.25]	62%
<i>rg</i>	0.11 [0.82]	0.38 [1.72]	-0.84 [1.72]	34% [-3.41]	0.13 [1.03]	0.11 [0.57]	-0.68 [-3.13]	54%
<i>fx</i>	0.11 [0.83]	0.15 [0.65]	-0.71 [0.65]	40% [-2.91]	0.10 [0.77]	-0.08 [-0.39]	-0.53 [-3.07]	63%
<i>pc</i>	0.11 [0.83]	0.09 [0.41]	-0.70 [0.41]	37% [-2.90]	0.13 [0.95]	0.17 [0.76]	-0.72 [-3.66]	57%
	Panel B: without fixed-exchange rate currencies							
<i>if</i>	0.14 [0.94]	0.19 [0.97]	-0.79 [0.97]	40% [-3.64]	0.16 [1.15]	0.36 [2.15]	-0.78 [-4.55]	51%
<i>ir</i>	0.17 [1.16]	-0.16 [-0.83]	-0.65 [-0.83]	32% [-3.02]	0.17 [1.23]	0.18 [1.41]	-0.78 [-3.97]	48%
<i>rg</i>	0.13 [0.93]	0.28 [1.39]	-0.69 [1.39]	46% [-3.34]	0.18 [1.32]	0.18 [0.98]	-0.79 [-4.03]	49%
<i>fx</i>	0.16 [1.08]	0.23 [0.99]	-0.64 [0.99]	44% [-3.03]	0.12 [0.91]	0.02 [0.10]	-0.70 [-4.28]	59%
<i>pc</i>	0.15 [1.06]	0.17 [0.76]	-0.65 [0.76]	42% [-3.08]	0.16 [1.19]	0.06 [0.25]	-0.70 [-4.31]	53%

Table 3.6: Portfolio-level asset pricing tests: macro uncertainty

This table presents portfolio-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (dol) and macro uncertainty shocks (Δu_m) computed as innovations to the cross-country average of forecast dispersions on current account (ca), inflation rate (if), short-term interest rate (ir), real economic growth (rg), and foreign exchange rate (fx). The first principal component of these innovations is referred to as pc . All macro uncertainty shocks are orthogonalized by projecting each Δu_m on the remaining uncertainty shocks. As test assets, we employ six portfolios sorted on forward discounts (carry trade portfolios) and six portfolios sorted on net foreign asset positions and the share of external liabilities denominated in foreign currency (global imbalance portfolios). The table reports estimates of the factor loadings b , factor price λ and cross-sectional R^2 obtained via GMM procedure. t -statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. HJ denotes the Hansen and Jagannathan (1997) distance measure (with simulated p -value in parentheses) for the null hypothesis that the normalized maximum pricing error is equal to zero. $\mathcal{T}^W$ and $\mathcal{T}^H$ denote the White (2000) and Hansen (2005) reality check test statistics for the null hypothesis that the model based on ca has the smallest pricing error according to the squared HJ distance. We report p -values in parentheses obtained via 10,000 stationary bootstrap repetitions. Excess returns are net of bid-ask spreads and expressed in percentage per month. The portfolios are rebalanced monthly from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* (Panel A) and *Consensus Forecasts* (Panel B).

m	b_{dol}	b_m	λ_{dol}	λ_m	R^2	HJ	$\mathcal{T}^W$	$\mathcal{T}^H$					
Panel A: Blue Chip Economic Indicators													
ca	0.11	[1.67]	-1.60	[-2.70]	0.19	[1.50]	-1.58	[-2.70]	86%	0.31	(0.37)	(0.92)	(0.62)
if	0.09	[2.31]	-0.66	[-2.76]	0.20	[1.55]	-0.65	[-2.74]	23%	0.36	(0.01)		
ir	0.10	[1.51]	-1.83	[-2.17]	0.19	[1.46]	-1.82	[-2.20]	31%	0.37	(0.01)		
rg	0.05	[1.16]	-0.13	[-0.53]	0.19	[1.47]	-0.14	[-0.59]	16%	0.37	(0.01)		
fx	0.06	[1.36]	-0.05	[-0.20]	0.20	[1.53]	-0.06	[-0.21]	15%	0.36	(0.01)		
pc	0.04	[0.70]	-0.89	[-2.57]	0.19	[1.56]	-0.89	[-2.96]	39%	0.37	(0.01)		
Panel B: Consensus Forecasts													
ca	-0.03	[-0.67]	-1.30	[-4.01]	0.18	[1.46]	-1.29	[-4.36]	86%	0.23	(0.72)	(0.95)	(0.31)
if	-0.04	[-0.76]	1.46	[2.58]	0.19	[1.67]	1.45	[2.54]	34%	0.34	(0.01)		
ir	0.00	[0.00]	-1.49	[-2.60]	0.19	[1.53]	-1.48	[-2.98]	49%	0.34	(0.01)		
rg	0.02	[0.47]	-0.61	[-2.34]	0.18	[1.51]	-0.61	[-2.63]	28%	0.34	(0.01)		
fx	-0.04	[-0.71]	-1.29	[-2.72]	0.15	[1.25]	-1.28	[-3.12]	58%	0.36	(0.05)		
pc	0.01	[0.12]	-0.91	[-2.63]	0.19	[1.67]	-0.91	[-2.98]	48%	0.33	(0.03)		

Table 3.7: Portfolio-level asset pricing tests: horse race

This table presents portfolio-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (dol) and macro uncertainty shocks (Δu_m) computed as innovations to the cross-country average of forecast dispersions on current account (ca), inflation rate (if), short-term interest rate (ir), real economic growth (rg), and foreign exchange rate (fx). The first principal component of these innovations is referred to as pc . Current account uncertainty shocks are orthogonalized by projecting each Δu_{ca} on the remaining uncertainty shocks. As test assets, we employ six portfolios sorted on forward discounts (carry trade portfolios) and six portfolios sorted on net foreign asset positions and the percentage share of foreign currency-denominated external liabilities (global imbalance portfolios). The table reports estimates of the factor loadings b , factor price λ and cross-sectional R^2 obtained via GMM procedure. t -statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. HJ denotes the Hansen and Jagannathan (1997) distance measure (with simulated p -value in parentheses) for the null hypothesis that the normalized maximum pricing error is equal to zero. Excess returns are net of bid-ask spreads and expressed in percentage per month. The portfolios are rebalanced monthly from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* (Panel A) and *Consensus Forecasts* (Panel B).

m	b_{dol}	b_m	b_{ca}	λ_{dol}	λ_m	λ_{ca}	R^2	HJ							
Panel A: Blue Chip Economic Indicators															
if	0.11	[1.71]	-0.42	[-1.11]	-1.36	[-2.59]	0.19	[1.41]	-0.41	[-1.15]	-1.34	[-2.62]	88%	0.31	(0.33)
ir	0.11	[1.45]	-0.01	[-0.02]	-1.60	[-2.69]	0.19	[1.38]	0.00	[-0.01]	-1.58	[-2.68]	86%	0.31	(0.38)
rg	0.12	[1.77]	0.17	[0.48]	-1.71	[-2.68]	0.19	[1.42]	0.16	[0.47]	-1.69	[-2.68]	87%	0.30	(0.45)
fx	0.12	[1.72]	0.24	[0.62]	-1.75	[-2.70]	0.19	[1.45]	0.23	[0.66]	-1.72	[-2.71]	87%	0.29	(0.52)
pc	0.12	[1.71]	0.23	[0.60]	-1.76	[-2.70]	0.19	[1.45]	0.10	[0.30]	-1.73	[-2.70]	87%	0.30	(0.51)
Panel B: Consensus Forecasts															
if	-0.02	[-0.44]	-0.23	[-0.61]	-1.26	[-3.92]	0.18	[1.44]	-0.14	[-0.36]	-1.24	[-4.24]	86%	0.23	(0.64)
ir	-0.04	[-0.77]	-0.42	[-1.28]	-1.04	[-3.85]	0.18	[1.44]	-0.44	[-1.48]	-1.03	[-4.33]	89%	0.23	(0.66)
rg	-0.03	[-0.72]	-0.10	[-0.41]	-1.22	[-3.87]	0.18	[1.44]	-0.03	[-0.15]	-1.21	[-4.20]	86%	0.23	(0.63)
fx	-0.04	[-1.08]	-0.42	[-1.54]	-1.00	[-3.55]	0.15	[1.13]	-0.41	[-1.59]	-1.01	[-3.12]	81%	0.28	(0.49)
pc	-0.04	[-0.85]	-0.29	[-0.94]	-1.14	[-3.74]	0.18	[1.49]	-0.23	[-0.80]	-1.11	[-3.75]	88%	0.23	(0.68)

Table 3.8: Portfolio-level asset pricing tests: volatility risk

This table presents portfolio-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (dol), macro uncertainty shocks (Δu_m) and foreign exchange volatility shocks ($\Delta \sigma_{fx}$). Δu_m are constructed as innovations to the cross-country average of forecast dispersions on current account (ca), inflation rate (if), short-term interest rate (ir), real economic growth (rg), and foreign exchange rate (fx). The first principal component of these innovations is referred to as pc . All macro uncertainty shocks are then orthogonalized by projecting each Δu_m against the remaining ones. $\Delta \sigma_{fx}$ is constructed as innovations to the cross-country average of foreign exchange rate volatilities. As test assets, we employ six portfolios sorted on forward discounts (carry trade portfolios) and six portfolios sorted on net foreign asset positions and the percentage share of foreign currency-denominated external liabilities (global imbalance portfolios). The table reports estimates of the factor loadings b , factor price λ and cross-sectional R^2 obtained via GMM procedure. t -statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. HJ denotes the Hansen and Jagannathan (1997) distance measure (with simulated p -value in parentheses) for the null hypothesis that the normalized maximum pricing error is equal to zero. Excess returns are net of bid-ask spreads and expressed in percentage per month. The portfolios are rebalanced monthly from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*, respectively.

m	b_{dol}	b_m	b_σ	λ_{dol}	λ_m	λ_σ	R^2	HJ							
Panel A: Blue Chip Economic Indicators															
ca	0.14	[1.72]	-1.91	[-2.53]	0.16	[0.61]	0.19	[1.47]	-1.88	[-2.49]	0.09	[0.37]	87%	0.31	(0.29)
if	0.00	[0.02]	-0.91	[-2.83]	-0.61	[-2.99]	0.18	[1.40]	-0.88	[-2.76]	-0.56	[-4.28]	72%	0.33	(0.04)
ir	-0.02	[-0.37]	-0.32	[-0.51]	-0.53	[-2.22]	0.18	[1.36]	-0.33	[-0.54]	-0.53	[-3.82]	58%	0.35	(0.01)
rg	-0.01	[-0.27]	0.95	[2.27]	-0.81	[-2.96]	0.18	[1.59]	0.83	[2.13]	-0.66	[-3.67]	73%	0.32	(0.11)
fx	-0.03	[-0.54]	0.42	[1.30]	-0.59	[-2.77]	0.17	[1.34]	0.37	[1.14]	-0.54	[-4.20]	59%	0.33	(0.08)
pc	-0.04	[-0.70]	0.10	[0.39]	-0.61	[-2.73]	0.18	[1.35]	0.01	[0.03]	-0.57	[-4.42]	58%	0.34	(0.04)
Panel B: Consensus Forecasts															
ca	-0.03	[-0.94]	-1.03	[-4.07]	-0.20	[-0.94]	0.18	[1.46]	-1.03	[-4.31]	-0.25	[-1.55]	89%	0.23	(0.65)
if	-0.03	[-0.78]	0.42	[0.98]	-0.53	[-2.17]	0.18	[1.47]	0.45	[1.03]	-0.55	[-3.74]	67%	0.31	(0.03)
ir	-0.03	[-0.59]	-0.95	[-2.07]	-0.47	[-2.95]	0.18	[1.57]	-0.94	[-2.52]	-0.46	[-3.81]	79%	0.31	(0.05)
rg	0.00	[-0.10]	0.72	[2.27]	-0.92	[-3.53]	0.18	[1.47]	0.57	[1.98]	-0.80	[-4.38]	74%	0.31	(0.07)
fx	-0.04	[-1.02]	-0.39	[-0.98]	-0.49	[-2.23]	0.15	[1.08]	-0.54	[-1.64]	-0.62	[-4.52]	65%	0.35	(0.04)
pc	-0.01	[-0.19]	0.35	[1.06]	-0.76	[-2.97]	0.17	[1.46]	0.11	[0.36]	-0.64	[-4.68]	66%	0.31	(0.04)

Table 3.9: Portfolio-level asset pricing tests: market liquidity risk

This table presents portfolio-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (dol), macro uncertainty shocks (Δu_m) and foreign exchange market liquidity shocks ($\Delta mliq$). Δu_m are constructed as innovations to the cross-country average of forecast dispersions on current account (ca), inflation rate (if), short-term interest rate (ir), real economic growth (rg), and foreign exchange rate (fx). The first principal component of these innovations is referred to as pc . All macro uncertainty shocks are then orthogonalized by projecting each Δu_m against the remaining ones. $\Delta mliq$ is computed as innovations to the foreign exchange market liquidity factor of [Karnaukh, Ranaldo, and Söderlind \(forthcoming\)](#). As test assets, we employ six portfolios sorted on forward discounts (carry trade portfolios) and six portfolios sorted on net foreign asset positions and the percentage share of foreign currency-denominated external liabilities (global imbalance portfolios). The table reports estimates of the factor loadings b , factor price λ and cross-sectional R^2 obtained via GMM procedure. t -statistics based on [Newey and West \(1987\)](#) standard errors with [Andrews \(1991\)](#) optimal lag length are reported in brackets. HJ denotes the [Hansen and Jagannathan \(1997\)](#) distance measure (with simulated p -value in parentheses) for the null hypothesis that the normalized maximum pricing error is equal to zero. Excess returns are net of bid-ask spreads and expressed in percentage per month. The portfolios are rebalanced monthly from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*, respectively. We construct the market liquidity factor using daily bid and ask quotes from Bloomberg, and daily mid, low and high quotes from Thomson Reuters via Datastream.

m	b_{dol}	b_m	b_{mliq}	λ_{dol}	λ_m	λ_{mliq}	R^2	HJ
Panel A: Blue Chip Economic Indicators								
ca	0.12 [1.62]	-1.70 [-2.39]	0.05 [-2.39]	0.19 [1.44]	-1.68 [-2.34]	0.04 [0.14]	86%	0.31 (0.31)
if	0.01 [0.25]	-0.83 [-3.02]	-0.67 [-3.02]	0.19 [1.59]	-0.80 [-3.00]	-0.64 [-3.63]	81%	0.32 (0.09)
ir	-0.02 [-0.33]	-0.19 [-0.35]	-0.63 [-0.35]	0.18 [1.54]	-0.18 [-0.34]	-0.62 [-3.15]	69%	0.35 (0.01)
rg	0.01 [0.11]	0.93 [2.33]	-0.87 [-2.40]	0.19 [1.75]	0.82 [2.15]	-0.76 [-2.66]	85%	0.30 (0.30)
fx	-0.01 [-0.28]	0.59 [1.94]	-0.69 [-2.40]	0.18 [1.48]	0.53 [1.78]	-0.63 [-3.06]	73%	0.31 (0.20)
pc	-0.04 [-0.70]	0.62 [2.08]	-0.89 [-2.63]	0.18 [1.56]	0.49 [1.81]	-0.78 [-3.19]	73%	0.32 (0.22)
Panel B: Consensus Forecasts								
ca	-0.03 [-0.85]	-1.07 [-4.06]	-0.19 [-0.93]	0.18 [1.50]	-1.07 [-4.49]	-0.26 [-1.76]	89%	0.23 (0.63)
if	-0.03 [-0.76]	0.68 [1.61]	-0.46 [-1.55]	0.18 [1.58]	0.73 [1.52]	-0.54 [-3.14]	63%	0.32 (0.02)
ir	-0.02 [-0.29]	-0.95 [-2.01]	-0.41 [-2.36]	0.19 [1.64]	-0.92 [-2.20]	-0.34 [-2.33]	71%	0.32 (0.02)
rg	0.02 [0.43]	0.72 [1.95]	-0.88 [-2.35]	0.18 [1.59]	0.50 [1.74]	-0.70 [-3.72]	66%	0.32 (0.03)
fx	-0.04 [-1.07]	-0.66 [-1.52]	-0.40 [-1.29]	0.15 [1.30]	-0.75 [-2.07]	-0.52 [-3.31]	62%	0.35 (0.04)
pc	0.01 [0.23]	0.22 [0.60]	-0.65 [-2.45]	0.18 [1.60]	0.08 [0.22]	-0.60 [-4.38]	59%	0.32 (0.02)

Appendices

3.A Bootstrap simulation

The bootstrap algorithm associated with the Fama-MacBeth cross-sectional regressions consists of the following steps:

1. In the first step, we estimate betas with time series regressions of currency's i excess return rx_t^i on a constant and a pricing factor f_t as

$$rx_t^i = a + \beta^i f_t + \varepsilon_t^i.$$

In the second step, we perform cross-sectional regressions of individual excess returns on betas at each time period t as

$$rx_t^i = \beta^i \lambda_t + \alpha_t^i$$

and estimate λ as the average of the cross-sectional regression estimates, i.e. $\hat{\lambda} = T^{-1} \sum_{t=1}^T \hat{\lambda}_t$.

We consider for illustration purposes a one-factor linear pricing kernel. In our empirical analysis, f_t refers to a set of pricing factors.

2. We generate a sequence of pseudo-observations $\{rx_t^{*i}, f_t^*\}_{t=1}^T$ using the stationary bootstrap of [Politis and Romano \(1994\)](#). The procedure is based on resampling blocks of random length of excess returns and pricing factors realizations from the original sample $\{rx_t^i, f_t\}_{t=1}^T$. The expected block size is set according to [Patton, Politis, and White \(2009\)](#). This procedure will preserve both contemporaneous cross-correlations and serial correlations for excess returns and pricing factors. We repeat this exercise $R = 1,000$ times.

3. For each bootstrap replication, we execute the Fama-MacBeth regressions in step 1 using the artificial data rather than the original data. Specifically, we run $rx_t^{*i} = a^* + \beta^{*i} f_t^* + \varepsilon_t^{*i}$ and $rx_t^{*i} = \beta^{*i} \lambda_t^* + \alpha_t^{*i}$, and then save the estimate $\hat{\lambda}^* = T^{-1} \sum_{t=1}^T \hat{\lambda}_t^*$.
4. We construct the bootstrapped standard error as $\sqrt{\sum_{i=1}^R (\hat{\lambda}_i^* - \bar{\lambda}^*)^2 / (R - 1)}$, where $\bar{\lambda}^*$ is the mean of $\hat{\lambda}_i^*$.
5. We construct confidence intervals using the bias-corrected and accelerated (BC_a) percentile method which automatically adjusts for underlying higher order effects. See Chapter 13 in [Efron and Tibshirani \(1993\)](#) for a detailed description.

3.B Generalized method of moments

The asset pricing tests for currency-sorted portfolios employ a linear stochastic discount factor

$$M_t = 1 - (h_t - \mu)'b, \quad (3.B.1)$$

where h_t is a $k \times 1$ vector of pricing factors, $\mu = E[h_t]$ denotes the $k \times 1$ vector of factor means, and b is the $k \times 1$ vector of factor loadings. The $k \times 1$ vector of factor prices λ can be obtained via the relation $\lambda = \Sigma_h b$, where $\Sigma_h = E[(h_t - \mu)(h_t - \mu)']$ is the $k \times k$ factor covariance matrix. Following [Burnside \(2011\)](#) and [Menkhoff, Sarno, Schmeling, and Schrimpf \(2012a\)](#), we estimate the model parameters b jointly with the factor means μ and the elements of the factor covariance matrix Σ_h by considering the n moment conditions from Euler equation $E[RX_t(1 - (h_t - \mu)b')] = 0$, where RX_t denotes the $n \times 1$ vector of test asset excess returns, the k moment conditions $E[h_t - \mu] = 0$, and the $l = k(k + 1)/2$ moment conditions $E[\text{vech}((h_t - \mu)(h_t - \mu)' - \Sigma_h)] = 0$. In sum, we work with the following vector valued function

$$g(z_t, \theta) = \begin{bmatrix} RX_t[1 - (h_t - \mu)'b] \\ h_t - \mu \\ \text{vech}((h_t - \mu)(h_t - \mu)' - \Sigma_h) \end{bmatrix}, \quad (3.B.2)$$

where $\theta' = [b' \ \mu' \ \text{vech}(\Sigma_h)']$ contains the parameters and $z_t' = [RX_t' \ h_t']$ comprises the data. By employing the $(n + k + l) \times 1$ moment conditions $E[g(z_t, \theta)] = 0$ defined in Equation (3.B.2), we will incorporate estimation uncertainty arising from μ and Σ_h into the standard errors of the factor prices λ .²⁷

We estimate θ via a first-stage GMM estimator that minimizes $g_T'(\theta)W_T g_T(\theta)$, where $g_T(\theta) = T^{-1} \sum_{t=1}^T g(z_t, \theta)$ is the vector of sample moment conditions and W_T is a pre-specified weighting matrix based on the identity matrix I_N for the first N asset pricing moment conditions and a large weight assigned to the additional moment conditions for precise estimation of factor means and the factor covariance matrix elements. The estimator of the covariance matrix of $\sqrt{T}(\hat{\theta} - \theta)$ is

$$V_\theta = (a_T d_T)^{-1} a_T S_T a_T' [(a_T d_T)^{-1}]', \quad (3.B.3)$$

where $d_T = \partial g_T(\theta) / \partial \theta'$, $a_T = d_T' W_T$, and S_T is an estimator of the long-run covariance matrix the moment conditions, i.e. $S = \sum_{j=-\infty}^{\infty} E[g(z_t, \theta) g(z_{t-j}, \theta)']$. We use the Newey and West (1987) procedure, with the number of lags in the Bartlett kernel determined optimally by the data-driven method of Andrews (1991). Via delta method, we recover the estimator of the covariance matrix of $\sqrt{T}(\hat{\lambda} - \lambda)$ as

$$V_\lambda = \left(\frac{\partial \lambda}{\partial \theta'} \right) V_\theta \left(\frac{\partial \lambda}{\partial \theta'} \right)', \quad (3.B.4)$$

where $\partial \lambda / \partial \theta' = [\Sigma_h \ 0_k \ P]$ and $P = \partial \lambda / \partial \text{vech}(\Sigma_h)$. For instance,

$$P = \begin{bmatrix} b_1 & b_2 & 0 \\ 0 & b_1 & b_2 \end{bmatrix}$$

when $k = 2$.

