Macro uncertainty and currency premia*

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Abstract

This paper 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 macro forecasts. We find evidence that 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. Our results are consistent with a recent theory of exchange rate determination based on capital flows in imperfect financial markets.

Keywords: carry trade, currency risk premium, macro uncertainty, analyst forecasts, and global imbalances.

JEL Classification: F14, F31, F32, F34, G12, G15

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

Wadhwani (1999), Bank of England Monetary Policy Committee.

1 Introduction

Understanding the driving forces of carry trade returns has been at the center of a recent research agenda in international finance.[1] An important contribution comes from Gabaix and Maggiori (2015) who propose a novel theory of exchange rate determination where financial markets are imperfect and financiers absorb the imbalances in currency demand resulting from international trade and financial flows. Financiers, however, are financially constraint and in equilibrium the currencies of countries that require capital inflows – external debtor economies – have high expected returns such that financiers are compensated for bearing currency risk. In this model, capital flows drive both the size and the composition of financiers' balance sheets and, hence, determine both the level and dynamics of exchange rates. As a result, the risk-bearing capacity of financiers weakens when the variance of future imbalances rise. This causes an immediate currency depreciation and an expected future currency appreciation such that financiers have greater incentives to lend to external debtor countries.

Guided by this prediction, we test the sensitivity of currency excess returns to the volatility of future imbalances which we proxy using the cross-sectional dispersion of current account forecasts. Since a growing literature uses the dispersion of forecasts to quantify uncertainty, we also refer to our proxy as current account uncertainty.[2] In the model of Gabaix and Maggiori (2015), an increase in the variance of future imbalances corresponds to tighter financial constraints and, hence, we should expect that positive shocks to the dispersion of current account forecasts are associated with negative carry trade returns, and vice versa. We find strong empirical evidence that this is the case as investment currencies deliver low returns whereas funding currencies offer a hedge when current account forecast dispersion is unexpectedly high. In contrast, the forecast

[1] The carry trade is studied, among many others, in Brunnermeier, Nagel, and Pedersen (2009), Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), Lustig, Roussanov, and Verdelhan (2011), Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), Colacito and Croce (2013), Jurek (2014), Lettau, Maggiori, and Weber (2014), Bekaert and Panayotov (2015), Farhi, Fraiberger, Gabaix, Rancière, and Verdelhan (2015), Hassan and Mano (2015), Koijen, Pedersen, Moskowitz, and Vrugt (2015) and Mueller, Stathopoulos, and Vedolin (2015).

[2] See, for instance, Zarnowitz and Lambros (1987), Bomberger (1996), Bloom (2009), Beber, Breedon, and Buraschi (2010) and Baker, Bloom, and Davis (2013).

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. Our results hold for a broad sample of currencies and using market participants' expectations from two different surveys of international macro forecasts for the period from July 1993 to July 2013.

In addition to a component purely driven by the interest rate differential, the model of Gabaix and Maggiori (2015) also highlights the role of global imbalances as a separate driver of currency excess returns. Della Corte, Riddiough, and Sarno (2015) show that buying (selling) the currencies of extreme net debtor (creditor) countries with the highest (lowest) propensity to issue foreign currency denominated liabilities generates excess returns that are related to but different from those arising from a strategy that purely captures the interest rate differentials. In line with the prediction that external imbalances partly capture different information from interest rate differentials, we also show that an unexpected increase in the current account forecast dispersion can simultaneously explain negative (positive) excess returns on both high (low) interest rate countries and net external (creditor) debtor economies.[3] We further show that our measures of current account uncertainty are fundamentally linked to the (unobserved) volatility of future global imbalances which we calculate by means of a standard stochastic volatility model applied to monthly net exports over gross domestic product. Our analysis provides robust evidence on their long-run relationship.

We construct our cross-sectional forecast dispersions using data from *Blue Chip Economic Indicators* and *Consensus Forecasts*, to our knowledge the most comprehensive and long-dated international surveys of macro expectations available at monthly frequency and for a large cross-section of countries. Armed with these forecasts, we first construct for each macro variable country-level cross-sectional forecasts dispersions, and then take the cross-country average to determine their systematic component. Ultimately, we obtain measures of global uncertainty for current account, inflation rate, short-term interest rate, real economic growth, and foreign ex-

[3] While the model of Gabaix and Maggiori (2015) assumes for tractability that each country borrows or lends in its own currency, in practice most countries do not issue all their debt in their own currency (e.g., Eichengreen and Hausmann, 2005). Della Corte, Riddiough, and Sarno (2015) take the impact of foreign currency denominated debt into consideration and show that the currencies of countries with a higher propensity to issue liabilities in foreign currency offer a higher currency risk premium. These countries require much sharper depreciations to correct their external imbalances as suggested by the portfolio balance model of Gourinchas (2008).

change rate from each survey of market participants' expectations. In our exercise, we work with one-year ahead forecasts collected every month. This implicit overlapping structure generates a strong predictable component in our measures of 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 also consider a broad index of global economic uncertainty shocks that captures the common variation across all macro uncertainty measures by means of principal component analysis.

Our study is also closely related to a growing literature on the link between macro uncertainty and asset returns whereby forecast dispersion is regarded as a model-free measure of uncertainty.[4] In a recent paper Bali, Brown, and Tang (2015) construct a broad index of economic uncertainty based on the innovations to macroeconomic forecast dispersions and find a negative factor price of economic uncertainty in the cross-section of equity returns. The authors motivate their findings using the intertemporal hedging demand argument of Merton (1973) with macro uncertainty acting as a relevant state variable that affects consumption and investment decisions. When investors become more concerned about future outcomes, they reduce their optimal consumption in order to purchase at premium those assets that have higher covariance with economic uncertainty since they are viewed as hedging instruments against future negative shocks. The link between uncertainty and excess returns is more explicit in the asset pricing model of Anderson, Ghysels, and Juergens (2009) where uncertainty arise from the fact that investors have little knowledge about the dynamics of the true data generating process dictating the evolution of both asset returns and state variables. Intuitively, uncertainty is high when forecasters provide very different predictions about future economic fundamentals. In contrast, when forecast dispersion is low, it is likely that forecasters tend to agree about future economic fundamentals and hence uncertainty is low.[5]

While exchange rates are typically disconnected from economic fundamentals (see, for instance, Engel and West, 2005), a number of recent papers shows that global imbalances are

[4]Using a standard decomposition of forecast errors into a common and idiosyncratic shocks, Lahiri and Sheng (2010) show that uncertainty is simply the forecast dispersion among forecasters plus the variability of future aggregate shocks that accumulate over future forecast horizons.

[5]In their empirical analysis, Anderson, Ghysels, and Juergens (2009) focus only on uncertainty in mean returns. In contrast, our dataset allows us to potentially consider both sources of uncertainty.

indeed an important determinant of exchange rates. 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 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. Della Corte, Sarno, and Sestieri (2012) and Habib and Stracca (2012) extend this analysis in different directions and provide further empirical evidence on the fact that global imbalances are a key driver of exchange rates. Here, our evidence that current account uncertainty shocks command a negative premium in the cross-section of currency excess can be also rationalized using the setting of Anderson, Ghysels, and Juergens (2009), i.e., global imbalances act as a state variable for exchange rates but investors are uncertain about their evolution.[6]

We also build 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 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. As pointed out by the authors, however, volatility innovations are likely to capture shocks to state variables that are relevant to the evolution of the investors' investment opportunity set. Our study can be then seen as an attempt to shed light on the fundamental drivers of global volatility risk.

We start our asset pricing analysis using individual currency excess returns sorted on for-

[6] In 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.

ward discounts as test assets and our measures of macro uncertainty shocks as pricing factors. Since this exercise produces a large cross-section of excess returns, we can perform horse races among our different candidate measures of uncertainty and thus check at the outset whether the cross-sectional pricing power can be attributed to a specific measure of macro uncertainty or it is common to all of them.[7] We then move to examine the more traditional currency-sorted portfolios. In line with the prediction that currency excess returns are driven by both interest rate differentials and countries' external imbalances, we analyze jointly as test assets the forward discount sorted portfolios of Lustig, Roussanov, and Verdelhan (2011) as well as the global imbalance sorted portfolios of Della Corte, Riddiough, and Sarno (2015). In the same spirit, Colacito, Croce, Gavazzoni, and Ready (2015) provide a unified theoretical framework that replicates the properties of both carry trade and global imbalance portfolios. Our evidence suggests that the cross-section of currency excess returns is sensitive to current account uncertainty shocks as the model of Gabaix and Maggiori (2015) implies. We find consistent results across both country-level and portfolio-sorted excess returns. Finally, we provide a battery of robustness exercises and show that our key results remain quantitatively identical when we control for volatility, market liquidity and funding liquidity risk as well as monetary policy and economic policy 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 currency excess returns. Second, among a set of competing macro indicators, we provide empirical evidence on the key channel through which uncertainty affects currency risk premia. Our results complement the recent empirical evidence of Della Corte, Riddiough, and Sarno (2015) who show that global imbalances are an important driver of currency excess returns in addition to the well-know interest rate differential component, and provide novel empirical evidence that support the recent model of exchange rate determination of Gabaix and Maggiori (2015). Moreover, 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