3.C Internet appendix

²⁷The first-stage GMM will produce point estimates equivalent to using the Fama-BacBeth type two-pass regression method.

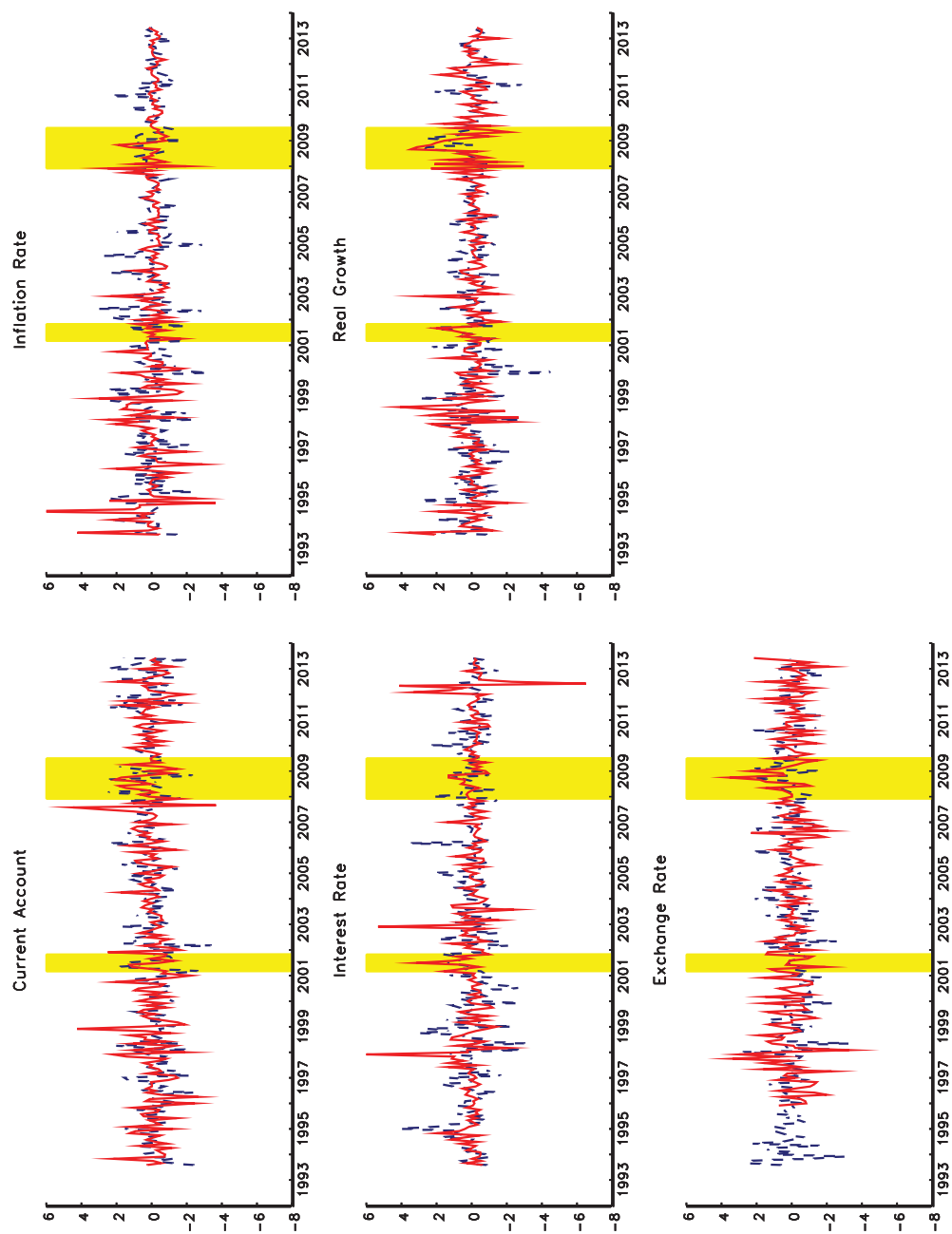


Figure 3.C.1: Macro uncertainty shocks

The figure presents measures of macro uncertainty shocks constructed as innovations to the cross-country averages of forecast dispersions. We use international macroeconomic forecasts collected from the *Blue Chip Economic Indicators* survey (dashed line) and the *Consensus Forecasts* survey (solid line). Shaded areas denote United States NBER-dated recession periods. We standardize the measures of global macro uncertainty to have zero means and unit variances for ease of comparison. The sample runs from July 1993 to July 2013.

Table 3.C.1: Country-level asset pricing tests: first difference

This table presents country-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (*dol*) and macro uncertainty shocks (Δu_m) computed as first difference to the cross-country average of forecast dispersions on current account (*ca*), inflation rate (*if*), short-term interest rate (*ir*), real economic growth (*rg*), and foreign exchange rate (*fx*). The first principal component of these innovations is referred to as *pc*. Orthogonalized macro uncertainty shocks are computed by projecting each Δu_m on the remaining uncertainty shocks. The table reports estimates of the factor price λ obtained via Fama-MacBeth procedure, the cross-sectional R^2 , and the *t*-statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length in brackets. A bolded λ denotes statistical significance at 5% (or lower) obtained via 1,000 stationary bootstrap repetitions. All excess returns are net of bid-ask spreads. The sample runs from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*.

Blue Chip Economic Indicators					Consensus Forecasts		
<i>m</i>	λ_{dol}	λ_m	λ_{ca}	R^2	λ_m	λ_{ca}	R^2
Panel A: macro uncertainty							
<i>ca</i>	0.13 [1.06]	-0.48 [-2.71]		41% 0.15 [1.17]	-0.46 [-2.79]		32%
<i>if</i>	0.11 [0.90]	0.18 [0.94]		27% 0.10 [0.73]	0.10 [0.53]		22%
<i>ir</i>	0.13 [1.03]	-0.05 [-0.23]		23% 0.10 [0.75]	0.00 [0.01]		26%
<i>rg</i>	0.11 [0.88]	0.29 [1.50]		48% 0.11 [0.86]	-0.09 [-0.57]		18%
<i>fx</i>	0.14 [1.11]	0.35 [1.75]		33% 0.12 [0.91]	-0.43 [-1.77]		37%
Panel B: (orthogonalized) macro uncertainty							
<i>ca</i>	0.12 [0.96]	-0.67 [-3.37]		46% 0.17 [1.32]	-0.65 [-3.73]		45%
<i>if</i>	0.15 [1.15]	-0.06 [-0.27]		35% 0.10 [0.73]	0.33 [1.62]		25%
<i>ir</i>	0.14 [1.14]	-0.46 [-1.95]		25% 0.10 [0.72]	0.05 [0.36]		25%
<i>rg</i>	0.13 [0.98]	0.31 [1.48]		32% 0.12 [0.90]	-0.20 [-1.01]		17%
<i>fx</i>	0.17 [1.34]	0.52 [2.60]		44% 0.13 [0.96]	-0.53 [-1.72]		43%
<i>pc</i>	0.13 [1.08]	0.29 [1.46]		32% 0.11 [0.82]	-0.21 [-1.01]		20%
Panel C: macro vs. (orthogonalized) current account uncertainty							
<i>if</i>	0.09 [0.72]	0.24 [1.19]	-0.72 [-3.62]	48% 0.17 [1.28]	0.26 [1.39]	-0.74 [-4.27]	53%
<i>ir</i>	0.10 [0.77]	0.15 [0.66]	-0.70 [-3.35]	41% 0.18 [1.31]	0.22 [1.47]	-0.83 [-4.07]	57%
<i>rg</i>	0.09 [0.76]	0.29 [1.53]	-0.61 [-3.15]	60% 0.18 [1.35]	0.07 [0.43]	-0.66 [-3.67]	48%
<i>fx</i>	0.12 [0.97]	0.35 [1.77]	-0.66 [-3.26]	54% 0.15 [1.12]	-0.20 [-0.82]	-0.55 [-3.44]	60%
<i>pc</i>	0.12 [0.94]	0.29 [1.47]	-0.66 [-3.26]	51% 0.17 [1.27]	0.04 [0.21]	-0.67 [-3.72]	47%

Table 3.C.2: Country-level asset pricing tests: VAR

This table presents country-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (*dol*) and macro uncertainty shocks (Δu_m) computed using a VAR to the cross-country average of forecast dispersions on current account (*ca*), inflation rate (*if*), short-term interest rate (*ir*), real economic growth (*rg*), and foreign exchange rate (*fx*). The first principal component of these innovations is referred to as *pc*. Orthogonalized macro uncertainty shocks are computed by projecting each Δu_m on the remaining uncertainty shocks. The table reports estimates of the factor price λ obtained via Fama-MacBeth procedure, the cross-sectional R^2 , and the *t*-statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length in brackets. A bolded λ denotes statistical significance at 5% (or lower) obtained via 1,000 stationary bootstrap repetitions. All excess returns are net of bid-ask spreads. The sample runs from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*.

Blue Chip Economic Indicators					Consensus Forecasts			
<i>m</i>	λ_{dol}	λ_m	λ_{ca}	R^2	λ_{dol}	λ_m	λ_{ca}	R^2
Panel A: macro uncertainty								
<i>ca</i>	0.13 [1.03]	-0.55 [-2.67]		31%	0.17 [1.28]	-0.64 [-3.64]		44%
<i>if</i>	0.12 [0.90]	0.17 [0.83]		26%	0.09 [0.66]	0.15 [0.82]		18%
<i>ir</i>	0.14 [1.12]	-0.22 [-1.12]		21%	0.10 [0.79]	-0.05 [-0.37]		20%
<i>rg</i>	0.12 [0.95]	0.27 [1.25]		39%	0.10 [0.77]	-0.15 [-1.00]		16%
<i>fx</i>	0.13 [1.02]	0.35 [1.43]		39%	0.12 [0.92]	-0.40 [-1.81]		37%
Panel B: (orthogonalized) macro uncertainty								
<i>ca</i>	0.12 [0.92]	-0.68 [-3.15]		33%	0.18 [1.35]	-0.77 [-4.04]		53%
<i>if</i>	0.14 [1.06]	0.02 [0.07]		29%	0.09 [0.71]	0.39 [1.79]		25%
<i>ir</i>	0.15 [1.21]	-0.41 [-1.80]		32%	0.11 [0.80]	-0.06 [-0.40]		21%
<i>rg</i>	0.14 [1.07]	0.32 [1.45]		33%	0.09 [0.69]	-0.27 [-1.46]		22%
<i>fx</i>	0.16 [1.20]	0.54 [2.26]		50%	0.13 [0.97]	-0.49 [-1.77]		39%
<i>pc</i>	0.13 [1.01]	0.28 [1.16]		36%	0.11 [0.80]	-0.16 [-0.92]		19%
Panel C: macro vs. (orthogonalized) current account uncertainty								
<i>if</i>	0.09 [0.71]	0.26 [1.23]	-0.73 [-3.36]	39%	0.16 [1.21]	0.39 [2.05]	-0.88 [-4.52]	55%
<i>ir</i>	0.12 [0.89]	-0.12 [-0.63]	-0.56 [-2.65]	28%	0.17 [1.30]	0.12 [0.84]	-0.78 [-3.84]	51%
<i>rg</i>	0.10 [0.79]	0.34 [1.63]	-0.68 [-3.32]	45%	0.18 [1.36]	0.13 [0.71]	-0.81 [-3.80]	51%
<i>fx</i>	0.12 [0.89]	0.32 [1.31]	-0.60 [-2.79]	44%	0.14 [1.09]	0.08 [0.35]	-0.83 [-4.19]	66%
<i>pc</i>	0.11 [0.86]	0.25 [1.04]	-0.60 [-2.85]	42%	0.19 [1.36]	0.22 [1.14]	-0.94 [-4.33]	58%

Table 3.C.3: Country-level asset pricing tests: equity volatility

This table presents country-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (*dol*), macro uncertainty shocks (Δu_m), equity volatility shocks ($\Delta \sigma_{vix}$), and equity market uncertainty shocks (Δu_{eq}). We compute Δu_m as innovations to the cross-country average of forecast dispersions on current account (*ca*), inflation rate (*if*), short-term interest rate (*ir*), real economic growth (*rg*), and foreign exchange rate (*fx*). The first principal component of these innovations is referred to as *pc*. All macro uncertainty shocks are orthogonalized by projecting each Δu_m on the remaining uncertainty shocks. We compute $\Delta \sigma_{vix}$ as innovations to the VIX index, and Δu_{eq} as innovations to the news-based equity market uncertainty measure of Baker, Bloom, and Davis (2013). The table reports estimates of the factor price λ obtained via Fama-MacBeth procedure, the cross-sectional R^2 , and the *t*-statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length in brackets. A bolded λ denotes statistical significance at 5% (or lower) obtained via 1,000 stationary bootstrap repetitions. All excess returns are net of bid-ask spreads. The sample runs from July 1993 to July 2013. Exchange rates and interest rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*. The VIX index is from Bloomberg whereas the news-based uncertainty measure is from Nicholas Bloom's website.

<i>m</i>	Blue Chip Economic Indicators				Consensus Forecasts			
	λ_{dol}	λ_m	λ_x	R^2	λ_{dol}	λ_m	λ_x	R^2
Panel A: macro uncertainty vs. equity volatility risk								
<i>ca</i>	0.12 [0.89]	-0.73 [-3.70]	-0.01 [-0.09]	42%	0.16 [1.24]	-0.57 [-3.35]	-0.18 [-1.85]	48%
<i>if</i>	0.13 [1.00]	-0.01 [-0.07]	-0.01 [-0.07]	46%	0.08 [0.63]	0.41 [2.29]	-0.23 [-2.46]	45%
<i>ir</i>	0.13 [1.01]	-0.37 [-1.85]	0.02 [0.21]	35%	0.08 [0.64]	0.02 [0.18]	-0.21 [-2.15]	30%
<i>rg</i>	0.12 [0.94]	0.51 [2.10]	-0.09 [-0.79]	38%	0.08 [0.62]	-0.12 [-0.64]	-0.19 [-1.95]	40%
<i>fx</i>	0.15 [1.11]	0.40 [1.63]	-0.01 [-0.13]	56%	0.09 [0.72]	-0.20 [-0.58]	-0.22 [-2.21]	55%
<i>pc</i>	0.12 [0.94]	0.10 [0.50]	0.01 [0.08]	41%	0.09 [0.69]	0.00 [-0.01]	-0.22 [-2.20]	39%
Panel B: macro uncertainty vs. equity market uncertainty								
<i>ca</i>	0.12 [0.95]	-0.67 [-3.99]	0.03 [0.19]	37%	0.17 [1.32]	-0.64 [-3.69]	-0.04 [-0.28]	56%
<i>if</i>	0.14 [1.11]	0.09 [0.42]	-0.10 [-0.68]	51%	0.09 [0.71]	0.45 [2.49]	-0.13 [-1.11]	47%
<i>ir</i>	0.14 [1.11]	-0.40 [-2.03]	-0.08 [-0.56]	38%	0.09 [0.72]	0.07 [0.50]	-0.23 [-1.91]	29%
<i>rg</i>	0.14 [1.14]	0.42 [1.98]	-0.21 [-1.44]	39%	0.08 [0.66]	-0.22 [-1.12]	-0.12 [-0.88]	44%
<i>fx</i>	0.16 [1.24]	0.43 [1.84]	-0.08 [-0.58]	55%	0.09 [0.73]	-0.22 [-0.64]	-0.15 [-0.93]	52%
<i>pc</i>	0.14 [1.08]	0.15 [0.74]	-0.03 [-0.24]	42%	0.10 [0.80]	-0.08 [-0.30]	-0.16 [-1.06]	42%

Table 3.C.4: Country-level asset pricing tests: simple long-short excess returns

This table presents country-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (*dol*) and macro uncertainty shocks (Δu_m) computed as innovations to the cross-country average of forecast dispersions on current account (*ca*), inflation rate (*if*), short-term interest rate (*ir*), real economic growth (*rg*), and foreign exchange rate (*fx*). The first principal component of these innovations is referred to as *pc*. Orthogonalized macro uncertainty shocks are computed by projecting each Δu_m on the remaining uncertainty shocks. The excess returns are calculated for each currency *i* as $RX_t^i = \gamma_{t-1}^i \times (S_t^i - F_{t-1}^i)/S_{t-1}^i$ where S_t^i and F_t^i are the spot and forward rate against the US dollar, respectively. We set $\gamma_t^i = 1$ (-1) if the forward discount ($S_t^i - F_t^i$)/ S_t^i is positive (negative). The table reports estimates of the factor price λ obtained via Fama-MacBeth procedure, the cross-sectional R^2 , and the *t*-statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length in brackets. A bolded λ denotes statistical significance at 5% (or lower) obtained via 1,000 stationary bootstrap repetitions. All excess returns are net of bid-ask spreads. The sample runs from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*.