[7]Working with country-level excess returns allows us also to address 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).

financial frictions channel.

The remainder of the paper is organized as follows. Section 2 provides the theoretical motivations for our empirical analysis. Section 3 describes the surveys of market participants' expectations on macro indicators, whereas Section 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 5 using country-level excess returns and in Section 6 using portfolio-level excess returns. Section 7 presents a number of extensions and robustness exercises, before concluding in Section 8. A separate Internet Appendix provides further robustness tests and additional results.

2 Motivations and testable hypothesis

This paper provides novel empirical evidence on the link between currency excess returns and measures of economic primitives quantified by the dispersion of market participants' expectations. Despite being empirical, our analysis relies on the theoretical foundations that characterize the portfolio balance approach to exchange rate determination pioneered by Kouri (1976). This class of models introduces a relationship between external imbalances and exchange rates in a framework where domestic currency denominated assets are imperfect substitutes for foreign currency denominated assets, uncovered interest rate parity does not hold and exchange rates move to equilibrate the demands and supplies derived from capital flows and current account transactions. Ultimately, the domestic currency depreciates whenever the current account is in deficit and appreciates when the current account is in surplus.

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 intermediaries face financial constraints that affect their ability to absorb the exchange rate risk arising from globally imbalanced capital flows. Since a global financial crisis disrupts the risk-bearing capacity of financiers, countries that require capital inflows will face a currency depreciation today and an expected currency appreciation in the future that compensates financiers for their currency risk taking.

In this model, the expected return to 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, pag. 1398]:

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

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 $R^\star$ 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 evolution of external imbalances (with exports normalized to unity), that is, when the domestic country is a net creditor at time $t = 0$, then it is expected to become a net importer at time $t = 1$ in order to offset its initial positive external imbalance.

The risk-bearing capacity of financiers plays an important role in this model since it causes carry trade returns to unwind. In this model, the ability of financiers to absorb risk depends on the riskiness of their balance sheets (i.e., exposure to currency mismatch) which is affected by 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 variance of exchange rates. It follows that the risk-bearing capacity worsens when the variance of future external imbalances increases as

$$\Gamma_0 = \gamma var(\iota_1)^\alpha, \tag{1}$$

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

Motivated by the prediction in Equation 1, we test whether the volatility of 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 international 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 volatility of future external imbalances on a global dimension.[8] 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 of this hypothesis and show that the volatility of 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. However, it is beyond the goal of this paper to discriminate among alternative theories that ultimately can rationalize our findings.

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

[8] Using 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.

foreign 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.[9] 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 Eurozone countries after the introduction of the Euro in January 1999 and replace them with the Euro area. The survey is carried out near the beginning of the month as the 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.[10] 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,

[9] The 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.

[10] This 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.

Norway, Peru, Philippines, Poland, Romania, Russia, Singapore, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, Ukraine, United Kingdom, United States, and Venezuela. After the introduction of the Euro in January 1999, we replace the Eurozone countries with the Euro area. 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.[11]

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.[12] 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

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

[12]In 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.

fixed-horizon forecasts (e.g., Dovern, Fritsche, and Slacalek, 2012; Buraschi and Whelan, 2012). In every month t, we construct a one-year constant maturity forecast f_t as a weighted average of year-end forecasts as follows

$$f_t = \frac{n}{12} f_{t+n|t} + \frac{12-n}{12} f_{t+12+n|t} \tag{2}$$

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 9^{th} of April 2001 are used as macro forecasts formed on the 6^{th} of April 2001.[13]

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

[13]Latin 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).