Blue Chip Economic Indicators					Consensus Forecasts									
m	λ_{dol}	λ_m	λ_{ca}	R^2	λ_{dol}	λ_m	λ_{ca}	R^2						
Panel A: macro uncertainty														
ca	0.25	[1.87]	-0.70	[-3.00]	19%	0.23	[1.74]	-0.45	[-2.93]	28%				
if	0.25	[1.98]	0.00	[0.01]	30%	0.19	[1.41]	-0.01	[-0.03]	2%				
ir	0.25	[1.86]	-0.24	[-1.23]	15%	0.19	[1.45]	0.02	[0.11]	<1%				
rg	0.25	[1.97]	0.08	[0.42]	29%	0.19	[1.39]	-0.32	[-1.87]	10%				
fx	0.26	[2.01]	0.06	[0.29]	24%	0.20	[1.51]	-0.31	[-1.44]	28%				
Panel B: (orthogonalized) macro uncertainty														
ca	0.25	[1.84]	-0.73	[-3.10]	13%	0.24	[1.80]	-0.58	[-3.46]	39%				
if	0.27	[2.01]	0.02	[0.10]	34%	0.18	[1.36]	0.42	[2.48]	8%				
ir	0.25	[1.83]	-0.33	[-1.49]	19%	0.19	[1.41]	0.09	[0.55]	1%				
rg	0.24	[1.75]	0.43	[1.77]	30%	0.16	[1.25]	-0.51	[-2.49]	15%				
fx	0.25	[1.99]	0.24	[1.04]	42%	0.20	[1.49]	-0.33	[-1.23]	28%				
pc	0.26	[2.03]	0.02	[0.08]	21%	0.20	[1.43]	-0.25	[-1.08]	13%				
Panel C: macro vs. (orthogonalized) current account uncertainty														
if	0.22	[1.65]	0.12	[0.57]	-0.70	[-3.02]	41%	0.22	[1.68]	0.36	[1.95]	-0.57	[-3.63]	29%
ir	0.25	[1.82]	-0.12	[-0.67]	-0.69	[-3.14]	13%	0.21	[1.56]	0.28	[1.70]	-0.62	[-3.18]	19%
rg	0.21	[1.61]	0.21	[1.05]	-0.76	[-3.18]	42%	0.22	[1.58]	-0.16	[-0.77]	-0.45	[-2.49]	41%
fx	0.22	[1.66]	0.07	[0.36]	-0.77	[-3.22]	36%	0.21	[1.55]	0.01	[0.01]	-0.47	[-2.96]	51%
pc	0.22	[1.66]	0.00	[0.00]	-0.77	[-3.20]	31%	0.24	[1.76]	0.18	[0.82]	-0.58	[-3.66]	41%

Table 3.C.5: Country-level asset pricing tests: top and bottom forecasts

This table presents country-level cross-sectional asset pricing results when we only use top 3 average and bottom 3 average forecasts from *Consensus Forecasts* to proxy for the cross-sectional dispersion of forecasts (i.e. we use a range-based measure as substitute of the cross-sectional standard deviation). Individual currency excess returns are used as test assets whereas the dollar (*dol*), the global macro uncertainty shocks (Δu_m), and the global foreign exchange volatility shocks ($\Delta \sigma_{fx}$) enter as pricing factors. Δu_m are computed as innovations to the cross-sectional dispersion of forecasts on current account (*ca*), inflation rate (*if*), short-term interest rate (*ir*), real economic growth (*rg*), and foreign exchange rate (*fx*). *pc* denotes the first principal component of these innovations. The excess return is calculated for each currency i as $RX_t^i = \gamma_{t-1}^i \times (S_t^i - F_{t-1}^i)/S_{t-1}^i$ where S_t^i and F_t^i are the spot and forward rate against the US dollar, respectively. We set $\gamma_t^i = 1$ (-1) if the forward discount ($S_t^i - F_t^i$)/ S_t^i in deviation from the cross-sectional median is positive (negative). The table reports estimates of the factor price of risk λ obtained via Fama-MacBeth procedure and the cross-sectional R^2 . A t -statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length is reported in brackets. A bold λ denotes statistical significance at 5% (or lower) based on bootstrapped confidence intervals obtained via 1,000 block-bootstrap repetitions. Excess returns are monthly and net of bid-ask spreads. The sample runs from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Consensus Forecasts*.

m	λ_{dol}	λ_u	λ_{ca}	R^2			
Panel A: macro uncertainty							
ca	0.16	[1.24]	-0.59	[-2.96]	31%		
if	0.10	[0.75]	0.12	[0.71]	22%		
ir	0.10	[0.77]	0.05	[0.39]	26%		
rg	0.10	[0.77]	-0.08	[-0.39]	24%		
fx	0.11	[0.83]	-0.34	[-1.54]	34%		
Panel B: (orthogonalized) macro uncertainty							
ca	0.19	[1.48]	-0.78	[-3.99]	48%		
if	0.10	[0.75]	0.27	[1.56]	28%		
ir	0.10	[0.75]	0.07	[0.48]	25%		
rg	0.09	[0.71]	-0.07	[-0.39]	22%		
fx	0.11	[0.89]	-0.53	[-2.05]	43%		
pc	0.10	[0.76]	-0.21	[-0.94]	20%		
Panel C: macro vs. (orthogonalized) current account uncertainty							
if	0.19	[1.44]	0.17	[1.02]	-0.79	[-4.07]	50%
ir	0.19	[1.41]	0.04	[0.30]	-0.72	[-3.82]	45%
rg	0.20	[1.48]	0.02	[0.07]	-0.81	[-4.16]	54%
fx	0.15	[1.15]	-0.07	[-0.33]	-0.75	[-4.08]	60%
pc	0.20	[1.49]	0.01	[0.05]	-0.85	[-4.10]	52%

Table 3.C.6: Country-level asset pricing tests: volatility risk and policy uncertainty

This table presents country-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (*dol*), macro uncertainty shocks (Δu_m), foreign exchange volatility shocks ($\Delta \sigma_{fx}$), monetary policy uncertainty shocks (Δu_{mp}), and economic policy uncertainty shocks (Δu_{ep}). We compute Δu_m as innovations to the cross-country average of forecast dispersions on current account (*ca*), inflation rate (*if*), short-term interest rate (*ir*), real economic growth (*rg*), and foreign exchange rate (*fx*). The first principal component of these innovations is referred to as *pc*. All macro uncertainty shocks are orthogonalized by projecting each Δu_m on the remaining uncertainty shocks. We compute $\Delta \sigma_{fx}$ as innovations to the cross-country average of foreign exchange rate volatilities, Δu_{mp} as innovations to the cross-country average variation of policy interest rates, and Δu_{ep} as innovations to the news-based economic policy uncertainty measure of Baker, Bloom, and Davis (2013). The table reports estimates of the factor price λ obtained via Fama-MacBeth procedure, the cross-sectional R^2 , and the *t*-statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length in brackets. A bolded λ denotes statistical significance at 5% (or lower) obtained via 1,000 stationary bootstrap repetitions. All excess returns are net of bid-ask spreads. The sample runs from July 1993 to July 2013. Exchange rates and interest rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*. The news-based uncertainty measure is from Nicholas Bloom's website.

Blue Chip Economic Indicators				Consensus Forecasts				
m	λ_{dol}	λ_m	λ_x	R^2	λ_{dol}	λ_m	λ_x	R^2
Panel A: macro uncertainty vs. foreign exchange volatility risk								
ca	0.12 [0.91]	-0.73	[-3.60] -0.02	[-0.12] 26%	0.18 [1.43]	-0.70	[-4.23] -0.03	[-0.19] 51%
if	0.14 [1.05]	0.02	[0.07] -0.04	[-0.31] 30%	0.09 [0.70]	0.43	[2.26] -0.18	[-1.31] 27%
ir	0.14 [1.05]	-0.37	[-1.78] 0.00	[-0.03] 31%	0.10 [0.74]	-0.01	[-0.09] -0.18	[-1.20] 16%
rg	0.14 [1.05]	0.41	[1.95] -0.10	[-0.71] 29%	0.09 [0.68]	-0.18	[-1.02] -0.15	[-1.01] 22%
fx	0.16 [1.18]	0.48	[1.89] -0.04	[-0.30] 44%	0.11 [0.82]	-0.28	[-0.89] -0.21	[-1.38] 39%
pc	0.14 [1.06]	0.34	[1.39] -0.11	[-0.76] 35%	0.10 [0.73]	-0.19	[-0.79] -0.17	[-1.15] 21%
Panel B: macro uncertainty vs. monetary policy uncertainty								
ca	0.11 [0.83]	-0.70	[-3.36] 0.27	[1.35] 45%	0.17 [1.24]	-0.89	[-4.97] 0.29	[1.35] 56%
if	0.13 [0.97]	-0.04	[-0.18] 0.21	[1.05] 50%	0.09 [0.68]	0.36	[1.92] 0.01	[0.03] 28%
ir	0.12 [0.90]	-0.32	[-1.69] 0.33	[1.80] 37%	0.11 [0.77]	0.00	[-0.01] -0.05	[-0.21] 17%
rg	0.13 [0.99]	0.29	[1.46] 0.06	[0.32] 40%	0.09 [0.65]	-0.19	[-1.04] 0.04	[0.21] 30%
fx	0.13 [0.99]	0.37	[1.52] 0.21	[1.05] 52%	0.10 [0.73]	-0.49	[-1.72] 0.00	[-0.02] 48%
pc	0.11 [0.86]	0.13	[0.61] 0.24	[1.30] 42%	0.08 [0.60]	-0.35	[-1.44] 0.09	[0.43] 36%
Panel C: macro uncertainty vs. economic policy uncertainty								
ca	0.12 [0.99]	-0.67	[-3.63] -0.01	[-0.03] 40%	0.18 [1.42]	-0.64	[-3.74] -0.12	[-0.84] 56%
if	0.15 [1.16]	0.04	[0.17] -0.09	[-0.48] 48%	0.10 [0.82]	0.42	[2.29] -0.23	[-1.63] 39%
ir	0.14 [1.10]	-0.31	[-1.57] -0.08	[-0.43] 37%	0.09 [0.74]	0.03	[0.20] -0.28	[-1.92] 26%
rg	0.16 [1.25]	0.41	[2.06] -0.25	[-1.42] 41%	0.10 [0.78]	-0.15	[-0.75] -0.20	[-1.26] 33%
fx	0.16 [1.29]	0.32	[1.46] -0.11	[-0.66] 57%	0.10 [0.83]	-0.14	[-0.47] -0.26	[-1.73] 53%
pc	0.13 [1.06]	0.11	[0.59] -0.07	[-0.39] 42%	0.11 [0.85]	-0.02	[-0.09] -0.25	[-1.64] 36%

Table 3.C.7: Country-level asset pricing tests: other economic indicators

This table presents country-level cross-sectional asset pricing results. Individual currency excess returns are used as test assets whereas the dollar (*dol*) and the global macro uncertainty shocks (Δu_m) enter as pricing factors. Δu_m are computed as innovations to the cross-sectional dispersion of forecasts on economic indicators not considered in the core analysis. The principal component is computed across all Δu_m , including the ones used in the core analysis. The excess return is calculated for each currency i as $R_i X_t^i = \gamma_{t-1}^i \times (S_t^i - F_{t-1}^i)/S_{t-1}^i$ where S_t^i and F_t^i are the spot and forward rate against the US dollar, respectively. We set $\gamma_t^i = 1$ (-1) if the forward discount $(S_t^i - F_t^i)/S_t^i$ in deviation from the cross-sectional median is positive (negative). The table reports estimates of the factor price of risk λ obtained via Fama-MacBeth procedure and the cross-sectional R^2 . A t -statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length is reported in brackets. Excess returns are monthly and net of bid-ask spreads. The sample runs from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Consensus Forecasts*.

m	standard deviation				range			
	λ_{dol}	λ_m	λ_{ca}	R^2	λ_{dol}	λ_m	λ_{ca}	R^2
Panel A: macro uncertainty								
<i>consumption growth</i>	0.11 [0.81]	0.16 [0.96]		21%	0.11 [0.80]	0.09 [0.52]		26%
<i>investment growth</i>	0.09 [0.71]	0.31 [1.76]		19%	0.10 [0.74]	0.30 [1.60]		19%
<i>industrial production</i>	0.12 [0.91]	-0.02 [-0.10]		19%	0.12 [0.90]	0.01 [0.05]		30%
<i>wages</i>	0.11 [0.85]	-0.16 [-0.93]		13%	0.10 [0.80]	-0.18 [-1.00]		20%
<i>unemployment rate</i>	0.12 [0.91]	0.22 [0.93]		20%	0.10 [0.75]	-0.05 [-0.25]		22%
<i>budget balance</i>	0.12 [0.94]	0.43 [1.85]		25%	0.10 [0.76]	-0.02 [-0.09]		29%
<i>long-term interest rate</i>	0.08 [0.54]	-0.12 [-0.51]		28%	0.08 [0.54]	-0.11 [-0.52]		30%
<i>principal component</i>	0.12 [0.93]	-0.32 [-1.51]		23%	0.10 [0.76]	-0.14 [-0.71]		16%
Panel B: macro uncertainty vs. (orthogonalized) current account uncertainty								
<i>consumption growth</i>	0.17 [1.32]	0.24 [1.48]	-0.60 [-3.43]	48%	0.18 [1.34]	0.03 [0.19]	-0.57 [-3.23]	34%
<i>investment growth</i>	0.17 [1.26]	0.48 [2.70]	-0.68 [-3.57]	33%	0.17 [1.26]	0.34 [1.89]	-0.53 [-2.90]	29%
<i>industrial production</i>	0.18 [1.32]	0.12 [0.54]	-0.60 [-3.69]	44%	0.18 [1.33]	-0.06 [-0.29]	-0.58 [-3.29]	42%
<i>wages</i>	0.17 [1.32]	-0.10 [-0.58]	-0.58 [-3.83]	49%	0.19 [1.42]	-0.32 [-1.79]	-0.65 [-3.55]	48%
<i>unemployment rate</i>	0.19 [1.38]	0.38 [1.47]	-0.59 [-3.52]	59%	0.18 [1.32]	-0.18 [-0.81]	-0.64 [-3.36]	43%
<i>budget balance</i>	0.19 [1.45]	0.40 [1.78]	-0.59 [-3.63]	49%	0.18 [1.36]	0.04 [0.19]	-0.59 [-3.12]	48%
<i>long-term interest rate</i>	0.15 [1.11]	-0.04 [-0.20]	-0.52 [-3.07]	43%	0.17 [1.21]	0.05 [0.25]	-0.55 [-2.92]	50%
<i>principal component</i>	0.16 [1.24]	-0.04 [-0.17]	-0.58 [-3.66]	47%	0.18 [1.39]	-0.02 [-0.08]	-0.63 [-3.23]	44%

Table 3.C.8: Summary statistics: carry trade portfolios

The table presents descriptive statistics of currency portfolios sorted on time $t - 1$ forward discounts or interest rate differential relative to the US. The first portfolio (P_1) contains low-yielding currencies whereas the last portfolio (P_6) contains high-yielding currencies. CAR is a long-short strategy that buys P_6 and sells P_1 . The table also reports the first order autocorrelation coefficient ($AC(1)$), the annualized Sharpe ratio (SR), Sortino ratio (SO), the maximum drawdown (MDD), and the frequency of portfolio switches ($freq$). t -statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. Excess returns are expressed in percentage per annum and adjusted for bid-ask spreads. The portfolio are rebalanced monthly from July 1993 to July 2013. Exchange rates are from *Datstream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*.

	P_1	P_2	P_3	P_4	P_5	P_6	DOL	CAR
	Blue Chip Economic Indicators							
<i>mean</i>	-1.57 [-1.00]	-0.60 [-0.38]	2.02 [1.26]	3.14 [1.87]	2.34 [1.19]	6.69 [3.25]	2.00 [1.34]	8.26 [4.08]
<i>median</i>	-1.75	0.53	0.82	3.70	3.15	9.07	2.61	11.53
<i>sdev</i>	6.86	6.68	7.15	7.20	8.09	8.56	6.42	8.01
<i>skew</i>	0.33	-0.23	-0.02	-0.44	-0.70	-0.36	-0.43	-0.48
<i>kurt</i>	4.54	4.49	4.18	5.38	5.57	7.16	4.81	4.82
<i>SR</i>	-0.23	-0.09	0.28	0.44	0.29	0.78	0.31	1.03
<i>SO</i>	-0.37	-0.12	0.43	0.56	0.37	0.97	0.43	1.41
<i>MDD</i>	0.45	0.37	0.26	0.25	0.30	0.24	0.23	0.18
<i>AC(1)</i>	0.05	0.08	0.01	0.08	0.12	0.11	0.07	0.19
<i>freq</i>	0.19	0.31	0.35	0.36	0.31	0.17	0.28	0.36
	Consensus Forecasts							
<i>mean</i>	-0.99 [-0.63]	-0.79 [-0.49]	1.16 [0.68]	2.34 [1.30]	3.63 [1.89]	6.77 [3.29]	2.02 [1.34]	7.76 [3.74]
<i>median</i>	-1.42	-0.94	0.62	1.67	3.53	8.03	2.49	9.97
<i>sdev</i>	7.03	7.02	7.02	7.48	7.73	8.39	6.34	8.43
<i>skew</i>	0.35	0.18	0.18	-0.13	-0.26	-0.13	0.04	-0.57
<i>kurt</i>	3.55	3.47	3.96	3.79	5.32	6.29	3.33	4.81
<i>SR</i>	-0.14	-0.11	0.17	0.31	0.47	0.81	0.32	0.92
<i>SO</i>	-0.25	-0.18	0.27	0.45	0.69	1.11	0.53	1.28
<i>MDD</i>	0.44	0.39	0.28	0.30	0.23	0.23	0.22	0.20
<i>AC(1)</i>	0.01	0.09	0.15	0.12	0.14	0.11	0.12	0.12
<i>freq</i>	0.21	0.31	0.33	0.33	0.30	0.16	0.28	0.37

Table 3.C.9: Summary statistics: global imbalance portfolios

The table presents descriptive statistics of currency portfolios sorted on time $t - 1$ net foreign asset position to gross domestic product (nfa), and the share of foreign liabilities in domestic currency (ldc). The first portfolio (P_1) contains currencies with high nfa and high ldc (creditor nations with external liabilities mainly in domestic currency) whereas the last portfolio (P_6) contains currencies with low nfa and low ldc (debtor nations with external liabilities mainly in foreign currency). IMB is a long-short strategy that buys P_6 and sells P_1 . The table also reports the first order autocorrelation coefficient ($AC(1)$), the annualized Sharpe ratio (SR), Sortino ratio (SO), the maximum drawdown (MDD), and the frequency of portfolio switches ($freq$). t -statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. Excess returns are expressed in percentage per annum and adjusted for bid-ask spreads. The portfolio are rebalanced monthly from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*.

	P_1	P_2	P_3	P_4	P_5	P_6	DOL	IMB
Blue Chip Economic Indicators								
<i>mean</i>	-0.22 [-0.14]	1.68 [1.03]	2.06 [1.23]	2.48 [1.33]	3.55 [1.83]	5.36 [2.61]	2.49 [1.61]	5.58 [3.22]
<i>median</i>	1.28	-0.19	2.82	4.35	4.24	5.94	3.25	5.40
<i>sdev</i>	6.39	7.04	7.09	7.90	8.65	8.68	6.66	6.87
<i>skew</i>	-0.18	0.04	-0.60	-0.60	-0.81	0.25	-0.48	1.23
<i>kurt</i>	3.63	4.22	4.85	5.05	7.01	6.35	5.01	9.03
<i>SR</i>	-0.03	0.24	0.29	0.31	0.41	0.62	0.37	0.81
<i>SO</i>	-0.05	0.37	0.37	0.41	0.52	0.93	0.50	1.49
<i>MDD</i>	0.47	0.36	0.25	0.32	0.27	0.23	0.23	0.13
<i>AC(1)</i>	0.11	0.06	0.08	0.08	0.02	0.10	0.07	0.14
<i>freq</i>	0.04	0.05	0.05	0.05	0.05	0.04	0.05	0.07
Consensus Forecasts								
<i>mean</i>	-0.22 [-0.14]	1.69 [1.02]	1.95 [1.15]	2.37 [1.25]	3.14 [1.57]	5.35 [2.51]	2.38 [1.52]	5.57 [3.43]
<i>median</i>	-0.70	-0.39	2.50	3.50	2.56	4.23	3.47	5.93
<i>sdev</i>	6.66	7.19	7.10	7.95	8.61	8.09	6.61	6.43
<i>skew</i>	0.06	0.16	-0.22	-0.35	0.18	0.27	0.01	0.68
<i>kurt</i>	3.57	3.09	4.10	5.29	4.91	4.25	3.45	5.59
<i>SR</i>	-0.03	0.24	0.27	0.30	0.36	0.66	0.36	0.87
<i>SO</i>	-0.05	0.41	0.40	0.42	0.58	1.14	0.59	1.59
<i>MDD</i>	0.46	0.35	0.25	0.34	0.30	0.22	0.23	0.12
<i>AC(1)</i>	0.10	0.05	0.11	0.11	0.07	0.21	0.12	0.16
<i>freq</i>	0.04	0.05	0.05	0.05	0.05	0.04	0.04	0.07

Table 3.C.10: Portfolio-level asset pricing tests: macro uncertainty

This table presents portfolio-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (dol) and macro uncertainty shocks (Δu_m) computed as innovations to the cross-country average of forecast dispersions on current account (ca), inflation rate (if), short-term interest rate (ir), real economic growth (rg), and foreign exchange rate (fx). As test assets, we employ six portfolios sorted on forward discounts (carry trade portfolios) and six portfolios sorted on net foreign asset positions and the share of external liabilities denominated in foreign currency (global imbalance portfolios). The table reports estimates of the factor loadings b , factor price λ and cross-sectional R^2 obtained via GMM procedure. t -statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. HJ denotes the Hansen and Jagannathan (1997) distance measure (with simulated p -value in parentheses) for the null hypothesis that the normalized maximum pricing error is equal to zero. $\mathcal{T}^W$ and $\mathcal{T}^H$ denote the White (2000) and Hansen (2005) reality check test statistics for the null hypothesis that the model based on ca has the smallest pricing error according to the squared HJ distance. We report p -values in parentheses obtained via 10,000 stationary bootstrap repetitions. Excess returns are net of bid-ask spreads and expressed in percentage per month. The portfolios are rebalanced monthly from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* (Panel A) and *Consensus Forecasts* (Panel B).

m	b_{dol}	b_m	λ_{dol}	λ_m	R^2	HJ	$\mathcal{T}^W$	$\mathcal{T}^H$					
Panel A: Blue Chip Economic Indicators													
ca	0.10	[1.61]	-1.29	[-2.69]	0.19	[1.43]	-1.27	[-2.73]	84%	0.33	(0.11)	(0.89)	(0.59)
if	0.09	[1.40]	-1.61	[-3.38]	0.19	[1.41]	-1.60	[-3.43]	63%	0.36	(0.01)		
ir	0.08	[1.23]	-1.48	[-2.33]	0.19	[1.41]	-1.47	[-2.42]	61%	0.37	(0.01)		
rg	0.03	[0.55]	-0.69	[-1.91]	0.19	[1.46]	-0.69	[-2.06]	31%	0.37	(0.01)		
fx	0.04	[0.68]	-0.84	[-2.48]	0.20	[1.58]	-0.84	[-2.84]	34%	0.37	(0.01)		
Panel B: Consensus Forecasts													
ca	-0.02	[-0.55]	-1.18	[-3.89]	0.18	[1.45]	-1.17	[-4.32]	87%	0.23	(0.72)	(0.93)	(0.27)
if	0.08	[1.68]	-0.83	[-1.94]	0.18	[1.59]	-0.82	[-1.95]	19%	0.34	(0.01)		
ir	-0.01	[-0.24]	-1.21	[-3.30]	0.19	[1.53]	-1.20	[-3.53]	63%	0.33	(0.02)		
rg	0.02	[0.46]	-0.62	[-2.62]	0.18	[1.51]	-0.62	[-3.15]	41%	0.33	(0.01)		
fx	-0.04	[-0.82]	-1.06	[-2.82]	0.15	[1.29]	-1.05	[-3.40]	61%	0.35	(0.06)		

Table 3.C.11: Portfolio-level asset pricing tests: Shanken standard errors

This table presents portfolio-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (dol) and macro uncertainty shocks (Δu_m) computed as innovations to the cross-country average of forecast dispersions on current account (ca), inflation rate (if), short-term interest rate (ir), real economic growth (rg), and foreign exchange rate (fx). The first principal component of these innovations is referred to as pc . All macro uncertainty shocks are orthogonalized by projecting each Δu_m on the remaining uncertainty shocks. As test assets, we employ six portfolios sorted on forward discounts (carry trade portfolios) and six portfolios sorted on net foreign asset positions and the share of external liabilities denominated in foreign currency (global imbalance portfolios). The table reports estimates of the factor loadings b , factor price λ and cross-sectional R^2 obtained via Fama-MacBeth procedure. t -statistic based on Shanken (1992) standard errors are reported in brackets. χ^2 denotes the test statistics (with p -value in parentheses) for the null hypothesis that all pricing errors are jointly zero. Excess returns are net of bid-ask spreads and expressed in percentage per month. The portfolios are rebalanced monthly from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* (Panel A) and *Consensus Forecasts* (Panel B).

m	b_{dol}	b_m	λ_{dol}	λ_m	R^2	χ^2					
Panel A: Blue Chip Economic Indicators											
ca	0.11	[2.54]	-1.60	[-2.28]	0.19	[1.55]	-1.58	[-2.28]	86%	7.18	(0.71)
if	0.09	[2.26]	-0.66	[-1.86]	0.20	[1.66]	-0.65	[-1.83]	23%	24.28	(0.01)
ir	0.10	[2.12]	-1.83	[-1.42]	0.19	[1.60]	-1.82	[-1.42]	31%	8.67	(0.57)
rg	0.05	[1.27]	-0.13	[-0.45]	0.19	[1.62]	-0.14	[-0.49]	16%	36.28	(0.01)
fx	0.06	[1.57]	-0.05	[-0.17]	0.20	[1.64]	-0.06	[-0.18]	15%	34.23	(0.01)
pc	0.04	[1.12]	-0.89	[-2.27]	0.19	[1.62]	-0.89	[-2.28]	39%	21.13	(0.03)
Panel B: Consensus Forecasts											
ca	-0.03	[-0.65]	-1.28	[-2.83]	0.18	[1.49]	-1.28	[-2.86]	86%	5.13	(0.89)
if	-0.04	[-0.65]	1.46	[1.87]	0.19	[1.56]	1.45	[1.89]	34%	9.88	(0.46)
ir	0.00	[-0.01]	-1.49	[-2.13]	0.19	[1.63]	-1.49	[-2.14]	50%	9.51	(0.49)
rg	0.02	[0.53]	-0.61	[-2.05]	0.18	[1.52]	-0.62	[-2.08]	29%	22.53	(0.02)
fx	-0.04	[-0.78]	-1.29	[-2.25]	0.15	[1.15]	-1.28	[-2.27]	58%	11.49	(0.33)
pc	0.00	[0.06]	-0.91	[-2.37]	0.18	[1.55]	-0.91	[-2.39]	51%	15.81	(0.11)

Table 3.C.12: Portfolio-level asset pricing tests: carry trade portfolios

This table presents portfolio-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (*dol*) and macro uncertainty shocks (Δu_m) computed as innovations to the cross-country average of forecast dispersions on current account (*ca*), inflation rate (*if*), short-term interest rate (*ir*), real economic growth (*rg*), and foreign exchange rate (*fx*). The first principal component of these innovations is referred to as *pc*. All macro uncertainty shocks are orthogonalized by projecting each Δu_m on the remaining uncertainty shocks. As test assets, we employ six portfolios sorted on forward discounts (carry trade portfolios). The table reports estimates of the factor loadings b , factor price λ and cross-sectional R^2 obtained via GMM procedure. t -statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. HJ denotes the Hansen and Jagannathan (1997) distance measure (with simulated p -value in parentheses) for the null hypothesis that the normalized maximum pricing error is equal to zero. $\mathcal{T}^W$ and $\mathcal{T}^H$ denote the White (2000) and Hansen (2005) reality check test statistics for the null hypothesis that the model based on *ca* has the smallest pricing error according to the squared HJ distance. We report p -values in parentheses obtained via 10,000 stationary bootstrap repetitions. Excess returns are net of bid-ask spreads and expressed in percentage per month. The portfolios are rebalanced monthly from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* (Panel A) and *Consensus Forecasts* (Panel B).

m	b_{dol}	b_m	λ_{dol}	λ_m	R^2	HJ	$\mathcal{T}^W$	$\mathcal{T}^H$					
Panel A: Blue Chip Economic Indicators													
ca	0.11	[1.27]	-1.76	[-1.90]	0.17	[1.25]	-1.74	[-1.98]	86%	0.20	(0.56)	(0.76)	(0.63)
if	0.11	[2.19]	-1.35	[-2.78]	0.18	[1.34]	-1.33	[-2.72]	35%	0.30	(0.01)		
ir	0.14	[0.92]	-4.21	[-0.96]	0.17	[1.14]	-4.18	[-0.98]	80%	0.23	(0.86)		
rg	0.05	[1.12]	-0.08	[-0.25]	0.18	[1.33]	-0.09	[-0.28]	10%	0.31	(0.01)		
fx	0.09	[1.65]	1.41	[1.67]	0.17	[1.36]	1.39	[1.82]	21%	0.29	(0.02)		
pc	0.02	[0.28]	-1.55	[-1.79]	0.18	[1.32]	-1.54	[-2.01]	45%	0.30	(0.01)		
Panel B: Consensus Forecasts													
ca	-0.05	[-0.65]	-1.52	[-3.16]	0.17	[1.23]	-1.50	[-3.53]	92%	0.14	(0.75)	(0.84)	(0.68)
if	-0.07	[-0.95]	1.86	[2.16]	0.18	[1.53]	1.84	[1.89]	38%	0.26	(0.02)		
ir	0.00	[-0.07]	-1.47	[-1.61]	0.18	[1.33]	-1.47	[-2.03]	38%	0.26	(0.02)		
rg	-0.02	[-0.23]	-1.22	[-1.97]	0.17	[1.30]	-1.21	[-2.06]	44%	0.26	(0.03)		
fx	-0.07	[-0.90]	-1.62	[-1.99]	0.13	[0.94]	-1.60	[-2.17]	73%	0.20	(0.59)		
pc	-0.04	[-0.56]	-1.54	[-2.09]	0.18	[1.27]	-1.53	[-2.17]	74%	0.20	(0.52)		

Table 3.C.13: Portfolio-level asset pricing tests: global imbalance portfolios

This table presents portfolio-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (dol) and macro uncertainty shocks (Δu_m) computed as innovations to the cross-country average of forecast dispersions on current account (ca), inflation rate (if), short-term interest rate (ir), real economic growth (rg), and foreign exchange rate (fx). The first principal component of these innovations is referred to as pc . All macro uncertainty shocks are orthogonalized by projecting each Δu_m on the remaining uncertainty shocks. As test assets, we employ six portfolios sorted on net foreign asset positions and the share of external liabilities denominated in foreign currency (global imbalance portfolios). The table reports estimates of the factor loadings b , factor price λ and cross-sectional R^2 obtained via GMM procedure. t -statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. HJ denotes the Hansen and Jagannathan (1997) distance measure (with simulated p -value in parentheses) for the null hypothesis that the normalized maximum pricing error is equal to zero. $\mathcal{T}^W$ and $\mathcal{T}^H$ denote the White (2000) and Hansen (2005) reality check test statistics for the null hypothesis that the model based on ca has the smallest pricing error according to the squared HJ distance. We report p -values in parentheses obtained via 10,000 stationary bootstrap repetitions. Excess returns are net of bid-ask spreads and expressed in percentage per month. The portfolios are rebalanced monthly from July 1993 to July 2013. Exchange rates are from *Datstream* whereas international forecasts are collected from *Blue Chip Economic Indicators* (Panel A) and *Consensus Forecasts* (Panel B).

m	b_{dol}	b_m	λ_{dol}	λ_m	R^2	HJ	$\mathcal{T}^W$	$\mathcal{T}^H$					
Panel A: Blue Chip Economic Indicators													
ca	0.11	[1.65]	-1.35	[-2.21]	0.21	[1.60]	-1.34	[-2.13]	94%	0.09	(0.95)	(0.94)	(0.66)
if	0.05	[1.14]	0.16	[0.30]	0.21	[1.59]	0.16	[0.32]	28%	0.21	(0.05)		
ir	0.03	[0.38]	1.53	[1.11]	0.21	[1.66]	1.52	[1.11]	44%	0.20	(0.26)		
rg	0.05	[1.15]	-0.14	[-0.35]	0.21	[1.56]	-0.15	[-0.39]	29%	0.22	(0.04)		
fx	0.04	[0.66]	-0.89	[-1.47]	0.22	[1.57]	-0.89	[-1.51]	47%	0.22	(0.03)		
pc	0.05	[0.91]	-0.55	[-1.59]	0.21	[1.53]	-0.55	[-1.70]	48%	0.22	(0.03)		
Panel B: Consensus Forecasts													
ca	-0.01	[-0.14]	-0.98	[-2.94]	0.19	[1.47]	-0.98	[-2.97]	81%	0.14	(0.65)	(0.69)	(0.51)
if	0.00	[-0.01]	0.91	[1.38]	0.20	[1.50]	0.91	[1.43]	32%	0.23	(0.02)		
ir	0.00	[0.03]	-1.54	[-1.83]	0.21	[1.56]	-1.53	[-1.83]	80%	0.16	(0.66)		
rg	0.04	[0.98]	-0.26	[-0.96]	0.19	[1.54]	-0.27	[-1.08]	25%	0.23	(0.02)		
fx	0.00	[-0.09]	-0.81	[-1.54]	0.17	[1.24]	-0.81	[-1.69]	42%	0.25	(0.10)		
pc	0.04	[0.78]	-0.42	[-1.16]	0.20	[1.56]	-0.42	[-1.29]	34%	0.22	(0.10)		

Table 3.C.14: Portfolio-level asset pricing tests: monetary policy uncertainty

This table presents portfolio-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (dol), macro uncertainty shocks (Δu_m) and monetary policy uncertainty shocks (Δu_{mp}). Δu_m are constructed as innovations to the cross-country average of forecast dispersions on current account (ca), inflation rate (if), short-term interest rate (ir), real economic growth (rg), and foreign exchange rate (fx). The first principal component of these innovations is referred to as pc . All macro uncertainty shocks are then orthogonalized by projecting each Δu_m against the remaining ones. Δu_{mp} is constructed as innovations to the cross-country average variation of policy interest rates. As test assets, we employ six portfolios sorted on forward discounts (carry trade portfolios) and six portfolios sorted on net foreign asset positions and the percentage share of foreign currency-denominated external liabilities (global imbalance portfolios). The table reports estimates of the factor loadings b , factor price λ and cross-sectional R^2 obtained via GMM procedure. t -statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. HJ denotes the Hansen and Jagannathan (1997) distance measure (with simulated p -value in parentheses) for the null hypothesis that the normalized maximum pricing error is equal to zero. Excess returns are net of bid-ask spreads and expressed in percentage per month. The portfolios are rebalanced monthly from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*, respectively. As policy rates, we use 1-month interest rates collected from Datastream.

m	b_{dol}	b_m	b_{mp}	λ_{dol}	λ_m	λ_{mp}	R^2	HJ							
Panel A: Blue Chip Economic Indicators															
ca	0.13	[1.87]	-1.82	[-2.79]	0.27	[0.82]	0.19	[1.46]	-1.80	[-2.72]	0.26	[0.76]	0.88	0.30	(0.54)
if	0.04	[0.97]	-0.82	[-2.79]	-0.69	[-1.91]	0.19	[1.45]	-0.84	[-2.84]	-0.73	[-2.51]	0.43	0.36	(0.00)
ir	0.05	[0.83]	-1.39	[-2.08]	-0.48	[-1.13]	0.19	[1.41]	-1.39	[-2.10]	-0.50	[-1.51]	0.40	0.37	(0.00)
rg	0.03	[0.56]	0.36	[1.08]	-0.75	[-1.88]	0.19	[1.43]	0.32	[1.01]	-0.74	[-2.35]	0.34	0.37	(0.00)
fx	0.02	[0.36]	0.17	[0.64]	-0.63	[-1.96]	0.19	[1.42]	0.20	[0.77]	-0.64	[-2.44]	0.32	0.36	(0.01)
pc	0.02	[0.43]	-0.69	[-2.29]	-0.28	[-1.07]	0.19	[1.51]	-0.69	[-2.55]	-0.28	[-1.18]	0.41	0.37	(0.00)
Panel B: Consensus Forecasts															
ca	-0.03	[-0.81]	-1.04	[-3.10]	-0.25	[-0.67]	0.18	[1.47]	-1.05	[-3.33]	-0.33	[-1.00]	0.87	0.23	(0.64)
if	-0.03	[-0.63]	0.19	[0.50]	-0.90	[-2.60]	0.18	[1.61]	0.20	[0.50]	-0.89	[-3.73]	0.72	0.31	(0.06)
ir	-0.02	[-0.43]	-0.41	[-0.85]	-0.80	[-2.37]	0.19	[1.56]	-0.46	[-1.06]	-0.82	[-3.39]	0.73	0.31	(0.09)
rg	-0.01	[-0.26]	0.60	[1.87]	-1.33	[-3.21]	0.19	[1.53]	0.44	[1.47]	-1.26	[-3.80]	0.79	0.30	(0.14)
fx	-0.08	[-1.78]	-0.62	[-1.61]	-0.79	[-1.87]	0.14	[1.22]	-0.77	[-2.20]	-0.89	[-2.68]	0.77	0.34	(0.10)
pc	-0.02	[-0.37]	0.14	[0.39]	-1.04	[-2.90]	0.18	[1.54]	-0.07	[-0.22]	-1.00	[-4.00]	0.72	0.31	(0.06)

Table 3.C.15: Portfolio-level asset pricing tests: economic policy uncertainty

This table presents portfolio-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (dol), macro uncertainty shocks (Δu_m) and economic policy uncertainty shocks (Δu_{ep}). Δu_m are constructed as innovations to the cross-country average of forecast dispersions on current account (ca), inflation rate (if), short-term interest rate (ir), real economic growth (rg), and foreign exchange rate (fx). The first principal component of these innovations is referred to as pc . All macro uncertainty shocks are then orthogonalized by projecting each Δu_m against the remaining ones. Δu_{ep} is constructed as innovations to the news-based economic policy uncertainty measure of Baker, Bloom, and Davis (2013). As test assets, we employ six portfolios sorted on forward discounts (carry trade portfolios) and six portfolios sorted on net foreign asset positions and the percentage share of foreign currency-denominated external liabilities (global imbalance portfolios). The table reports estimates of the factor loadings b , factor price λ and cross-sectional R^2 obtained via GMM procedure. t -statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. HJ denotes the Hansen and Jagannathan (1997) distance measure (with simulated p -value in parentheses) for the null hypothesis that the normalized maximum pricing error is equal to zero. Excess returns are net of bid-ask spreads and expressed in percentage per month. The portfolios are rebalanced monthly from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*, respectively. The news-based uncertainty measure is from Nicholas Bloom's website.

m	b_{dol}	b_m	b_{ep}	λ_{dol}	λ_m	λ_{ep}	R^2	HJ
Panel A: Blue Chip Economic Indicators								
ca	0.07 [1.23]	-1.29 [-2.54]	-0.29 [-2.54]	0.18 [-1.21]	0.18 [-1.46]	-0.39 [-2.56]	0.89 [-1.85]	0.29 (0.37)
if	0.01 [0.22]	-0.66 [-2.48]	-0.89 [-2.48]	0.19 [-3.13]	0.19 [-1.61]	-0.83 [-2.33]	0.74 [-3.70]	0.33 (0.03)
ir	-0.03 [-0.56]	0.23 [0.36]	-0.92 [0.36]	0.18 [-2.64]	0.16 [-1.60]	-0.89 [0.25]	0.67 [-3.26]	0.34 (0.01)
rg	0.00 [0.05]	0.61 [2.21]	-1.05 [2.21]	0.19 [-3.20]	0.19 [-1.68]	-0.97 [1.97]	0.74 [-3.78]	0.33 (0.03)
fx	-0.02 [-0.34]	0.11 [0.31]	-0.89 [0.31]	0.18 [-2.89]	0.18 [-1.56]	-0.90 [0.70]	0.67 [-3.83]	0.33 (0.06)
pc	-0.02 [-0.27]	-0.12 [-0.42]	-0.83 [-0.42]	0.18 [-2.82]	0.18 [-1.50]	-0.82 [-0.23]	0.67 [-3.62]	0.34 (0.03)
Panel B: Consensus Forecasts								
ca	-0.03 [-0.60]	-1.12 [-3.77]	-0.20 [-3.77]	0.18 [-0.77]	0.18 [-1.41]	-0.26 [-4.12]	0.88 [-1.07]	0.21 (0.72)
if	-0.02 [-0.33]	0.74 [1.55]	-0.55 [1.55]	0.17 [-1.69]	0.17 [-1.46]	-0.58 [1.50]	0.58 [-2.15]	0.30 (0.05)
ir	0.00 [-0.04]	-1.01 [-2.07]	-0.48 [-2.07]	0.18 [-2.32]	0.18 [-1.44]	-0.48 [-2.26]	0.68 [-2.38]	0.30 (0.06)
rg	0.06 [0.91]	1.18 [2.61]	-1.43 [2.61]	0.17 [-3.14]	0.17 [-1.28]	-1.15 [2.25]	0.66 [-3.47]	0.27 (0.34)
fx	-0.03 [-0.54]	-0.93 [-2.03]	-0.23 [-2.03]	0.15 [-0.89]	0.15 [-1.24]	-0.29 [-2.27]	0.59 [-1.17]	0.33 (0.05)
pc	0.04 [0.68]	0.38 [1.02]	-0.92 [1.02]	0.17 [-2.57]	0.17 [-1.33]	-0.89 [0.80]	0.53 [-3.16]	0.29 (0.16)

Table 3.C.16: Portfolio-level asset pricing tests: funding liquidity risk

This table presents portfolio-level cross-sectional asset pricing results for a linear factor model based on the dollar factor (dol), macro uncertainty shocks (Δu_m) and foreign exchange market liquidity shocks ($\Delta fliq$). Δu_m are constructed as innovations to the cross-country average of forecast dispersions on current account (ca), inflation rate (if), short-term interest rate (ir), real economic growth (rg), and foreign exchange rate (fx). The first principal component of these innovations is referred to as pc . All macro uncertainty shocks are then orthogonalized by projecting each Δu_m against the remaining ones. $\Delta fliq$ is computed as innovations to the cross-country average of the LIBOR-OIS spread. As test assets, we employ six portfolios sorted on forward discounts (carry trade portfolios) and six portfolios sorted on net foreign asset positions and the percentage share of foreign currency-denominated external liabilities (global imbalance portfolios). The table reports estimates of the factor loadings b , factor price λ and cross-sectional R^2 obtained via GMM procedure. t -statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag length are reported in brackets. HJ denotes the Hansen and Jagannathan (1997) distance measure (with simulated p -value in parentheses) for the null hypothesis that the normalized maximum pricing error is equal to zero. Excess returns are net of bid-ask spreads and expressed in percentage per month. The portfolios are rebalanced monthly from July 1993 to July 2013. Exchange rates are from *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*, respectively. To construct the LIBOR-OIS spread, we collect data from Bloomberg and Global Financial Data for major economies.

m	b_{dol}	b_m	b_{fliq}	λ_{dol}	Panel A: Blue Chip Economic Indicators										
					λ_m	λ_{fliq}	R^2	HJ							
ca	0.07	[1.21]	-1.27	[-2.61]	-0.24	[-0.90]	0.18	[1.46]	-1.28	[-2.65]	-0.35	[-1.37]	88%	0.29	(0.25)
if	-0.02	[-0.30]	-0.79	[-3.10]	-0.90	[-2.74]	0.18	[1.47]	-0.77	[-3.17]	-0.87	[-4.09]	84%	0.30	(0.18)
ir	-0.05	[-1.03]	0.02	[0.04]	-0.87	[-2.40]	0.18	[1.51]	0.15	[0.28]	-0.85	[-3.71]	73%	0.32	(0.03)
rg	-0.03	[-0.50]	0.84	[2.23]	-1.12	[-2.34]	0.18	[1.56]	0.62	[1.85]	-0.93	[-3.19]	87%	0.27	(0.50)
fx	-0.04	[-0.91]	0.60	[1.80]	-0.93	[-2.65]	0.17	[1.52]	0.47	[1.35]	-0.82	[-4.11]	77%	0.28	(0.34)
pc	-0.07	[-1.22]	0.54	[2.01]	-1.14	[-2.73]	0.17	[1.51]	0.30	[1.15]	-0.99	[-4.25]	77%	0.29	(0.31)
Panel B: Consensus Forecasts															
ca	-0.04	[-0.92]	-1.16	[-3.76]	-0.16	[-0.54]	0.18	[1.44]	-1.19	[-4.18]	-0.45	[-2.57]	87%	0.22	(0.59)
if	-0.06	[-1.32]	0.61	[1.25]	-0.54	[-1.36]	0.17	[1.49]	0.66	[1.31]	-0.59	[-2.90]	51%	0.31	(0.02)
ir	-0.05	[-0.82]	-1.13	[-2.06]	-0.49	[-1.72]	0.18	[1.48]	-1.14	[-2.52]	-0.52	[-2.97]	69%	0.30	(0.04)
rg	-0.08	[-1.32]	1.24	[2.62]	-1.52	[-2.14]	0.17	[1.43]	1.03	[2.36]	-1.31	[-3.50]	61%	0.28	(0.49)
fx	-0.05	[-1.11]	-1.03	[-2.53]	-0.20	[-1.10]	0.15	[1.25]	-1.02	[-2.92]	-0.24	[-1.38]	60%	0.35	(0.03)
pc	-0.02	[-0.52]	-0.48	[-1.57]	-0.37	[-1.82]	0.18	[1.58]	-0.49	[-1.88]	-0.39	[-2.64]	51%	0.31	(0.02)

Chapter 4

Acceleration and reversal¹

4.1 Introduction

Previous literature has established that historical stock price series contain information about its future returns. The signals for the formulation of trading strategies were mainly constructed in terms of the relative price changes (past returns). In this work, motivated by [Xiong and Ibbotson \(2015\)](#), we attempt to analyse how the concept of price acceleration fits in the research picture, whether the long-short strategies based on it are profitable, and whether it is different from a simple past return signal.