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 United Kingdom. After the introduction of the Euro in January 1999, we remove the data for individual Eurozone countries and replace them with 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. The net excess return from buying foreign currency for a month is computed as $RX^l_{t+1} \simeq (S^b_{t+1} - F^a_t)/S^a_t$, where a indicates the ask price, b the bid price, and l a long position in a foreign currency. If the investor buys foreign currency at time t but decides to maintain the position at time $t+1$, the net excess return is calculated as $RX^l_{t+1} \simeq (S_{t+1} - F^a_t)/S^a_t$. Similarly, if the investor closes the position in foreign currency at time $t+1$ already existing at time t, the net excess return is defined as $RX^l_{t+1} \simeq (S^b_{t+1} - F_t)/S^b_t$. The net excess return from selling foreign currency for a month is computed as $RX^s_{t+1} \simeq (F^b_t - S^a_{t+1})/S^b_t$, where s stands for a short position on a foreign currency. If the foreign currency leaves the strategy at time t and the short position is rolled over at time $t+1$, the net excess return is constructed as $RX^s_{t+1} \simeq (F^b_t - S_{t+1})/S^b_t$. Similarly, if the investor closes a short position on the foreign currency at time $t+1$ already existing at time t, the net excess return is computed as $RX^s_{t+1} \simeq (F_t - S^a_{t+1})/S^b_t$.

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.[14] 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.

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 $f^{i,k}_{m,t}$ 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

$$u^k_{m,t} = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}\left[f^{i,k}_{m,t} - f^{k}_{m,t}\right]^2} \tag{3}$$

where N_t is the number of forecasts on the macro variable m available at time t for the country k, and $f^k_{m,t}$ is the cross-sectional average of $f^{i,k}_{m,t}$. When data are only available for top and bottom forecasts for a particular series, we replace Equation (3) with a simple range-based measure in line

[14] See e.g. Della Corte, Ramadorai, and Sarno (2015) for the description of the currency options data.

with Bali, Brown, and Caglayan (2014). Denoting as $f^{h,k}_{m,t}$ and $f^{l,k}_{m,t}$ the top and bottom forecasts, respectively, we compute the range-based standard deviation of the forecasts at time t for each country k as

$$u^k_{m,t} = \sqrt{\ln\left[\frac{1+f^{h,k}_{m,t}}{1+f^{l,k}_{m,t}}\right]}. \tag{4}$$

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

$$u_{m,t} = \frac{1}{K_t}\sum_{k=1}^{K_t} u^k_{m,t}, \tag{5}$$

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 1 about here

We display our macro forecast dispersions, standardized to have zero means and unit variances for ease of comparison, in Figure 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.[15] 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).

[15]For *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.

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). 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.

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.[16] If forecasters share the same perceived variance of their forecast error components, then uncertainty can be

[16]Commonly 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).

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:

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

where 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 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)-(4). 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 1 ABOUT HERE

Table 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.[17]

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

[17] Our 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 (2015).

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 (2015) 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.

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, Ranaldo, 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.[18] We report the correlation matrix of Δu_m for both *Blue Chip Economic Indicators* and *Consensus Forecasts* in Table 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 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 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

$$\Delta u_{m,t} = a + \sum_{j \neq m} b_j \Delta u_{j,t} + \sigma_m \varepsilon_{m,t}. \tag{6}$$

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 $\Delta u_{m,t}$.

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

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:

$$RX_t^i = a^i + \beta_{dol}^i dol_t + \beta_m^i \Delta u_{m,t} + \varepsilon_t^i. \tag{7}$$

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

$$RX_t^i = \beta_{dol}^i \lambda_{dol,t} + \beta_m^i \lambda_{m,t} + \alpha_t^i, \tag{8}$$

and estimate λ and α^i as the average of the cross-sectional regression estimates, i.e. $\widehat{\lambda}_c = T^{-1} \sum_{t=1}^{T} \widehat{\lambda}_{c,t}$ and $\widehat{\alpha}^i = T^{-1} \sum_{t=1}^{T} \widehat{\alpha}_t^i$. 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 about here

Panel A of Table 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 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, 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 2 and 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 (7) and (8). In Figure 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, 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.[19] 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 presents asset pricing tests with orthogonalized shocks as defined in Equation (6) 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 runs a horse race exercise between current account and the competing pricing factors. Here we use orthogonalized uncertainty shocks as

[19]Recall 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.