We build several empirical measures of acceleration and compare them to the previous signals from the academic literature. We show that acceleration measures are mostly independent from other, traditional, price-based signals – such as 1-month reversal and 12-2-month momentum. Then we study the properties of equity portfolios, constructed by sorting stocks into deciles based on a particular signal. We find that there is a large spread in average returns for such acceleration portfolios. Acceleration low-minus-high (LMH) strategies, that go long the portfolio with quickly decelerating price stocks and short the portfolio with quickly accelerating price stocks, produce large positive mean returns, even after the transaction costs are taken into account.

As a next step we switch to the formal analysis of the risk properties of these portfolios and long-short strategies. We show that classic as well as contemporary state-of-the-art equity factor models are having trouble explaining the mean returns on acceleration portfolios. In particular,

¹This chapter is based on the collaborative work with Oleg Komarov.

even the 1-month reversal was not adding much help to the explanatory power of traditional risk factors. However, the reversal factor constructed on a shorter lookback period of 5 trading days was able to price well the acceleration-based portfolios.

The remainder of the paper is organized as follows. Section 4.2 provides the motivation for the empirical analysis in relation to the current literature. Section 4.3 describes the data and provides the details on how acceleration measures are constructed. Section 4.4 shows that our acceleration-sorted portfolios produce a robust monotonic pattern in mean returns. We then present the formal analysis on the risk-return trade-off in Section 4.5. We conclude the study and provide suggestions for further research in Section 4.6.

4.2 Acceleration

There is an extensive academic literature exploring how past price information predicts future realised returns in the cross-section of stocks.² However, in the past the academic community was predominantly interested in understanding how price *changes* help to forecast returns. In this paper we would like to explore how helpful, from the predictability point of view, is to look at the *changes of changes*. In particular, we ask the question whether the speed with which a stock price is going up or down is an important piece of information, over and above the information contained in the direction and size of the stock price move (which was studied previously).

From another standpoint, typically one looks at a certain signal formation (lookback) period, e.g. a month, and takes the percentage changes between the end and the beginning of period prices. For us it was interesting to explore whether, holding formation period fixed, price information *within* the period was also useful for the formulation of trading strategy. A study of acceleration became a natural first simple test to take in exploring this research direction.

Subsequently, we identified, to our knowledge, the only work that is closely related to ours, written by two industry researchers – [Xiong and Ibbotson \(2015\)](#). They claim that twelve month momentum and one month reversal are two parts of the same phenomenon. The authors refer to this phenomenon as acceleration. In particular, [Xiong and Ibbotson \(2015\)](#) analyse the 12-month

²Some classic references are: [De Bondt and Thaler \(1985\)](#) for long run reversal, [Jegadeesh and Titman \(1993\)](#) for medium-term momentum, and [Jegadeesh \(1990\)](#) for short run reversal.

lookback period and build the empirical measure of medium-term acceleration over this period by subtracting average last 6 months returns from the average first 6 months returns.³ The authors find that acceleration is informative about the probability and the magnitude of a stock price reversal.

Our work is different as we look at a shorter lookback period of one month. There are two reasons for this. First, if acceleration results in a price deviating from fundamentals, then such deviation is likely to be very transitory, and, hence, it makes sense to concentrate on a shorter period than a year in order to try and profit from the correction. Second, even in the work of [Xiong and Ibbotson \(2015\)](#) one is argued to profit by being a contrarian: going long those stocks that accelerated the least (or decelerated the most) and short those that accelerated the most. It is important to compare which of the two contrarian strategies – short-run reversal or acceleration – has the more informative signal. To have a fair playing field, it is, thus, reasonable to set the lookback horizon on which the reversal was previously studied.

We do not exclude ex-ante the possibility that acceleration is related to the traditional reversal. For instance, [Da, Liu, and Schaumburg \(2014\)](#) argue that it is not every stock that goes down (up) in the previous month should recover (fall) in the next. In particular, one should adjust past returns for fundamentals – news about cashflows and discount rates – in order to lock in a more “clean” signal for reversal. An intuition for this is the following. If a firm’s stock went down because its profitability outlook has deteriorated, resulting in lower expected dividends, then one would not expect the price to recover unless the outlook improved. Separately, if the risk factor beta of the first stock is 1 and that of a second stock is 2, then given the factor realises 1% return would on average drive the first stock up by 1% and the second stock by 2%. If the risk factor mean return is 1%, it is clear that the second stock should not necessarily be expected to underperform the first in the next period. [Da, Liu, and Schaumburg \(2014\)](#) conclude that the “cleaned” reversal strategy returns are stronger than traditional reversal and link its economic explanation to the liquidity and investor sentiment stories. To us it seems unlikely that the news

³This is not the only work that attempts to combine the momentum and reversal signals’ information in order to provide a single factor explanation. [Han, Zhou, and Zhu \(2015\)](#) also look at combining various price signals with different lookback horizons through one factor. They call this factor a trend and show, that a strategy based on it outperforms the traditional short-term reversal, medium-term momentum and long-run reversal strategies and is not spanned by these strategies.

are transmitted and incorporated into the prices every month in such a way that leads to visible accelerating behaviour. Therefore, it could be the case that our acceleration measure is capturing in a simpler way the “cleaned” reversal.⁴

We also do not dispute that any of the theories put forward for the reversal could actually be behind the acceleration. In this article we do not take a particular stand on what might cause acceleration. As with reversal explanation, there could be competing theories from both – behavioural finance and rational expectations literature.⁵ Our main task is to empirically establish whether acceleration is a separate phenomenon as e.g. argued by [Xiong and Ibbotson \(2015\)](#).

4.3 Data

This section begins with the description of the equity price database and its filtering procedures. It proceeds with the construction of price-based trading signals. We then present the data on the risk factors used in our main empirical analysis.

Signals. We take all equity prices from the Center for Research in Security Prices (CRSP) database. We only keep common stocks with the share-type code of 10 or 11. We use return data adjusted for firm events, e.g. stock splits or distributions, and complement it with delisting returns as in [Beaver, McNichols, and Price \(2007\)](#) to avoid selection bias. Our cross section includes a total of 9569 US equities and an average of 4052 stocks per date. The sample covers the two most recent decades going from January 1993 until December 2014.

We consider five signals throughout our analysis. All signals are built with the daily stock price observations at the end of a one-month lookback (formation) period which precedes a holding

⁴Our acceleration measure could also be related to the measure of proximity to the price high over the lookback period by [George and Hwang \(2004\)](#). Thank you to James Sefton for pointing it out.

⁵Rational expectations theories of reversal are often based on the liquidity issues. [Avramov, Chordia, and Goyal \(2006\)](#) argue that reversal strategy returns are stronger for lower liquidity stocks. [Nagel \(2012\)](#) suggests average returns to reversal strategy reflect the market maker’s liquidity-bearing capacity; moreover, there is significant time variation in this liquidity provision. [So and Wang \(2014\)](#) find consistent evidence for this story via inventory risk channel by studying reversal profits around scheduled information releases. An alternative rational agents story is that by [Johnson \(forthcoming\)](#), who claims that delegated fund management with performance evaluation versus the benchmark can generate reversal patterns. Finally, the story in [Etula, Rinne, Suominen, and Vaittinen \(2015\)](#) combines the institutional asset management friction, argued to be related to the monthly cash management cycle, with the limited liquidity-bearing capacity by market makers to explain aggregate market-level reversals. There is still an unsettled empirical debate on whether the higher share of institutional investors increases ([Johnson, forthcoming; Etula, Rinne, Suominen, and Vaittinen, 2015](#)) or decreases ([Cheng, Hameed, Subrahmanyam, and Titman, forthcoming](#)) return reversals.

period. We start with two proxies for acceleration in returns, acA and $ac5$. To build the former signal, we linearly interpolate prices between the beginning and the end of the formation period and measure the area between the interpolated and the actual realised prices over the month. We do so, by adding the deviations of actual prices from the interpolated ones:

$$acA = \sum_{t=1}^{N-1} \left[\frac{P_N - P_0}{N} t - P_t \right] \quad (4.1)$$

where N counts the number of trading days of the formation month and P_0 is the last price from the preceding month.

A somewhat simpler proxy of acceleration, $ac5$, is defined as:

$$ac5 = la5 - fi5 \quad (4.2)$$

where $la5$ is the average return on the last five trading days of the formation month and $fi5$ is the average return on the first five trading days of the same month. Bottom-line, $ac5$ measures how different the returns were in the beginning of the lookback period compared to its end through a simple linear non-parametric model.

Furthermore, we also consider $fi5$ and $la5$ as separate signals. Finally, since our focus is mainly directed to one-month lookback horizons, a natural benchmark choice to include is the reversal strategy by [Jegadeesh \(1990\)](#). The corresponding signal, which we label as rev , is simply the prior-month return.

We note that to facilitate the comparison across signals the holding period is always fixed at one month horizon, despite the fact that lookback for some signals effectively constitutes only a week. One should notice that $la5$ is very similar to the weekly-rebalanced strategy considered by [Lehmann \(1990\)](#) and others. We will argue in the Section 4.4 that in fact it is preferable not to decrease the holding period for $la5$ only to make it consistent with the formation period.⁶

To avoid the bias induced by the bid-ask bounce⁷, we use mid-to-mid returns both for the signal

⁶We will sometimes abuse the notation and refer to e.g. acA as portfolios of stocks sorted on the corresponding signal or the low-minus-high trading strategy that is long low signal portfolio and short high signal portfolio, depending on the context.

⁷A seminal work in this regard is [Roll \(1984\)](#).

generation and the holding period (e.g. [Da, Liu, and Schaumburg, 2014](#); [Lou, Polk, and Skouras, 2015](#)). Moreover, we skip stocks that have missing daily observations during the formation period. Finally, each signal is de-meaned by its industry-average as in [Novy-Marx \(2013\)](#).⁸ We follow standard literature practice, e.g. [Goyal \(2014\)](#), and use the Standard Industry Classification (SIC) codes from the COMPUSTAT-merged database to classify each stock into one of the 49 Fama and French industry portfolios, which are retrieved from professor Kenneth French’s Data Library.

Risk factors and test assets. We consider some of the classic and contemporary factor models from the empirical equity pricing literature. We start by including [Fama and French \(1993\)](#) 3-factor model which comprises excess market return (MKT), small minus big capitalisation stocks (SMB), and high minus low book-market price stocks (HML). We also look at [Fama and French \(2015\)](#) 5-factor model (FF5) which adds additionally to the 3-factor model the variables capturing the exposure to firm’s operating profitability (RMW) and investment policy (CMA). Furthermore, we analyze a related q -factor model by [Hou, Xue, and Zhang \(2015\)](#) which instead of RMW and CMA use IA and ROE factors. Furthermore, we also include in the tests three variations of original models based on FF5. The first model is augmented with the liquidity factor from [Pastor and Stambaugh \(2003\)](#). The second model adds three price-based variables: the time-series momentum from [Moskowitz, Ooi, and Pedersen \(2012\)](#) together with the cross-sectional momentum (UMD) and short-term reversal factors from professor Kenneth French’s Data Library. The last model appends *la5*, our own short-term reversal factor, to the FF5. In total we have six factor models that we put to the test in our empirical analysis. Table [4.A.2](#) summarizes the details on the risk factors, the sources of the data and the reference models.

We also gathered data on 32 Fama-French portfolios triple-sorted on size, profitability, and investment. These portfolios will constitute the external test assets in our joint asset pricing tests. This data comes from professor Kenneth French’s Data Library.

⁸Our main results are not affected by the choice of using industry-adjusted signals.

4.4 Preliminary analysis

This section serves two main purposes. First, it indicates that acceleration signals are different from the traditional price-based signals typically considered in the academic literature. Second, it shows that portfolios sorted on the acceleration signals are producing a monotonic pattern in mean returns, leading to high profitability of the low-minus-high strategies which is robust to transaction costs.

Signal comparison. Table 4.1 presents the time series averages of the cross-sectional correlations between any two signals. Specifically, below the main diagonal are Spearman rank correlations; above the main diagonal are Pearson linear correlations. In bold are the numbers higher than 0.3 in absolute value. Since both correlation types provide a very similar picture, we choose to concentrate our attention only on the lower diagonal matrix (Spearman case).

TABLE 4.1 ABOUT HERE

In the correlation matrix we report additional signals to give a big picture view on how our acceleration measures compare to the broad universe of the more traditional price-based signals. The listed *trd* signal is the regression coefficient of prices on a time-trend, i.e. it is the coefficient b from the time-series regression specified by $P_t = a + bt + \varepsilon$ with $t = 1, 2, \dots, N$. Similarly, but as an additional proxy for acceleration, *acR* is the regression coefficient of prices on a quadratic time-trend, i.e. b_2 from the regression $P_t = a + b_1t + b_2t^2 + \varepsilon$. The *acH* is a variation of *ac5* where instead of five days we take the last and first half of the month.⁹ The *std₀* and *std* signals are two measures of the daily standard deviation of returns over the formation month. The former assumes a null mean, i.e. adds up squared returns, while the latter uses the sample mean in the calculations. Finally, we also report *mom*, the signal of the momentum strategy by Jegadeesh and Titman (1993), which is the return over the previous twelve months skipping the most recent month.

⁹We prefer *acA* and *ac5* over *acR* and *acH*. *acR* uses a parametric model, which necessary means the slope is estimated with an error. *acH* uses the difference in average daily returns over adjacent periods (analogous to Xiong and Ibbotson, 2015) which is likely to dilute the informativeness of the signal – indeed, in unreported results we find *acH* is less profitable than the two acceleration proxies considered in the main analysis.

The correlation matrix provides a clear evidence of two distinct features of our main acceleration signals. First, none of them is significantly correlated with any of the traditional price-based signals: 1-month reversal, standard deviation, and 12-2-month momentum. Second, all acceleration proxies are highly correlated among each other.¹⁰ *la5* (*fi5*) is by construction correlated positively (negatively) with *ac5* (Equation 4.2); because other acceleration proxies correlate highly with *ac5* such positive (negative) correlations with *la5* (*fi5*) are transmitted to all of them. To sum up, acceleration signals seem to convey different information from traditional price-based signals.

Portfolio sorts and LMH strategies. At each point in time signals, described in detail above, are used to sort stocks into deciles which are then used to construct value-weighted portfolios.¹¹ We exclude equities that, at the time of portfolio formation, have a price below \$5 or a market capitalization in the lowest New York Stock Exchange (NYSE) decile. The procedure is repeated for each signal, and portfolios are rebalanced monthly. Table 4.2 collects descriptive statistics on those portfolios and on the low-minus-high, LMH, strategy that goes long the low-signal portfolio and shorts the high-signal portfolio.¹² Each row of Panel A reports the average gross returns on the 10 portfolios for a particular signal. The embedded sparklines conveniently outline a monotonically increasing pattern in mean returns – as we go from high-signal portfolio to the low-signal portfolio – for *la5*, *ac5* and *acA*, while *fi5* it stays completely flat. Portfolio returns for *rev* at first seem to steepen up as we lower the signal, but lose completely ground on the two portfolios with the lowest signal. In fact, the strategy ends up totalling a gross LMH, of just 17 basis points (bps).¹³ Much better off are both acceleration strategies which exhibit a convincing LMH return of 1.2% (14.4% annualized) which is topped only by *la5* at approximately 1.6% (19% ann.). In complete contrast, the LMH for *fi5* is even slightly negative at -11bps per month.

TABLE 4.2 ABOUT HERE

¹⁰In addition to the signals reported in the correlation matrix we extensively explored other variations of the *acN*-variants, where $N = 1, 2, \dots, 10$, and time-trend regressions. Results do not change qualitatively and are available upon request.

¹¹Our main conclusions remain unchanged if instead we work with equal-weighted portfolios.

¹²Detailed descriptive statistics at the portfolio level are reported in the Appendix Table 4.A.1.

¹³This result is consistent with Lou, Polk, and Skouras (2015), who look at a very similar sample horizon and find no profitability in one-month reversal strategy.

Panel B of Table 4.2 reports descriptive statistics of LMH gross returns. Based on standard deviation, all strategies are fairly risky but while *la5*, *acA*, and *ac5* compensate volatility with returns, *rev* and *fi5* fail to do so. As already outlined in Panel A, *la5* achieves the best average return but at a slightly higher standard deviation, of 5.8%, than the acceleration strategies, which exhibit a volatility of about 5%. In terms of Sharpe Ratio (SR), the annualized figures for *la5*, *acA* and *ac5* are 0.95, 0.86, and 0.84, respectively.

Essentially, the strategies split up in two groups with the profitable *la5*, *acA* and *ac5* on one side and the *rev* and *fi5* on the other side. On one hand, this result is conceptually consistent for the acceleration strategies, as already described by the correlations in Table 4.1. On the other hand, we would expect them to differ from *la5*. But, since *ac5* subtracts *fi5* from *la5* and the former does not seem to be informative about future returns, evidence suggests that *de facto* power of acceleration might simply be stemming from *la5* component (the argument extends to *acA* from *ac5* since both exhibit high correlations). However, Panel B leaves a few points of advantage to the acceleration strategies in terms of stand-alone riskiness. Minimum monthly return (*min*) and maximum drawdown (*MDD*) settle respectively at about -9% and 22% for e.g. *acA* while *la5* records -14% and 30%. Statistics on the duration in months of the MDDs seems to also play against *la5*.

Figure 4.1 shows the cumulative returns on the five main LMH strategies. We can observe from it how the profitable group – *la5*, *acA* and *ac5* – realises steady gains from the beginning of the period until 2000. Afterwards, the three strategies take the most advantage of the *dotcom* bubble until 2002 and remain mostly flat until roughly 2009. This period is responsible for the differences in the MDD statistics which placed the acceleration signals at a slight advantage over *la5*. However, the graph clearly shows how at best the profitable group did not lose money, and none of the signals really came ahead. Finally, the group resumed the steady rise from 2009 onwards, with e.g. *acA* gaining more than 9% per year (gross). Moreover, the group shows countercyclical behaviour and remains profitable during NBER recessions, which are marked in the figure by the grey bands.

FIGURE 4.1 ABOUT HERE

The figure characterizes *fi5* and *rev* in a different way. We know already from Table 4.2 that

those two strategies are not profitable on average during our period of analysis. Still, the graph shows how *rev* was persistently trending up until mid 2004. After 2004 reversal started losing money more or less persistently until the end of the study. The reason for this structural break is interesting to explore but is outside the scope of the current paper. A plausible lead for an explanation to the ceased profitability of *rev* might lie in the length of the formation period. If we look at *la5*, the strategy is upward-trending from 2009 onwards while reversal is not. The only difference in the design of the two signals lies in the shorter lookback period of *la5*, which might suggest a further investigation into the optimal length of the formation period.

Additionally, we examine closer the average holding period return. Figure 4.A.1 presents the breakdown of the holding period by trading days. We notice that *acA*, and *ac5* as well as *la5* earn positive returns beyond the first trading week. On the contrary, *rev* is only profitable in the initial five trading days and then fluctuates around zero. This result is interesting because it suggests the traditional one-month lookback reversal signal is only informative about the one-week ahead LMH returns, while the one-week lookback contains information about the strategy profitability in the subsequent weeks. This observation gives supporting motivation to fixing holding period at one month for *la5*. Lastly, the mean returns for *fi5* always stay roughly flat at zero, again hinting on the uninformative nature of the signal.

Transaction cost analysis. In the previous section we identified a profitable signal group in *la5*, *acA*, and *ac5*. Therefore, market makers, being able to transact at close to mid prices, can take advantage of these investment opportunities. Now we show that in a cost-minimization exercise the corresponding LMH returns remain statistically significant even net of transaction costs. Hence, buy-side investors are also likely to make money implementing acceleration and weekly reversal strategies in the equity market. Throughout the paper we implicitly assume that the nominal trade size is sufficiently small not to bear much price impact (*non-proportional* transaction cost) during trading.¹⁴ Thus, our main task is to make LMH profitable in the presence of bid-ask spread (*proportional* transaction cost). To this end, we run the exercise where at the time of portfolio formation we only keep stocks from the cheapest quoted bid-ask spread quintile

¹⁴For the analysis of the price impact on reversal strategies see e.g. Avramov, Chordia, and Goyal (2006) based on Korajczyk and Sadka (2004). In addition, we also ignore the cost of short-selling the securities.

and form value-weighted portfolios with the remaining equities.¹⁵

The results of the transaction cost analysis are reported in Table 4.3. In addition to the average returns by portfolio, the sparklines and the corresponding LMH strategy return, Panel A also reports the estimates of transaction cost ($Tcost$) and standard error of the mean (se) for the gross LMH returns. The main observations from Panel A in Table 4.2 apply here: we observe similar monotonic patterns in average returns by portfolio, and the gross LMH returns are preserved. When we deduct $Tcost$ from the LMH for the profitable group, the difference is statistically significant – greater than roughly twice the reported standard error as indicated by bold numbers. For instance, *la5* is left with a monthly 1.4% ($> 1.96 \times 0.51\% = 1.0\%$) net return and *acA* gets about 1% ($> 0.9\%$).¹⁶ Table 4.3 Panel B shows that the bulk of the firms left applying such filter are large. There are roughly ten times more firms from the highest market cap quintile than there are from the lowest. Hence, stocks that have low quoted bid-ask spreads tend to be big firms.

TABLE 4.3 ABOUT HERE

Our results are different from those of Avramov, Chordia, and Goyal (2006) for the weekly reversal. In their empirical design the latter consider equally-weighted portfolios and in the base case analysis do not impose size and price filters on the equity universe, while we do. Each of those aspects very likely increases the impact of small stocks on the conclusions of the transaction cost analysis.

To sum up, we notice that, opposed to standard 1-month reversal factor, there is a strong monotonically increasing pattern in portfolio mean returns for *acA*, *ac5*, and *la5* as we move from a low-signal portfolio to a high-signal portfolio. This makes LMH strategies – which go long the former portfolio and fund the purchase by shorting the latter – based on those signals very profitable in gross terms. In fact, we argue that these profits survive the reasonable transaction cost

¹⁵This method is similar to one of the cost-minimizing methods examined in Novy-Marx and Velikov (2014). These authors do conditional double sort: for each size decile they only consider the lowest (effective) bid-ask spread decile to be included in the equity universe. In such a way, one tries to decrease the bid-ask spread component of transaction costs. The other two methods, that authors look at, concentrate at decreasing the turnover of LMH strategies, which is another component of $Tcost$.

¹⁶Our estimates of transaction costs are conservative, as the effective bid-ask spread estimates are typically lower than quoted analogues (see e.g. Avramov, Chordia, and Goyal, 2006).

estimates *provided* we impose a certain cost-minimizing technique which restricts further our tradable stock universe. Finally, we note that based on the preliminary analysis acceleration signals do not seem to offer much to what *la5* is already offering as a profitable signal (perhaps, except for certain stand-alone strategy risk characteristics such as duration of maximum drawdown). Next we explore in more detail the risk-return properties of our return series.

4.5 Spanning by factor models

In this section we analyse the risk properties of constructed portfolios as well as the LMH strategies described in the previous section. We first look at risk-adjusted returns of LMH strategies with respect to the cutting-edge factor models from the empirical equity pricing literature by running univariate time-series regressions.¹⁷ Then we look at the cross-section and test formally whether traditional factor models can price the portfolios from the univariate signal sorts. To preview our results, we find that existing factor models are struggling to explain the returns on acceleration and reversal strategies. However, we are able to explain the outlined puzzle by introducing LMH based on *la5* as a risk factor. Furthermore, incorporating this factor helps to price the acceleration and reversal portfolios, suggesting a strong factor structure in these portfolio returns.

Empirical setting. In the absence of arbitrage opportunities, if test assets are constructed to be zero-cost, Euler equation implies that risk-adjusted returns for each asset i should be zero: $E_t[R_{t+1}^i M_{t+1}] = 0$ for some existing stochastic discount factor (SDF) M_t . We assume SDF is affine in factors:

$$M_t = 1 - (f_t - \mu_f)'b \quad (4.1)$$

where f_t is the set of pricing factors, μ_f represents unconditional factor means and b 's are also known as factor loadings. Equation 4.1 implies a beta-pricing model where the expected excess return on portfolio i depends on the factor risk prices λ and the corresponding risk quantities β^i :

$$E[R_t^i] = \lambda' \beta^i \quad (4.2)$$

¹⁷Both the dependent and independent variables in the regression are taken to be gross returns for consistency.

with the factor prices obtained via the factor loadings: $\lambda \equiv V_f b$. V_f is the variance-covariance matrix of the factors, and β^i is equivalent to the regression coefficients of each portfolio's excess return R_t^i on the factors f_t and a constant: $\beta^i \equiv V_f^{-1} \text{cov}(R_t^i, f_t)$.

Univariate analysis. Table 4.4 displays the results of univariate time-series monthly frequency regressions of LMH strategies' returns on risk factors described in detail above (see also Table 4.A.2) and a constant. The table is organized in panels by signal. The coefficient α corresponds to the constant in the regression and subsequent rows of a panel show the corresponding factor loadings (betas). Since all our factors are tradable assets, we can interpret α as a pricing error or a risk-adjusted return. The last row of a panel shows the measure of fit – adjusted R^2 coefficient – of the regression.

TABLE 4.4 ABOUT HERE

One can notice that not only the mean excess return on *rev* is economically and statistically small, but so are its risk-adjusted returns, which are typically even smaller and, if anything, tend to be negative. The returns of *rev* do not load significantly on any of the factors, except on the market return and, unsurprisingly, on the reversal factors. Moreover, controlling for *la5* makes risk-adjusted return on the strategy negative and statistically significant at the 5% level. In the last model specification the measure of fit improves considerably compared to earlier specifications but still remains very low at 16% level. The analysis confirms the disappointing profitability of the reversal strategy based on a 1-month lookback period.

Similar conclusions hold for *fi5*. Neither the raw nor the risk-adjusted return is large enough to be statistically different from zero. The strategy loads positively on the market and 1-month reversal and (marginally) negatively on the cross-sectional momentum factor. Since *fi5* is independent from *la5* (see Table 4.1), it is not very surprising that the loading on *la5* in this panel is not as large as that in the panel for *rev*.

There is a very different picture for *la5*. The MKT factor loading is only significantly positive for model (2). At the same time, the loading on the HML factor becomes negative and significant as does the loading on the IA factor. Nevertheless, the risk-adjusted return on *la5* even tends to be higher than the raw return (admittedly, so does the corresponding standard error) and it is

always strongly statistically significant. Importantly, including factors, that utilise other price-related information – model (5), does not add much to the explanation of the puzzlingly positive *la5* returns – even the loading on STREV is less than one standard error from zero. R_{adj}^2 is again very low across all models and at most achieves a value of 11%.

Finally, acceleration strategies *ac5* and *ac4* seem to be largely unrelated to any of the traditional factors. Contrary to *rev* and *fi5*, they do not load positively on the market and 1-month reversal – if anything, there is (not very strong) evidence for negative loadings. Opposed to *la5*, they also do not seem to have strongly negative loadings on HML and IA factors. However, once the 5-day reversal LMH strategy is added in as an additional factor, instead of the 1-month reversal, to Fama and French (2015), the monthly α drops by 80bps to 40bps – a three-fold drop. It still remains significant, but at the 10% level. R_{adj}^2 also jumps – from below 10% for models (1 – 5) to about 35% for the last model. In factor specification (6) there is also more robust evidence of a negative loading on the market.

To sum up, the current state-of-the-art empirical equity factor models provide a poor explanation for the positive return on the 5-day reversal and acceleration strategies. Information content of the latter is not subsumed by the standard risk factors, but the large chunk of this information seems to be contained in *la5*. Nonetheless, acceleration strategies seem to provide some new information, valuable in a portfolio context. Next, switching from univariate time-series analysis, we study how well can the factor models jointly price multiple test assets.

Joint tests. Two families of joint tests are employed – time-series and cross-sectional. Emphasizing one more time that all our factors are tradable assets, we can apply the methodology described in Cochrane (2005, ch. 12.1). In particular, tradability allows us to interpret intercepts from time-series regressions of test asset returns on the factors as pricing errors.¹⁸ The null of the times-series asset pricing test is that all pricing errors jointly are equal to zero. We apply general method of moments (GMM) by Hansen (1982) to Equation 4.2 to estimate the β parameters and test the null via Hansen’s *J*-test.¹⁹ Throughout the analysis the long run variance-covariance matrix of the sample moments is estimated with Newey and West (1987) and optimal number of

¹⁸This is because factor risk prices, λ , can be estimated simply as times-series averages of the factors.

¹⁹In this paper the empirical unconditional asset pricing tests are performed only (i.e. instrument set contains only a constant).

lags according to [Andrews \(1991\)](#).

We also employ two versions of the cross-sectional asset pricing test (see e.g. [Cochrane, 2005](#), ch. 12.2) where λ parameter estimation is part of the problem. First, we compute the HJ distance measure of [Hansen and Jagannathan \(1997\)](#). We report simulated p -values for the null hypothesis that the HJ distance is equal to zero as in [Jagannathan and Wang \(1996\)](#). The advantage of the HJ distance is that its estimates can be compared across different competing models opposed to e.g. J -test and many other analogous tests. We estimate the parameters of unconditional Euler equation (see footnote 19) with SDF given in Equation 4.1 by means of GMM.

In addition, we run a traditional Fama-MacBeth-type two-pass ordinary least squares regression. In the first step, we run time series regressions of each asset's i excess return on a constant and the factors in order to estimate the betas:

$$R_t^i = a^i + f_t' \beta^i + \varepsilon_t^i \quad (4.3)$$

In the second step, we perform cross-sectional regressions of all asset excess returns on betas in order to estimate λ_t :

$$R_t^i = \hat{\beta}^{i'} \lambda_t + \alpha_t. \quad (4.4)$$

We then compute the factor risk prices as the average of these slope coefficient estimates: $\hat{\lambda} = T^{-1} \sum_{t=1}^T \hat{\lambda}_t^{OLS}$.²⁰ The null of the test is that all cross-sectional pricing errors $E[R_t^i] - \lambda' \beta^i$ from the beta model (Equation 4.2) are jointly equal to zero. Statistical inference is based on [Shanken \(1992\)](#).

We use the same factors and model specifications as in the univariate time-series analysis of LMH strategies (Table 4.A.2). Table 4.5 shows the outcomes of the tests. Each section of four rows considers a particular underlying signal studied in the paper. In brackets are the p -values for the corresponding asset pricing tests. The bolded numbers indicate p -values lower or equal to 0.05. χ_{TS}^2 denotes the time-series asset pricing test result with the null of jointly zero pricing errors from time-series regressions. The distribution of the test statistic is $\chi^2(N)$ where N corresponds to the number of test assets (which in this case is nine). χ_{XS}^2 denotes the cross-sectional asset

²⁰Note that in the second stage regression we do not add a constant to capture the common over- or under-pricing in the cross section of excess returns.

pricing test with the null of jointly zero cross-sectional pricing errors. The distribution of the test statistic is $\chi^2(N - K)$ which is different from that of the time-series test statistic because K -dimensional price of risk parameter λ is estimated as part of the methodology which removes some degrees of freedom. HJ dist refers to the [Hansen and Jagannathan \(1997\)](#) distance. The null of the corresponding test is that asset pricing model is correctly specified (HJ dist = 0). To save space we do not report the results for *rev* and *fi5*, as the analysis above showed neither the raw nor the risk-adjusted returns on portfolios generated by those signals create enough spread in mean returns to be interesting to explain via the pricing model.²¹

TABLE 4.5 ABOUT HERE

In Panel A we choose portfolios 2 – 10 from the univariate signal sorts, described in Table 4.2, as test assets for empirical pricing exercises, considering one signal at a time. In particular, we fund each long position in portfolios 2 – 10 out of the corresponding short position in portfolio 1. In such a way we construct the test assets in excess return form and lever the portfolio exposure to the factor of interest, compared to an alternative of funding long positions via the risk free rate.

For *la5* we notice that based on the time-series joint test neither [Fama and French \(1993\)](#) nor the more recently proposed factors are able to price the set of nine portfolios. The test strongly rejects the null of zero pricing errors with all p-values below 1%. There is not much support, however, coming from the cross-sectional tests. We attribute this to the fact that additional number of parameters (e.g. λ) need to be estimated as part of the methodology. For instance, in the case of model specification (5) which contains five factors, the χ^2 test statistic has only $9 - 8 = 1$ degrees of freedom. This also explains why most price of risk estimates have large standard errors and are, thus, not statistically different from zero (Table 4.A.3). Finally, as we add *la5*-based LMH as a factor to the [Fama and French \(2015\)](#) in specification (6) even the time series test cannot reject the null of a correctly specified model. In fact, λ point estimate corresponding to *la5* risk factor is the only one statistically different from zero and is equal to 1.60 – economically indistinguishable from the time series average of LMH *la5* of 1.59. Since the

²¹Also to conserve space the price of risk estimates together with cross-sectional R^2 coefficients are reported in the Appendix Tables 4.A.3-4.A.4.

latter is the λ estimate in the time-series test the result is very comforting.

The results from the asset pricing tests on *acA* and *ac5* are very similar to those on *la5*. The traditional factor models are struggling to explain mean returns in the time-series, and the pricing errors are jointly statistically different from zero. Once, the *la5*-based factor is added there are no spreads in mean returns left unexplained, and p-values for the *acA* and *ac5* stand at 27% and 18%, respectively. Nonetheless, the same problem with cross-sectional tests is visible – they are not informative about relative performance of competing models. Interestingly, the only significant price of risk estimate is again that for *la5* factor on *ac5*-based test assets. Its point estimate is 2.34 – this is, admittedly, higher than the time-series average of 1.60 but it is less than one standard error away from it, which, again, gives us confidence in the interpretation of the results.

In order to make cross-sectional tests more informative we add 32 portfolios studied in [Fama and French \(2015\)](#) to the set of test assets universe from Panel A. The former are triple-sorted independently on size, operating profitability, and investment and taken in excess of the 1-month risk-free rate. The results are presented in Table 4.5 Panel B.

For *la5* we again notice that the joint time-series test is rejected by traditional models. A word of caution is due, however – the test rejects the null even in the case of considering only 32 Fama-French portfolios in the asset pricing exercises.²² Not surprisingly, even the model specification (6) is now rejected by the test; although, we never suggested that adding our *la5* factor to the more traditional models should produce *the* model which is able to price all the assets. Therefore, we downplay the time-series test results in Panel B as adding two sets of assets – known in advance to be difficult to price – is not an interesting hurdle (not) to pass. What is more interesting are the outcomes of the cross-sectional joint tests: the first four model specifications are now strongly rejected by the data with the p-values for the test all less than 1%. Same conclusions are reached looking at the *HJ* distance which is statistically different from zero for the same group of models²³; for the case of model by [Hou, Xue, and Zhang \(2015\)](#) the statistical significance is marginal at the 10% level. The MKT and HML price of risk estimates are significantly positive for [Fama and](#)

²²This is also in line with what [Fama and French \(2015\)](#) conclude using a similar time-series test based on [Gibbons, Ross, and Shanken \(1989, GRS\)](#): “The GRS test easily rejects all models considered for all LHS portfolios and RHS factors. [...] In short, the GRS test says all our models are incomplete descriptions of expected returns.”

²³This is important, considering only [Fama and French \(1993\)](#) model is rejected by the cross-sectional tests when 32 Fama-French portfolios are considered, while models (2 – 6) are not rejected.

French (1993) model (see Table 4.A.4). Nevertheless, λ on HML is not different from zero once RMW and CMA are added as factors (consistent with the conclusions of Fama and French, 2015), while that on MKT remains significant.²⁴ For the model specifications (5-6) neither of the two cross-sectional tests is able to reject the null. We see that HJ distance is 6-11bps lower compared to models (1-4) and the p-values are comfortably above the 10% threshold. λ on $la5$ is significant at 2.27 which is within one standard error from the time-series average of 1.60.

Finally, we would like to point out that the none-rejection of the specification (5) in cross-sectional asset pricing tests is regarded by us as suspicious. Hence, we prefer to ignore this result. There are three reasons for this. First, it is the specification with the most factors and, hence, the most parameters to estimate – the distribution of the test statistics has less degrees of freedom. Therefore, it feels to us as partly reflecting the same problem described when running the tests in Panel A. Second, in unreported checks we re-run the cross-sectional tests using Fama and French (2015) factors and only one price-based factor at a time, instead of three lumped together. All three new factor models are then rejected. Third, we noticed in the univariate time series analysis that LMH based on $la5$ has a significant alpha with respect to model specification (5) with none of the betas save for HML being statistically different from zero.

For $ac5$ and acA we consistently observe very similar test results to that for $la5$. We again notice that models (1-4) tend to be rejected by cross-sectional tests. Nonetheless, there is less evidence coming from the HJ statistic; admittedly, the point estimates are close to being borderline significant. Prices of risk of MKT, CMA, and RMW factors are again significantly positive. Perhaps, what is most important, $la5$ can price well the acceleration-sorted portfolios with no significant pricing errors left. This also echoes the conclusions reached in the preliminary analysis of Section 4.4.

To sum up, the evidence from the joint tests is consistent with the univariate time-series analysis. The traditional models cannot jointly explain the cross section of very short-term reversal and acceleration portfolios. However, $la5$ seems to price well the set of acceleration portfolios.

²⁴Interestingly, SMB price of risk in Hou, Xue, and Zhang (2015) model is marginally significantly positive. However, since their model is rejected in many of the tests we do not pursue its variations further.

4.6 Conclusion

In this paper, we looked at some claims made about the price acceleration giving an informative trading signal. We built several empirical measures of acceleration and compared them to the price signals from the previous academic literature. We do find that acceleration signal leads to the construction of the long-short (LMH) trading strategies that deliver high profits. Moreover, those profits are not explained by the state-of-the-art equity factor models. However, all of the LMH profitability and cross-sectional variation in portfolios' mean returns are reconciled once we add our *la5* factor – a simple reversal strategy with a one trading week lookback horizon and one month holding period – to the off-the-shelf models. Taken together, our results cast doubt on acceleration being a separate phenomenon.

Among the points on our agenda for future research is the plan to analyze the reversal strategy as a function of the lookback period. Our empirical analysis of this paper indicatively points to the fact that with time the demand for trade immediacy (liquidity) has been met with the increasing supply. Thus, the profitable lookback period for the reversal strategy likely has been shrinking. For instance, [Cooper \(1999\)](#), working on an earlier 1962-1993 sample, concludes: “a security is more likely to have greater reversals if it has incurred two, rather than just one, consecutive weeks of losses or gains.” However, we do not find support for this claim in our 1993-2015 sample. If we look at the longer time span using 1-month reversal strategy from Kenneth French's Data Library we see that its mean return (Sharpe ratio) in 1960-1970s, 1980-1990s, and 2000-2015s was 93bps (1.30), 37bps (0.53), and 20bps (0.16), respectively. Therefore, what we uncover is not a recent, cyclical phenomenon and most likely is part of the long-term trend. Such analysis should also partly address a debatable issue on whether the reversal strategy returns are profitable (e.g. [Da, Liu, and Schaumburg, 2014](#)) or not (e.g. [Avramov, Chordia, and Goyal, 2006](#)) – as the profits likely to change with time, holding the lookback horizon fixed. Is the reversal strategy likely to disappear altogether? It is interesting to investigate whether our finding that *la5* is the best performing strategy is related to [Etula, Rinne, Suominen, and Vaittinen \(2015\)](#). In the case their story is right and continuing to rebalance the strategy at month-end, in the future the optimal lookback period should not necessarily become much shorter than 3 days, which they argue in the

paper is the focal point related to institutional investors' monthly cash management cycle. This and other issues in our research agenda are outside the scope of the current paper, however.