described in Equation (6) 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:

$$\widehat{E}[RX^i] = \underset{[0.86]}{0.12}\beta^i_{dol} - \underset{[-2.16]}{\mathbf{0.49}}\beta^i_{ca} + \underset{[1.14]}{0.20}\beta^i_{if} - \underset{[-1.26]}{0.25}\beta^i_{ir} + \underset{[0.96]}{0.21}\beta^i_{rg} + \underset{[1.72]}{0.41}\beta^i_{fx} \tag{9}$$

$$\widehat{E}[RX^i] = \underset{[0.94]}{0.13}\beta^i_{dol} - \underset{[-4.64]}{\mathbf{0.84}}\beta^i_{ca} + \underset{[0.18]}{0.03}\beta^i_{if} + \underset{[1.75]}{0.20}\beta^i_{ir} + \underset{[0.53]}{0.10}\beta^i_{rg} + \underset{[0.14]}{0.04}\beta^i_{fx}. \tag{10}$$

where $\widehat{E}[RX^i]$ denotes the average excess return for currency i predicted by the model whereas the βs are the slope estimates from the first-stage Fama-MacBeth regressions. We display t-statistics 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 (9) refers to *Blue Chip Economic Indicators* whereas Equation (10) 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 4 about here

We present the fit of the asset pricing models defined in Equations (9) and (10) in Figure 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).[20] The model-predicted excess returns lie very close to the 45 degree line, suggesting

[20]The 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

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 4 about here

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 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.[21]

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).

[21] The 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.

In the second subset, we employ the exchange rate classification index of Ilzetzki, Reinhart, and Rogoff (2011) and retain only floating and quasi-floating currencies as test assets.[22]

TABLE 5 ABOUT HERE

We report these asset pricing tests in Table 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. 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.

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 IA.1; (ii) we estimate a VAR with two lags to compute macro uncertainty innovations in Table IA.2; (iii) (iv) we replace foreign exchange volatility innovations with VIX innovations and equity market uncertainty shocks in Table IA.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 IA.4; (v) we proxy cross-sectional dispersion using a range-based estimator for *Consensus Forecasts*'s data in Table IA.5; and (vi) we run country-level asset pricing tests for additional economic indicators covered by *Consensus Forecasts* in Table IA.7.

[22]The data are available on Ethan Ilzetzki's website at monthly frequency until the end of 2010. We extend the sample to July 2013 by forward filling.

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.[23] 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:

$$E[RX_t^j M_t] = 0, \tag{11}$$

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:

$$E[RX_t^j] = \lambda' \beta^j \tag{12}$$

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 (12) and the factor loadings in equation (11) is given by $\lambda = \Sigma_h b$ with Σ_h denoting the covariance matrix of the factors. We estimate the parameters of Equation (11) via the generalized method of moments (GMM) of Hansen (1982) with a prespecified weighting

[23] We refer to their work for the underlying data description and the construction methodology.

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 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 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 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^2s 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 5 ABOUT HERE

Figure 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-Jagannthan 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 $j = 1, \ldots, K$ index the asset pricing models reported in Table 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

$$H_0 : \max_{j=2,\ldots,K}(d^2_{T,1} - d^2_{T,j}) \leq 0, \tag{13}$$

where $d^2_{T,j}$ 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

$$H_1 : \max_{j=2,\ldots,K}(d^2_{T,1} - d^2_{T,j}) > 0, \tag{14}$$

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

$$\mathcal{T}^W = \max_{j=2,\ldots,K} \sqrt{T}(d^2_{T,1} - d^2_{T,j}), \qquad \mathcal{T}^H = \max(\mathcal{T}^W, 0). \tag{15}$$

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

$$p_W = \frac{1}{R}\sum_{r=1}^{R} \#(\mathcal{T}^W_r > \mathcal{T}^W), \qquad p_H = \frac{1}{R}\sum_{r=1}^{R} \#(\mathcal{T}^H_r > \mathcal{T}^H), \tag{16}$$

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 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.[24]

We also run a simple horse race exercise as an alternative statistical procedure to check

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

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 7 about here

We report these results in Table 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 6-7 coupled with the sample correlations in Figure 5 confirm our key results on the pricing performance of the current account uncertainty shocks.

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 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 8 about here

We report asset pricing tests in Table 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.[25] 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 IA.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 $u_{mp,t} = T_t^{-1}\sum_{\tau\in T_t}(\sum_{k\in K_\tau}|\Delta i_\tau^k|/K_\tau)$, where Δi_τ^k is the daily change in the 1-month interest rate for currency k. In Table IA.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

[25]Results 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%.

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.[26]

[26] This 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.