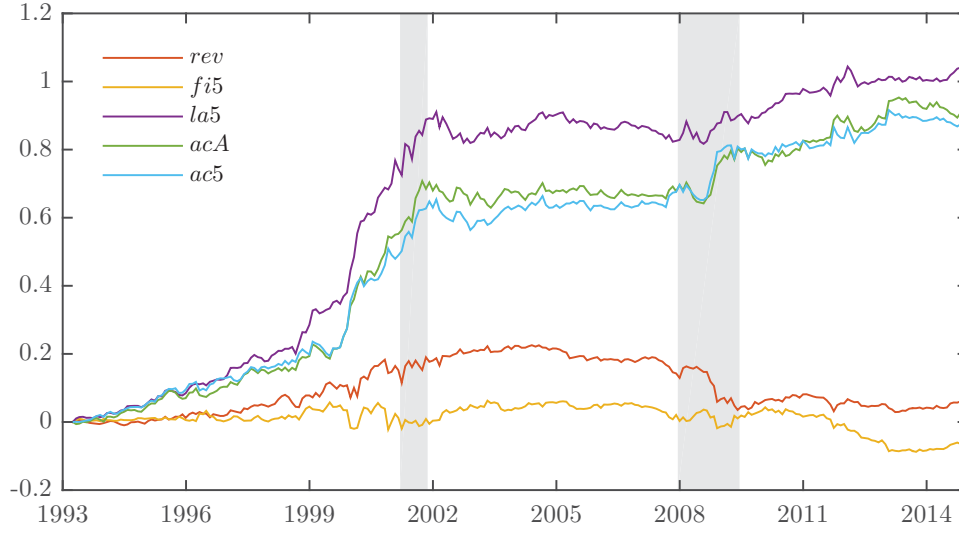


Figure 4.1: Cumulative returns on low-minus-high strategies

The figure presents cumulative returns on low-minus-high (LMH) strategies. All LMH series are rebased to 1 at the beginning of the period of analysis and scaled by their respective return standard deviation. Shaded areas denote NBER recessions. For each signal stocks are sorted every month into 10 value-weighted portfolios and the LMH strategy goes long the low signal portfolio and short the high signal portfolio. Definitions of signals: *rev* is the previous month return; *fi5* is the average return over the first five trading days of the previous month; *la5* is the average return over the last five trading days of the previous month; *acA* is the sum of daily deviations of the price from the linearly interpolated line between the beginning and the end of the previous month prices; *ac5* is the difference between *la5* and *fi5*. All quantities are calculated on a monthly frequency. The equity price data are taken from the Center for Research in Security Prices (CRSP) database. The sample excludes prices below 5 US dollars and prices corresponding to market cap below the first NYSE decile at the time of portfolio formation. Signals are industry-adjusted by subtracting from each raw stock signal its respective industry average signal. The period of study is from January 1993 to December 2014.

Table 4.1: Correlations among signals

This table presents the time series averages of the cross-sectional correlations between signals. Specifically, below the main diagonal are Spearman rank correlations; above the main diagonal are Pearson linear correlations. In bold are the numbers higher than 0.3 in absolute value. Definitions of signals: *rev* is the previous month return; *fi5* is the average return over the first five trading days of the previous month; *la5* is the average return over the last five trading days of the previous month; *acR* is the coefficient from the regression of prices on squared time (including constant and time) using daily observations over the previous month; *acA* is the sum of daily deviations of the price from the linearly interpolated line between the beginning and the end of the previous month prices; *ac5* is the difference between *la5* and *fi5*; *acH* is the difference between the average daily returns in the last half and the first half of the previous month; *std₀* and *std* are standard deviations of daily returns over the previous month – the former assumes zero mean while the latter takes sample mean in the calculations; *mom* is the return over the previous 12 months, excluding the most recent month. All quantities are calculated on a monthly frequency. The equity price data are taken from the Center for Research in Security Prices (CRSP) database. The sample excludes prices below 5 US dollars and prices corresponding to market cap below the first NYSE decile at the time of portfolio formation. Signals are industry-adjusted by subtracting from each raw stock signal its respective industry average signal. The period of study is from January 1993 to December 2014.

	<i>rev</i>	<i>trd</i>	<i>fi5</i>	<i>la5</i>	<i>acR</i>	<i>acA</i>	<i>ac5</i>	<i>acH</i>	<i>std₀</i>	<i>std</i>	<i>mom</i>
<i>rev</i>		.88	.46	.42	-.01	-.03	-.04	-.02	.05	.04	.00
<i>trd</i>	.90		.19	.27	-.01	.06	.05	.05	.04	.03	.00
<i>fi5</i>	.50	.21		-.01	-.38	-.62	-.69	-.47	.03	.02	.00
<i>la5</i>	.45	.28	.00		.49	.58	.65	.44	.06	.05	-.02
<i>acR</i>	-.02	-.01	-.41	.52		.79	.63	.88	.02	.02	-.02
<i>acA</i>	-.03	.07	-.65	.61	.81		.88	.86	.01	.01	-.02
<i>ac5</i>	-.05	.04	-.72	.68	.66	.89		.67	.01	.01	-.02
<i>acH</i>	-.03	.05	-.51	.47	.89	.86	.70		.00	.00	-.02
<i>std₀</i>	.12	.10	.08	.07	-.02	-.03	-.02	-.02		.997	-.01
<i>std</i>	.11	.08	.08	.06	-.02	-.03	-.01	-.02	.998		-.01
<i>mom</i>	.00	.00	.00	-.01	-.02	-.01	-.01	-.01	-.06	-.06	

Table 4.3: Portfolios and low-minus-high strategies – transaction cost analysis

This table presents some descriptive statistics on individual stocks, portfolios, and low-minus-high (LMH) strategies in the equity universe restricted to the lowest bid-ask spread quintile. For each signal stocks are sorted every month into 10 value-weighted portfolios and the LMH strategy goes long the low signal portfolio and short the high signal portfolio. Definitions of signals: rev is the previous month return; $f\%5$ is the average return over the first five trading days of the previous month; $la5$ is the average return over the last five trading days of the previous month; acA is the sum of daily deviations of the price from the linearly interpolated line between the beginning and the end of the previous month prices; $ac5$ is the difference between $la5$ and $f\%5$. In Panel A the first ten columns depict the average portfolio returns. For each LMH strategy the panel also shows its mean (gross) return, standard error of the mean (se) computed using Newey and West (1987), average estimate of transaction costs ($Tcost$). In bold are the coefficients that remain significant net of transaction costs at the 5% level, i.e. when $LMH - Tcost > 1.96 \times se$. Panel B presents the analysis of the typical stock size in the lowest bid-ask spread quintile. All quantities are calculated on a monthly frequency and expressed in percent. The equity price data are taken from the Center for Research in Security Prices (CRSP) database. The sample excludes prices above first bid-ask spread quintile, below 5 US dollars, and prices corresponding to market cap below the first NYSE decile at the time of portfolio formation. Signals are industry-adjusted by subtracting from each raw stock signal its respective industry average signal. The period of study is from January 1993 to December 2014.

Panel A: Descriptive statistics on signal-sorted and LMH portfolios in the lowest BA quintile													
	<i>High</i>	2	3	4	5	6	7	8	9	<i>Low</i>		<i>LMH</i>	<i>Tcost</i> <i>se</i>
<i>rev</i>	0.83	0.27	0.93	0.74	0.99	1.02	0.97	1.25	1.06	0.96		0.13	0.34 0.30
<i>f%5</i>	0.90	1.03	0.70	0.77	0.62	0.99	1.02	1.09	1.09	0.50		-0.40	0.34 0.30
<i>la5</i>	-0.48	0.43	0.57	0.62	1.10	0.84	0.99	1.20	1.34	1.26		1.74	0.34 0.51
<i>acA</i>	-0.19	0.65	0.50	0.82	0.97	1.26	0.90	1.03	1.24	1.13		1.32	0.34 0.44
<i>ac5</i>	-0.11	0.64	0.79	0.68	1.03	0.74	1.00	1.13	1.06	1.10		1.22	0.34 0.45
Panel B: Breakdown of stocks in the lowest BA quintile by size													
Size group	0-20%		20-40%		40-60%		60-80%		80-100%				
Average count	21		46		84		131		219				

Table 4.4: Risk-adjusted low-minus-high strategies' returns

This table presents the results of time-series regressions of low-minus-high (LMH) strategies' returns on risk factors. For each signal stocks are sorted every month into 10 value-weighted portfolios and the LMH strategy goes long the low signal portfolio and short the high signal portfolio. Definitions of signals: *rev* is the previous month return; *fi5* is the average return over the first five trading days of the previous month; *la5* is the average return over the last five trading days of the previous month; *acA* is the sum of daily deviations of the price from the linearly interpolated line between the beginning and the end of the previous month prices; *ac5* is the difference between *la5* and *fi5*. Factor models used in the analysis are described in Appendix Table 4.A.2. α coefficient corresponds to the constant in the regression. Newey and West (1987) standard errors are shown in parentheses and statistical significance at the 10, 5 and 1% level is marked respectively with *, ** and ***. All quantities are calculated on a monthly frequency. The equity price data are taken from the Center for Research in Security Prices (CRSP) database. The sample excludes prices below 5 US dollars and prices corresponding to market cap below the first NYSE decile at the time of portfolio formation. Signals are industry-adjusted by subtracting from each raw stock signal its respective industry average signal. The period of study is from January 1993 to December 2014.

	(1)	(2)	(3)	(4)	(5)	(6)
<i>rev</i>						
α	0.17 (0.317)	-0.07 (0.313)	-0.14 (0.347)	-0.09 (0.301)	-0.16 (0.310)	N/A -0.60** (0.257)
MKT		0.44*** (0.129)	0.47*** (0.137)	0.45*** (0.114)	0.43*** (0.113)	0.40*** (0.110)
SMB		-0.17 (0.227)	-0.09 (0.209)	-0.07 (0.196)	-0.09 (0.197)	-0.04 (0.196)
HML		0.01 (0.210)		0.06 (0.229)	0.08 (0.233)	0.16 (0.226)
RMW				0.21 (0.207)	0.19 (0.208)	0.28 (0.223)
CMA				-0.27 (0.294)	-0.27 (0.292)	-0.23 (0.304)
IA			-0.08 (0.303)			
ROE			0.18 (0.204)			
LIQ					0.13 (0.092)	
UMD						
TSMOM						
STREV						
<i>la5</i>						0.30*** (0.107)
R^2_{adj}		0.09	0.08	0.09	0.09	0.16

	(1)	(2)	(3)	(4)	(5)	(6)	
<i>fi5</i>							
α	-0.11 (0.282)	-0.25 (0.285)	-0.25 (0.318)	-0.21 (0.291)	-0.23 (0.298)	-0.07 (0.278)	-0.29 (0.261)
MKT		0.26** (0.104)	0.25** (0.102)	0.24*** (0.086)	0.24*** (0.086)	0.04 (0.084)	0.24*** (0.082)
SMB		-0.11 (0.163)	-0.05 (0.149)	-0.05 (0.165)	-0.06 (0.167)	-0.03 (0.154)	-0.05 (0.162)
HML		0.00 (0.219)		0.08 (0.165)	0.09 (0.172)	-0.14 (0.141)	0.10 (0.164)
RMW				0.09 (0.277)	0.08 (0.282)	0.11 (0.240)	0.10 (0.282)
CMA				-0.27 (0.287)	-0.27 (0.286)	-0.03 (0.206)	-0.27 (0.288)
IA			-0.06 (0.295)				
ROE			0.05 (0.255)				
LIQ					0.03 (0.101)		
UMD						-0.21* (0.115)	
TSMOM						-0.08 (0.108)	
STREV						0.52*** (0.131)	
<i>la5</i>							0.05 (0.105)
R^2_{adj}		0.03	0.02	0.03	0.03	0.20	0.03
<i>la5</i>							
α	1.60*** (0.421)	1.59*** (0.424)	1.92*** (0.471)	1.73*** (0.473)	1.69*** (0.482)	1.84*** (0.513)	N/A
MKT		0.20** (0.090)	0.08 (0.115)	0.14 (0.108)	0.14 (0.107)	0.09 (0.105)	
SMB		-0.06 (0.165)	-0.07 (0.161)	-0.12 (0.137)	-0.13 (0.137)	-0.11 (0.139)	
HML		-0.46*** (0.164)		-0.33** (0.159)	-0.32** (0.153)	-0.41** (0.166)	
RMW				-0.23 (0.284)	-0.24 (0.281)	-0.21 (0.305)	
CMA				-0.14 (0.281)	-0.14 (0.283)	-0.07 (0.298)	
IA			-0.76*** (0.233)				
ROE			-0.26 (0.161)				
LIQ					0.08 (0.076)		
UMD						-0.06 (0.126)	
TSMOM						-0.08 (0.113)	
STREV						0.13 (0.172)	
<i>la5</i>							
R^2_{adj}		0.09	0.11	0.09	0.09	0.09	

		(1)	(2)	(3)	(4)	(5)	(6)
<i>acA</i>							
α	1.23*** (0.361)	1.34*** (0.374)	1.40*** (0.410)	1.29*** (0.383)	1.33*** (0.394)	1.27*** (0.377)	0.40* (0.230)
MKT		-0.06 (0.085)	-0.07 (0.089)	-0.04 (0.079)	-0.03 (0.076)	0.07 (0.091)	-0.11* (0.065)
SMB		-0.15 (0.116)	-0.12 (0.127)	-0.14 (0.118)	-0.13 (0.119)	-0.15 (0.114)	-0.08 (0.106)
HML		-0.19 (0.188)		-0.24 (0.168)	-0.25 (0.170)	-0.13 (0.150)	-0.06 (0.143)
RMW				0.06 (0.258)	0.07 (0.259)	0.06 (0.234)	0.18 (0.162)
CMA				0.08 (0.287)	0.08 (0.283)	-0.04 (0.255)	0.15 (0.215)
IA			-0.32 (0.249)				
ROE			0.04 (0.168)				
LIQ					-0.07 (0.085)		
UMD						0.13 (0.100)	
TSMOM						-0.02 (0.109)	
STREV						-0.25** (0.124)	
<i>la5</i>							
R^2_{adj}		0.01	0.01	0.00	0.00	0.05	0.52*** (0.063)
<i>ac5</i>							
α	1.24*** (0.353)	1.40*** (0.358)	1.51*** (0.423)	1.37*** (0.384)	1.40*** (0.396)	1.36*** (0.368)	0.46** (0.213)
MKT		-0.12 (0.088)	-0.14 (0.100)	-0.11 (0.085)	-0.10 (0.080)	0.01 (0.085)	-0.18*** (0.067)
SMB		-0.14 (0.104)	-0.14 (0.117)	-0.15 (0.112)	-0.14 (0.115)	-0.16 (0.114)	-0.09 (0.100)
HML		-0.26 (0.193)		-0.30** (0.151)	-0.31** (0.155)	-0.18 (0.131)	-0.12 (0.122)
RMW				-0.01 (0.270)	0.00 (0.271)	-0.01 (0.249)	0.12 (0.167)
CMA				0.09 (0.286)	0.09 (0.284)	-0.03 (0.259)	0.17 (0.217)
IA			-0.35 (0.268)				
ROE			-0.07 (0.212)				
LIQ					-0.06 (0.092)		
UMD						0.14 (0.092)	
TSMOM						-0.02 (0.105)	
STREV						-0.26* (0.142)	
<i>la5</i>							
R^2_{adj}		0.02	0.02	0.02	0.02	0.07	0.53*** (0.075)

Table 4.5: Asset pricing tests

The table presents asset pricing results. Each section of four rows corresponds to a particular signal. For each signal stocks are sorted every month into 10 value-weighted portfolios. In Panel A portfolios 2-10 in excess of portfolio 1 serve as test assets; in Panel B Fama and French (2015) 32 portfolios – triple-sorted on size, operating profitability, and investment and taken in excess of the 1-month risk-free rate – are added to the set of test assets from Panel A. Definitions of signals: *fi5* is the average return over the first five trading days of the previous month; *la5* is the average return over the last five trading days of the previous month; *acA* is the sum of daily deviations of the price from the linearly interpolated line between the beginning and the end of the previous month prices; *ac5* is the difference between *la5* and *fi5*. For each set of test assets the columns of the table report asset pricing results for six asset pricing models described in Appendix Table 4.A.2. In brackets are the p-values for the corresponding asset pricing tests. The bolded numbers indicate p-values lower or equal to 0.05. χ^2_{TS} denotes the time-series asset pricing test obtained via general method of moments (GMM) procedure with the null of jointly zero pricing errors from time-series regressions (see Cochrane, 2005, ch. 12.1). Long run variance-covariance matrix of the sample moments is estimated with Newey and West (1987) and optimal number of lags according to Andrews (1991). χ^2_{XS} denotes the cross-sectional Fama-MacBeth-type asset pricing test using Shanken (1992) standard errors with the null of jointly zero cross-sectional pricing errors (see Cochrane, 2005, ch. 12.2-3). *HJ* dist refers to the Hansen and Jagannathan (1997) distance; the null of the corresponding test is that asset pricing model is correctly specified (*HJ* dist = 0). For the corresponding price of risk estimates please consult Tables 4.A.3-4.A.4 in Appendix. The equity price data are taken from the Center for Research in Security Prices (CRSP) database. The sample excludes prices below 5 US dollars and prices corresponding to market cap below the first NYSE decile at the time of portfolio formation. Signals are industry-adjusted by subtracting from each raw stock signal its respective industry average signal. The period of study is from January 1993 to December 2014.

		(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 9 test assets							
<i>la5</i>							
	χ^2_{TS} test	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.14]
	χ^2_{XS} test	[0.99]	[0.97]	[0.94]	[0.91]	[0.51]	[0.92]
	<i>HJ</i> dist	0.21	0.23	0.19	0.15	0.18	0.06
	<i>HJ</i> test	[0.91]	[0.87]	[0.75]	[0.77]	[0.23]	[0.93]
<i>acA</i>							
	χ^2_{TS} test	[0.00]	[0.03]	[0.04]	[0.04]	[0.03]	[0.27]
	χ^2_{XS} test	[0.55]	[0.67]	[1.00]	[0.99]	[0.91]	[0.99]
	<i>HJ</i> dist	0.27	0.25	0.04	0.04	0.02	0.04
	<i>HJ</i> test	[0.18]	[0.15]	[1.00]	[0.99]	[0.90]	[0.99]
<i>ac5</i>							
	χ^2_{TS} test	[0.00]	[0.02]	[0.04]	[0.05]	[0.02]	[0.18]
	χ^2_{XS} test	[0.54]	[0.45]	[0.33]	[0.95]	[0.47]	[0.44]
	<i>HJ</i> dist	0.22	0.23	0.21	0.12	0.13	0.12
	<i>HJ</i> test	[0.31]	[0.33]	[0.16]	[0.95]	[0.51]	[0.34]
Panel B: 9 + FF 32 test assets							
<i>la5</i>							
	χ^2_{TS} test	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	χ^2_{XS} test	[0.00]	[0.00]	[0.00]	[0.00]	[0.25]	[0.23]
	<i>HJ</i> dist	0.54	0.50	0.49	0.49	0.42	0.43
	<i>HJ</i> test	[0.01]	[0.06]	[0.03]	[0.03]	[0.71]	[0.21]
<i>acA</i>							
	χ^2_{TS} test	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	χ^2_{XS} test	[0.00]	[0.03]	[0.03]	[0.03]	[0.44]	[0.64]
	<i>HJ</i> dist	0.50	0.45	0.45	0.45	0.40	0.38
	<i>HJ</i> test	[0.05]	[0.25]	[0.14]	[0.13]	[0.56]	[0.55]
<i>ac5</i>							
	χ^2_{TS} test	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	χ^2_{XS} test	[0.00]	[0.01]	[0.01]	[0.03]	[0.29]	[0.46]
	<i>HJ</i> dist	0.50	0.47	0.46	0.45	0.41	0.40
	<i>HJ</i> test	[0.04]	[0.12]	[0.10]	[0.17]	[0.49]	[0.39]

Appendices

4.A Extra figures and tables

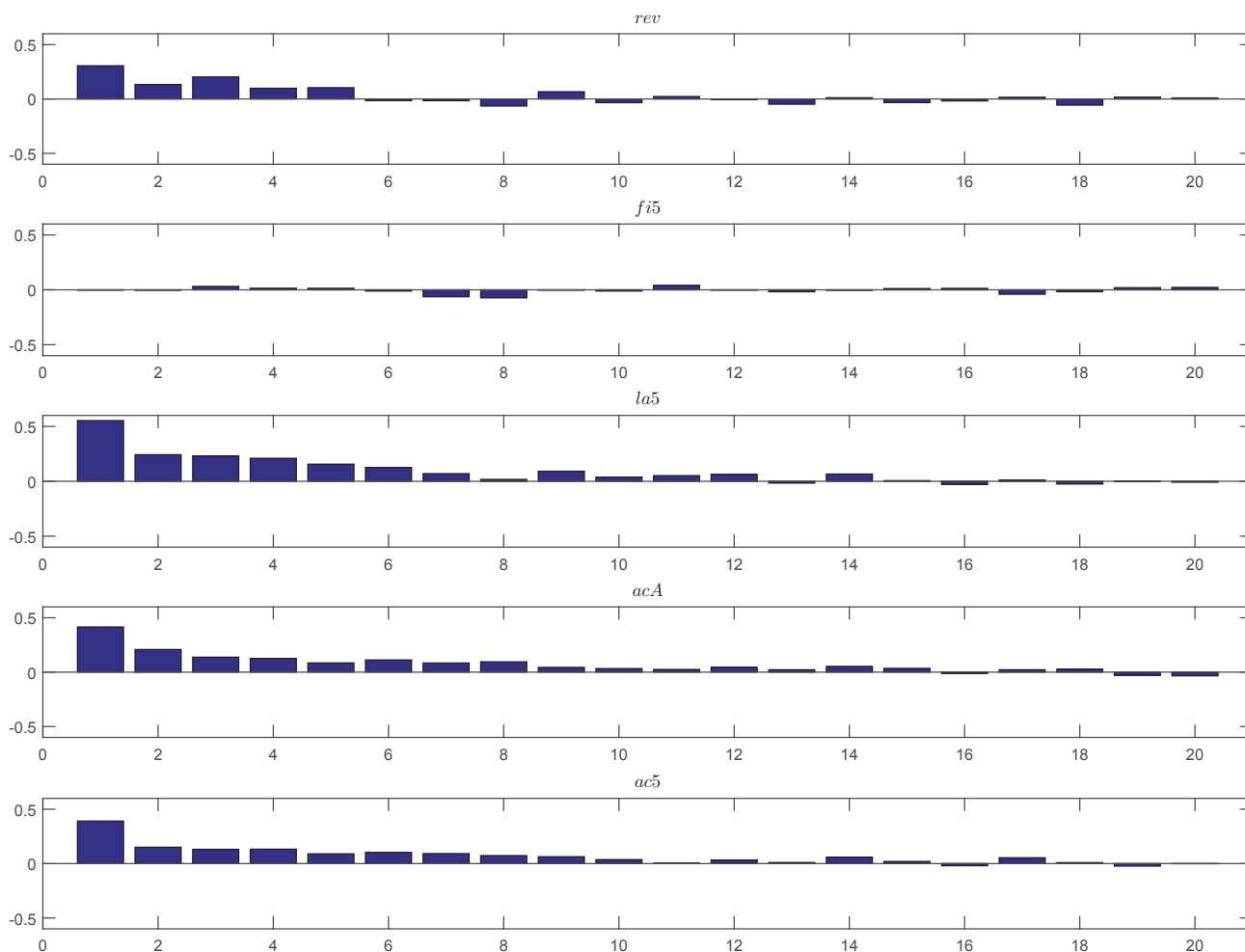


Figure 4.A.1: Average returns on low-minus-high strategies – breakdown by day

The figure presents mean holding period returns on low-minus-high (LMH) strategies. The monthly holding period is broken down by trading days with each bar representing average return on a particular day since the last strategy rebalancing date. For each signal stocks are sorted every month into 10 value-weighted portfolios and the LMH strategy goes long the low signal portfolio and short the high signal portfolio. Definitions of signals: *rev* is the previous month return; *fi5* is the average return over the first five trading days of the previous month; *la5* is the average return over the last five trading days of the previous month; *acA* is the sum of daily deviations of the price from the linearly interpolated line between the beginning and the end of the previous month prices; *ac5* is the difference between *la5* and *fi5*. All quantities are calculated on a monthly frequency and expressed in percent. The equity price data are taken from the Center for Research in Security Prices (CRSP) database. The sample excludes prices below 5 US dollars and prices corresponding to market cap below the first NYSE decile at the time of portfolio formation. Signals are industry-adjusted by subtracting from each raw stock signal its respective industry average signal. The period of study is from January 1993 to December 2014.