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 9, we construct the market liquidity factor of Karnaukh, Ranaldo, and Söderlind (2015) and then run portfolio-level asset pricing tests using its innovations $\Delta mliq$ as an additional pricing factor.[27]

TABLE 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.

In Table IA.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 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

[27] We 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.

space the following stochastic volatility model

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

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).[28]

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 regression

$$v_{t+12} = \alpha_v + \beta_v u_{ca,t} + \sum_{i=-j}^{j} b_{v,i} \Delta u_{ca,t-i} + \epsilon_{t+12} \tag{17}$$

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

[28] Alternatively, 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.

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 (17) 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:

$$v_t = \underset{[35.56]}{0.67} + \underset{[5.25]}{0.92} u_{ca,t-12} + \epsilon_t \qquad R^2 = 11\% \tag{18}$$

$$v_t = \underset{[34.69]}{0.52} + \underset{[15.93]}{0.23} u_{ca,t-12} + \epsilon_t \qquad R^2 = 67\%, \tag{19}$$

where Equation (18) reports results *Blue Chip Economic Indicators* and Equation (19) 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 (17) for the 12-month lagged v_t, and (iii) we control Equation (17) 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.

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.

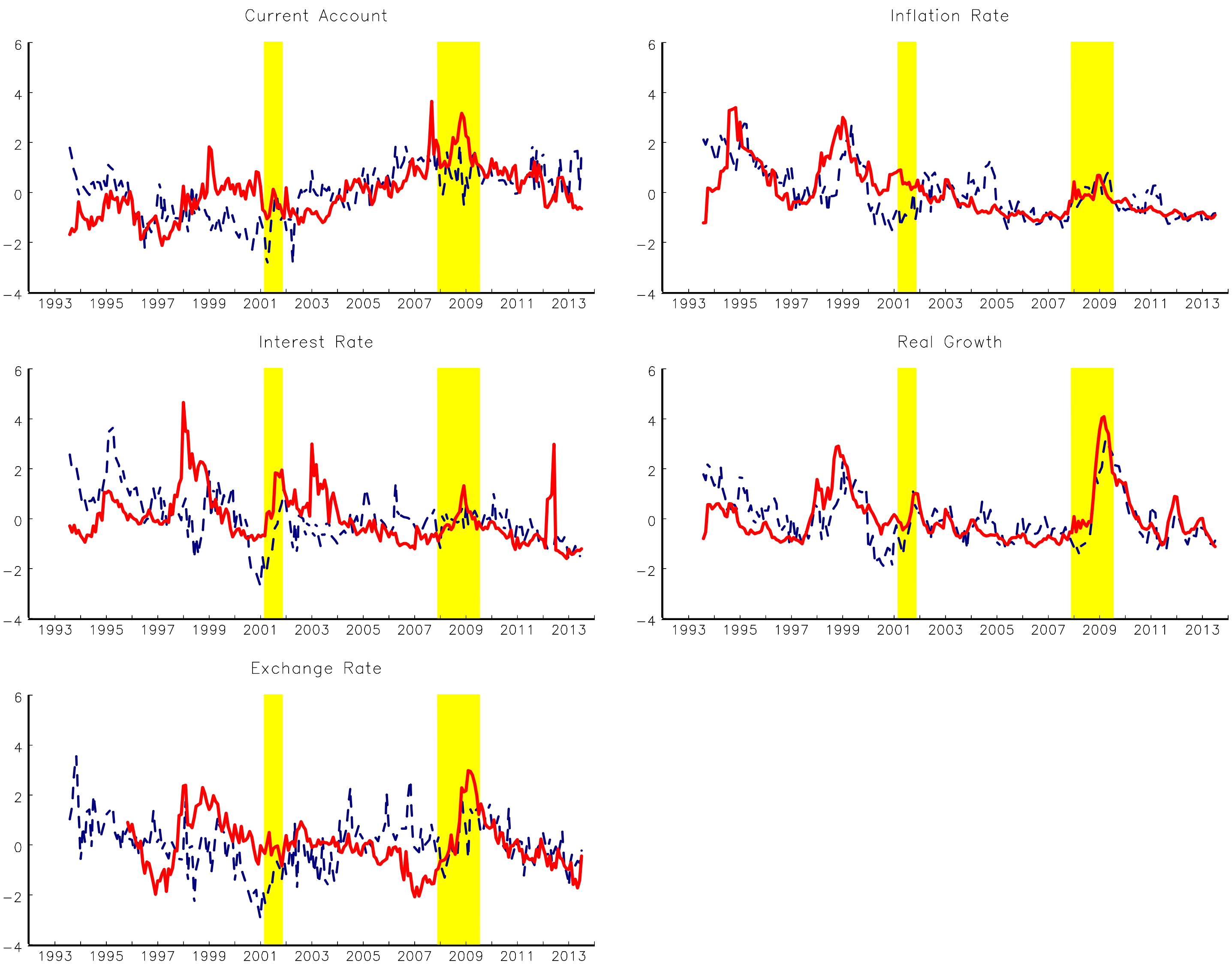

Figure 1: Measures of macro uncertainty

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.

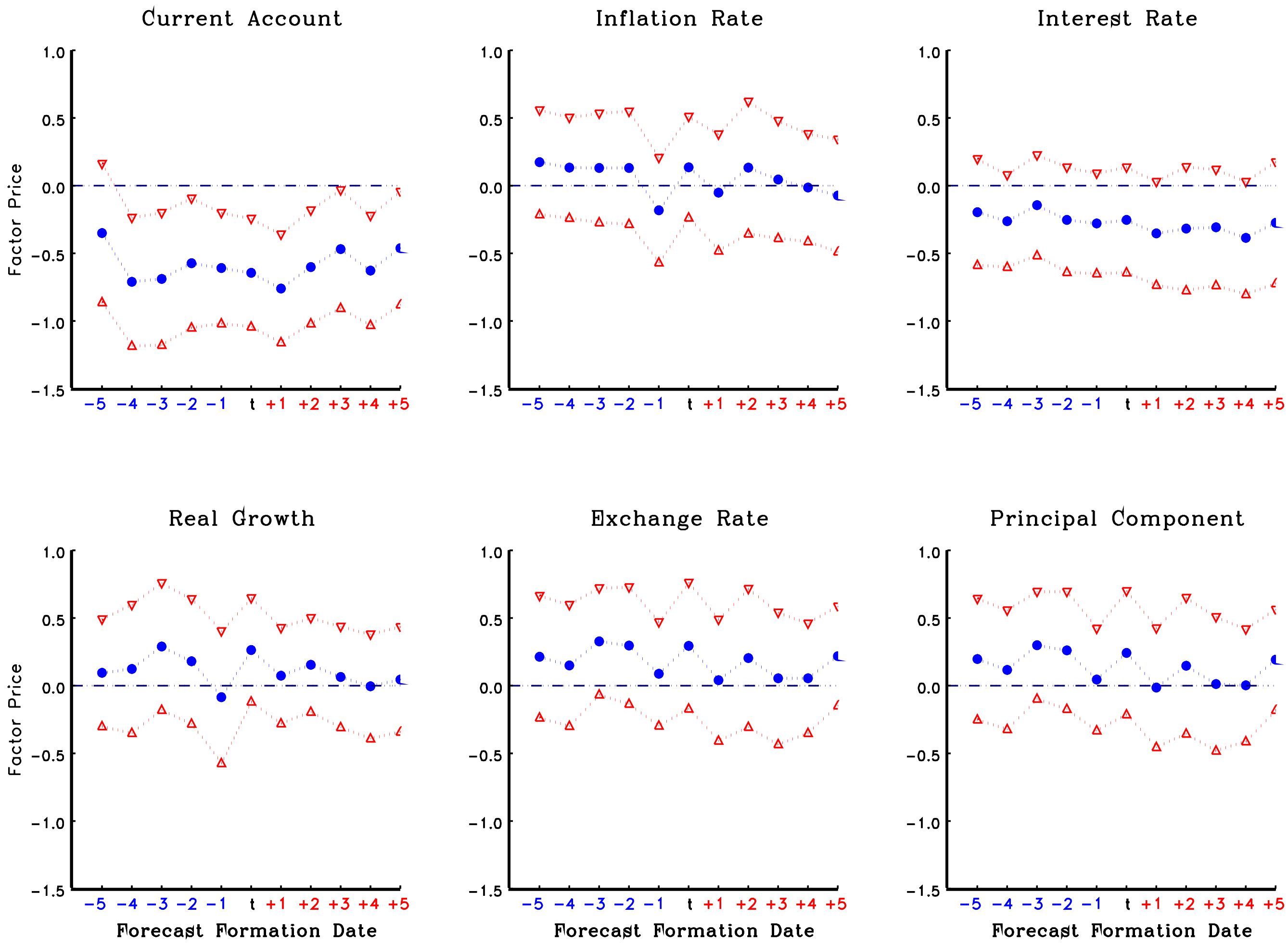

Figure 2: Forecasts formation dates: Blue Chip Economic Indicators

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.