Table 4.A.1: Descriptive statistics on portfolios

rev	<i>High</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>	<i>7</i>	<i>8</i>	<i>9</i>	<i>Low</i>
<i>mean</i>	0.51	0.47	0.66	0.82	0.93	0.87	0.99	1.12	0.87	0.68
<i>std</i>	6.63	4.90	4.48	4.33	4.31	4.47	4.78	5.46	6.29	8.24
<i>med</i>	1.54	0.86	1.41	1.44	1.43	1.23	1.43	1.73	1.19	1.59
<i>skew</i>	-0.21	-0.51	-0.81	-0.69	-0.55	-0.52	-0.67	-0.96	-0.56	-0.91
<i>kurt</i>	6.61	4.39	4.31	4.02	4.75	4.71	5.20	5.77	5.67	6.57
<i>AC</i> ₁	0.06	0.02	0.12	0.10	0.08	0.02	0.07	0.15	0.01	0.07
<i>turn</i>	0.88	0.90	0.90	0.89	0.89	0.89	0.89	0.91	0.90	0.86
<i>Tcost</i>	0.52	0.44	0.43	0.45	0.45	0.45	0.47	0.47	0.50	0.61
fi5	<i>High</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>	<i>7</i>	<i>8</i>	<i>9</i>	<i>Low</i>
<i>mean</i>	0.82	0.84	0.87	0.58	0.79	0.93	0.87	0.93	0.82	0.72
<i>std</i>	7.28	5.38	4.44	4.48	4.58	4.45	4.53	5.07	6.27	8.14
<i>med</i>	1.16	1.50	1.57	1.32	1.33	1.38	1.67	1.73	1.34	1.30
<i>skew</i>	0.05	-0.59	-0.49	-0.85	-0.82	-0.92	-0.48	-0.73	-1.09	-0.74
<i>kurt</i>	8.41	4.95	4.28	4.42	5.09	5.32	4.27	6.41	7.44	7.33
<i>AC</i> ₁	0.07	0.01	0.04	0.12	0.09	0.12	0.10	0.07	0.13	0.08
<i>turn</i>	0.87	0.90	0.90	0.89	0.89	0.89	0.90	0.90	0.90	0.86
<i>Tcost</i>	0.54	0.46	0.45	0.45	0.46	0.45	0.45	0.46	0.49	0.54
la5	<i>High</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>	<i>7</i>	<i>8</i>	<i>9</i>	<i>Low</i>
<i>mean</i>	-0.30	0.42	0.49	0.71	0.80	0.91	0.93	1.03	1.14	1.29
<i>std</i>	6.61	5.22	4.74	4.43	4.26	4.41	4.70	4.86	5.77	8.06
<i>med</i>	0.97	1.28	1.13	1.18	1.31	1.46	1.59	1.45	1.56	1.61
<i>skew</i>	-1.06	-1.03	-0.99	-0.54	-0.65	-0.81	-0.92	-0.85	-0.83	-0.14
<i>kurt</i>	5.38	6.05	5.28	4.11	4.83	5.36	5.54	5.81	5.19	6.89
<i>AC</i> ₁	0.17	0.04	0.09	0.10	0.11	0.05	0.12	0.10	0.09	0.00
<i>turn</i>	0.86	0.90	0.90	0.89	0.89	0.89	0.89	0.90	0.90	0.86
<i>Tcost</i>	0.57	0.47	0.45	0.47	0.46	0.46	0.46	0.46	0.45	0.59
acA	<i>High</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>	<i>7</i>	<i>8</i>	<i>9</i>	<i>Low</i>
<i>mean</i>	-0.07	0.39	0.63	0.82	0.73	0.90	0.84	0.87	1.32	1.16
<i>std</i>	7.57	5.58	4.76	4.45	4.41	4.32	4.46	4.76	5.58	7.50
<i>med</i>	0.70	1.06	1.43	1.36	1.42	1.43	1.55	1.55	1.68	1.18
<i>skew</i>	-1.04	-0.69	-1.00	-0.77	-0.73	-0.66	-0.63	-0.78	-0.60	0.16
<i>kurt</i>	5.46	5.65	5.21	4.28	4.41	4.37	3.74	4.38	5.69	7.08
<i>AC</i> ₁	0.15	0.11	0.13	0.08	0.13	0.01	0.13	0.09	0.04	0.03
<i>turn</i>	0.85	0.89	0.90	0.89	0.89	0.89	0.90	0.90	0.89	0.86
<i>Tcost</i>	0.59	0.48	0.47	0.45	0.45	0.44	0.44	0.46	0.47	0.57
ac5	<i>High</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>	<i>7</i>	<i>8</i>	<i>9</i>	<i>Low</i>
<i>mean</i>	-0.06	0.64	0.72	0.79	0.88	0.79	0.76	0.88	1.11	1.16
<i>std</i>	7.68	5.57	4.86	4.62	4.19	4.26	4.49	4.97	5.70	7.39
<i>med</i>	0.85	1.36	1.42	1.25	1.14	1.46	1.53	1.32	1.49	1.60
<i>skew</i>	-0.98	-0.86	-0.92	-0.75	-0.59	-0.54	-0.97	-0.89	-0.69	-0.05
<i>kurt</i>	5.91	5.50	4.70	5.16	3.89	4.88	4.78	5.44	5.67	6.34
<i>AC</i> ₁	0.13	0.08	0.16	0.06	0.10	0.04	0.12	0.11	0.01	0.04
<i>turn</i>	0.85	0.90	0.90	0.89	0.89	0.89	0.89	0.90	0.90	0.85
<i>Tcost</i>	0.60	0.47	0.47	0.44	0.45	0.45	0.44	0.46	0.47	0.59

Table 4.A.2: Description of factor models

	MKT	SMB	HML	RMW	CMA	IA	ROE	LIQ	UMD	TSMOM	STREV	<i>la5</i>
(1)	x	x	x									
(2)	x	x				x	x					
(3)	x	x	x	x	x							
(4)	x	x	x	x	x			x				
(5)	x	x	x	x	x				x	x	x	
(6)	x	x	x	x	x							x
References to related academic works												
(1)	Fama and French (1993)											
(2)	Hou, Xue, and Zhang (2015)											
(3)	Fama and French (2015, FF5)											
(4)	FF5, Pastor and Stambaugh (2003)											
(5)	FF5, Jegadeesh and Titman (1993), Moskowitz, Ooi, and Pedersen (2012), Jegadeesh (1990)											
(6)	FF5, Lehmann (1990)											
MKT*	Brief description of the underlying factor exposure					Data source						
SMB*	broad market minus risk-free rate					website of Kenneth French						
HML	small minus big market capitalization					website of Kenneth French						
RMW	high minus low book/market price ratio					website of Kenneth French						
	robust minus weak operating profitability					website of Kenneth French						
CMA	conservative minus aggressive investment policy					website of Kenneth French						
IA	low minus high book assets growth					personal communication with Lu Zhang						
ROE	high minus low return on book equity					personal communication with Lu Zhang						
LIQ	high minus low exposure to market liquidity					website of Lubos Pastor						
UMD	XS momentum (winners minus losers), 12-2m lookback					website of Kenneth French						
TSMOM	TS momentum (via futures market), 12m lookback					website of Applied Quantitative Research (AQR)						
STREV	XS reversal (losers minus winners), 1m lookback					website of Kenneth French						
<i>la5</i>	XS reversal (losers minus winners), 5d lookback					authors' own calculations						

* For Hou, Xue, and Zhang (2015) model the MKT and SMB are taken from the same data source as IA and ROE

Table 4.A.3: Asset pricing tests – price of risk estimates (for Table 4.5 Panel A)

In addition, the table also shows R^2 from the second stage (cross-sectional) regression.

	(1)	(2)	(3)	(4)	(5)	(6)
<i>rev</i>						
MKT	0.62 (0.805)	1.06 (0.804)	0.59 (1.148)	0.67 (1.131)	0.49 (1.890)	−0.57 (1.446)
SMB	−0.03 (0.706)	0.03 (0.986)	0.28 (0.982)	0.22 (0.956)	−0.88 (1.117)	0.58 (1.024)
HML	0.80 (0.635)		−0.55 (1.150)	−0.18 (1.197)	−0.05 (1.358)	−1.19 (1.424)
RMW			0.60 (1.061)	−0.23 (1.231)	0.22 (1.592)	0.84 (1.253)
CMA			0.67 (0.630)	0.92 (0.648)	−0.18 (1.337)	0.59 (0.717)
IA		0.96 (0.634)				
ROE		−0.94 (1.942)				
LIQ				1.41 (1.335)		
UMD					3.22 (3.181)	
TSMOM					1.46 (3.723)	
STREV					0.26 (0.581)	
<i>la5</i>						1.77 (2.263)
R^2_{adj}	0.08	0.26	0.47	0.46	0.13	0.51

	(1)	(2)	(3)	(4)	(5)	(6)
<i>fi5</i>						
MKT	0.03 (1.588)	0.07 (1.502)	0.26 (2.913)	0.29 (3.043)	0.27 (10.911)	0.23 (2.610)
SMB	0.65 (1.083)	0.54 (0.580)	-2.41 (2.764)	-2.40 (2.766)	-2.64 (3.602)	-2.38 (3.566)
HML	0.43 (1.271)		-2.35 (3.018)	-2.36 (3.035)	-2.58 (4.620)	-2.31 (4.514)
RMW			0.10 (1.287)	0.13 (1.548)	0.14 (2.103)	0.08 (1.534)
CMA			0.41 (0.845)	0.42 (0.870)	0.36 (1.563)	0.41 (0.815)
IA		0.58 (0.493)				
ROE		-0.80 (0.645)				
LIQ				0.08 (2.386)		
UMD					1.41 (3.516)	
TSMOM					0.46 (7.391)	
STREV					-0.44 (2.919)	
<i>la5</i>						1.11 (4.368)
R^2_{adj}	-0.08	0.17	0.90	0.88	0.76	0.87
<i>la5</i>						
MKT	-8.74 (7.852)	-2.21 (5.996)	-7.61 (11.434)	-7.65 (11.188)	-9.45 (19.127)	-0.27 (3.977)
SMB	-5.27 (3.558)	-4.04 (3.045)	-5.28 (3.617)	-4.08 (2.935)	-6.32 (7.688)	-1.94 (1.243)
HML	-6.28 (4.984)		-5.55 (6.440)	-4.54 (5.607)	-6.86 (12.905)	-0.97 (2.292)
RMW			0.71 (4.883)	0.01 (4.601)	1.06 (8.693)	0.04 (2.081)
CMA			-1.24 (5.149)	-1.71 (5.323)	-0.65 (10.166)	0.63 (2.078)
IA		-4.52 (3.729)				
ROE		7.61 (6.404)				
LIQ				4.71 (7.077)		
UMD					2.14 (21.396)	
TSMOM					3.54 (15.189)	
STREV					-4.52 (9.111)	
<i>la5</i>						1.60*** (0.360)
R^2_{adj}	0.52	0.48	0.29	0.51	-1.07	0.97

	(1)	(2)	(3)	(4)	(5)	(6)
<i>acA</i>						
MKT	−3.62 (2.230)	−4.26 (2.788)	−0.26 (3.542)	−0.38 (3.711)	−0.57 (4.520)	−0.37 (4.017)
SMB	−2.93** (1.490)	−0.21 (1.775)	−2.62 (2.702)	−2.59 (2.706)	−1.35 (5.848)	−2.78 (3.808)
HML	−3.24* (1.665)		−3.26 (2.468)	−3.33 (2.552)	−2.75 (3.347)	−3.59 (5.675)
RMW			0.89 (3.076)	0.98 (3.216)	1.66 (3.928)	1.02 (3.864)
CMA			0.53 (2.947)	0.39 (3.213)	0.14 (3.668)	0.46 (3.268)
IA		−2.43* (1.309)				
ROE		3.40* (1.745)				
LIQ				0.73 (2.982)		
UMD					2.19 (10.479)	
TSMOM					0.11 (3.133)	
STREV					−1.36 (4.300)	
<i>la5</i>						0.96 (2.147)
R^2_{adj}	0.36	0.21	0.98	0.98	0.99	0.98
<i>ac5</i>						
MKT	−2.10* (1.268)	−1.76 (1.890)	−1.95 (1.460)	0.57 (3.599)	1.19 (6.139)	−0.30 (0.995)
SMB	−2.65** (1.227)	−3.51 (2.370)	−2.50* (1.373)	0.14 (2.960)	0.03 (3.366)	−0.32 (0.889)
HML	−2.05** (0.929)		−2.20** (0.961)	−2.85 (2.388)	−1.67 (2.730)	0.27 (0.929)
RMW			0.96 (0.920)	2.68 (2.898)	2.65 (3.509)	0.44 (0.690)
CMA			−0.91 (0.933)	0.87 (2.565)	−2.02 (3.198)	−0.38 (0.645)
IA		−1.41 (1.061)				
ROE		0.86 (2.016)				
LIQ				−6.11 (7.541)		
UMD					5.95 (6.987)	
TSMOM					7.76 (16.022)	
STREV					−0.43 (4.638)	
<i>la5</i>						2.34*** (0.800)
R^2_{adj}	0.02	−0.67	−0.45	0.46	−1.29	0.54

Table 4.A.4: Asset pricing tests – price of risk estimates (for Table 4.5 Panel B)

In addition, the table also shows R^2 from the second stage (cross-sectional) regression.

	(1)	(2)	(3)	(4)	(5)	(7)
<i>rev</i>						
MKT	0.84*** (0.272)	0.84*** (0.275)	0.88*** (0.272)	0.90*** (0.272)	0.90*** (0.273)	0.85*** (0.273)
SMB	0.12 (0.200)	0.37* (0.213)	0.19 (0.199)	0.18 (0.199)	0.17 (0.199)	0.18 (0.199)
HML	0.81*** (0.237)		0.09 (0.269)	0.16 (0.270)	0.33 (0.316)	0.16 (0.280)
RMW			0.37** (0.175)	0.36** (0.175)	0.33* (0.175)	0.42** (0.175)
CMA			0.34** (0.137)	0.34** (0.137)	0.30** (0.138)	0.35** (0.138)
IA		0.27* (0.142)				
ROE		0.60** (0.257)				
LIQ				-0.69 (0.662)		
UMD					2.01*** (0.637)	
TSMOM					1.40 (0.862)	
STREV					-0.18 (0.910)	
<i>la5</i>						2.28** (1.144)
R^2_{adj}	0.84	0.91	0.91	0.91	0.96	0.92

	(1)	(2)	(3)	(4)	(5)	(7)
<i>fi5</i>						
MKT	0.84*** (0.272)	0.84*** (0.275)	0.88*** (0.272)	0.90*** (0.272)	0.90*** (0.273)	0.85*** (0.273)
SMB	0.12 (0.200)	0.37* (0.213)	0.19 (0.199)	0.18 (0.199)	0.17 (0.199)	0.18 (0.199)
HML	0.81*** (0.237)		0.09 (0.269)	0.16 (0.270)	0.33 (0.317)	0.16 (0.280)
RMW			0.37** (0.175)	0.36** (0.175)	0.33* (0.175)	0.42** (0.175)
CMA			0.34** (0.137)	0.34** (0.137)	0.30** (0.138)	0.35** (0.138)
IA		0.27* (0.142)				
ROE		0.60** (0.257)				
LIQ				-0.69 (0.662)		
UMD					2.00*** (0.638)	
TSMOM					1.40 (0.865)	
STREV					-0.19 (0.925)	
<i>la5</i>						2.28** (1.146)
R^2_{adj}	0.84	0.91	0.91	0.91	0.96	0.92
<i>la5</i>						
MKT	0.84*** (0.272)	0.84*** (0.275)	0.88*** (0.272)	0.90*** (0.272)	0.90*** (0.273)	0.85*** (0.273)
SMB	0.12 (0.200)	0.37* (0.213)	0.19 (0.199)	0.18 (0.199)	0.17 (0.199)	0.18 (0.199)
HML	0.81*** (0.237)		0.09 (0.269)	0.16 (0.270)	0.33 (0.317)	0.16 (0.280)
RMW			0.37** (0.175)	0.36** (0.175)	0.33* (0.175)	0.42** (0.175)
CMA			0.34** (0.137)	0.34** (0.137)	0.30** (0.138)	0.35** (0.138)
IA		0.27* (0.142)				
ROE		0.60** (0.257)				
LIQ				-0.69 (0.662)		
UMD					2.00*** (0.638)	
TSMOM					1.40 (0.865)	
STREV					-0.18 (0.927)	
<i>la5</i>						2.27** (1.132)
R^2_{adj}	0.83	0.91	0.91	0.91	0.96	0.92

	(1)	(2)	(3)	(4)	(5)	(7)
<i>acA</i>						
MKT	0.84*** (0.272)	0.84*** (0.275)	0.88*** (0.272)	0.90*** (0.272)	0.90*** (0.273)	0.85*** (0.273)
SMB	0.12 (0.200)	0.37* (0.213)	0.19 (0.199)	0.18 (0.199)	0.17 (0.199)	0.18 (0.199)
HML	0.81*** (0.237)		0.09 (0.269)	0.16 (0.270)	0.33 (0.317)	0.16 (0.280)
RMW			0.37** (0.175)	0.36** (0.175)	0.33* (0.175)	0.42** (0.175)
CMA			0.34** (0.137)	0.34** (0.137)	0.30** (0.138)	0.35** (0.138)
IA		0.27* (0.142)				
ROE		0.60** (0.257)				
LIQ				-0.69 (0.662)		
UMD					2.00*** (0.638)	
TSMOM					1.40 (0.865)	
STREV					-0.19 (0.928)	
<i>la5</i>						2.28** (1.141)
R^2_{adj}	0.84	0.91	0.91	0.91	0.96	0.92
<i>ac5</i>						
MKT	0.84*** (0.272)	0.84*** (0.275)	0.88*** (0.272)	0.90*** (0.272)	0.90*** (0.273)	0.85*** (0.273)
SMB	0.12 (0.200)	0.37* (0.213)	0.19 (0.199)	0.18 (0.199)	0.17 (0.199)	0.18 (0.199)
HML	0.81*** (0.237)		0.09 (0.269)	0.16 (0.270)	0.33 (0.317)	0.16 (0.280)
RMW			0.37** (0.175)	0.36** (0.175)	0.33* (0.175)	0.42** (0.175)
CMA			0.34** (0.137)	0.34** (0.137)	0.30** (0.138)	0.35** (0.138)
IA		0.27* (0.142)				
ROE		0.60** (0.257)				
LIQ				-0.69 (0.662)		
UMD					2.00*** (0.638)	
TSMOM					1.41 (0.865)	
STREV					-0.19 (0.928)	
<i>la5</i>						2.28** (1.141)
R^2_{adj}	0.84	0.91	0.91	0.91	0.96	0.92

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