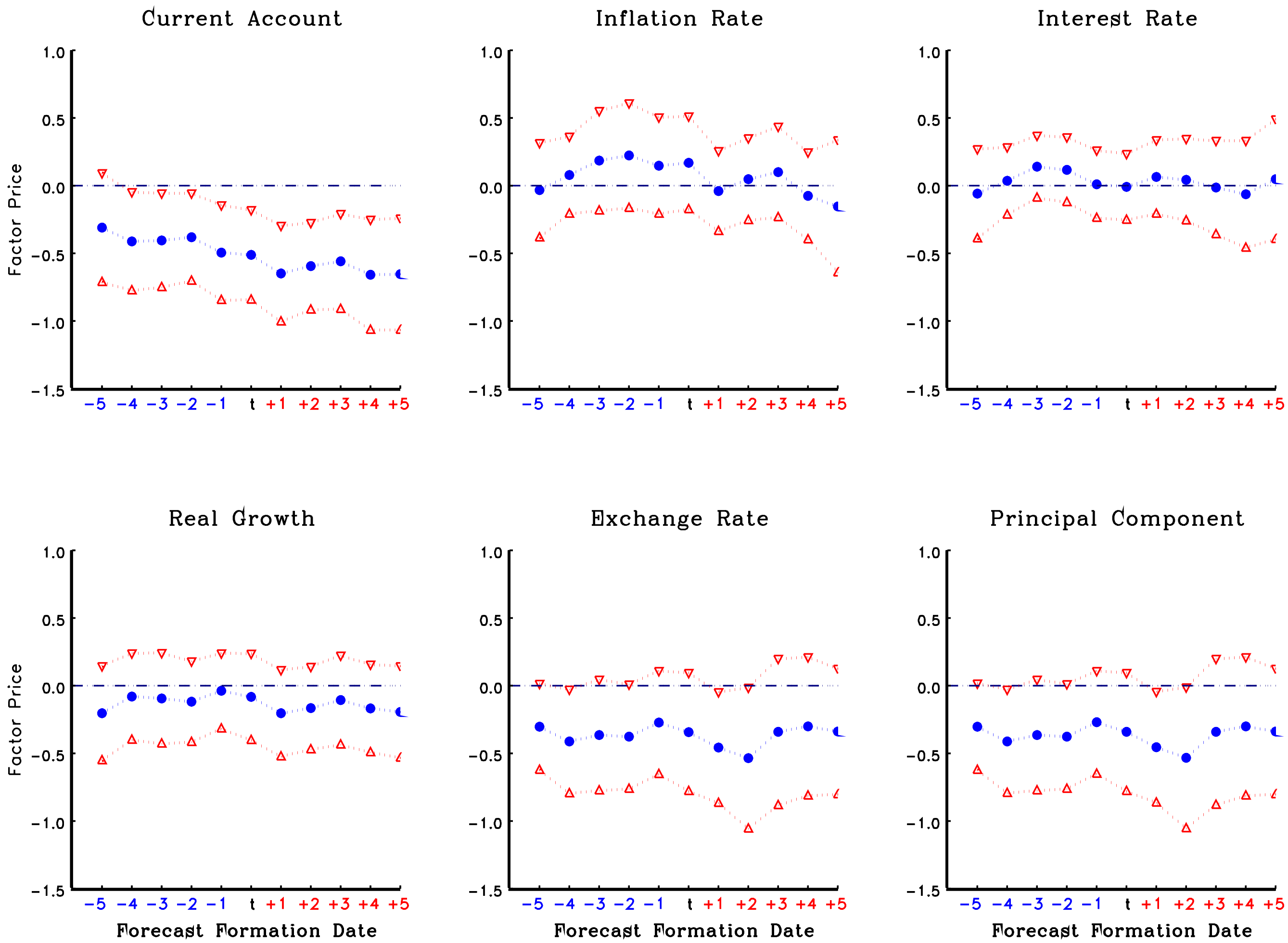

Figure 3: Forecasts formation dates: Consensus Forecasts

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.

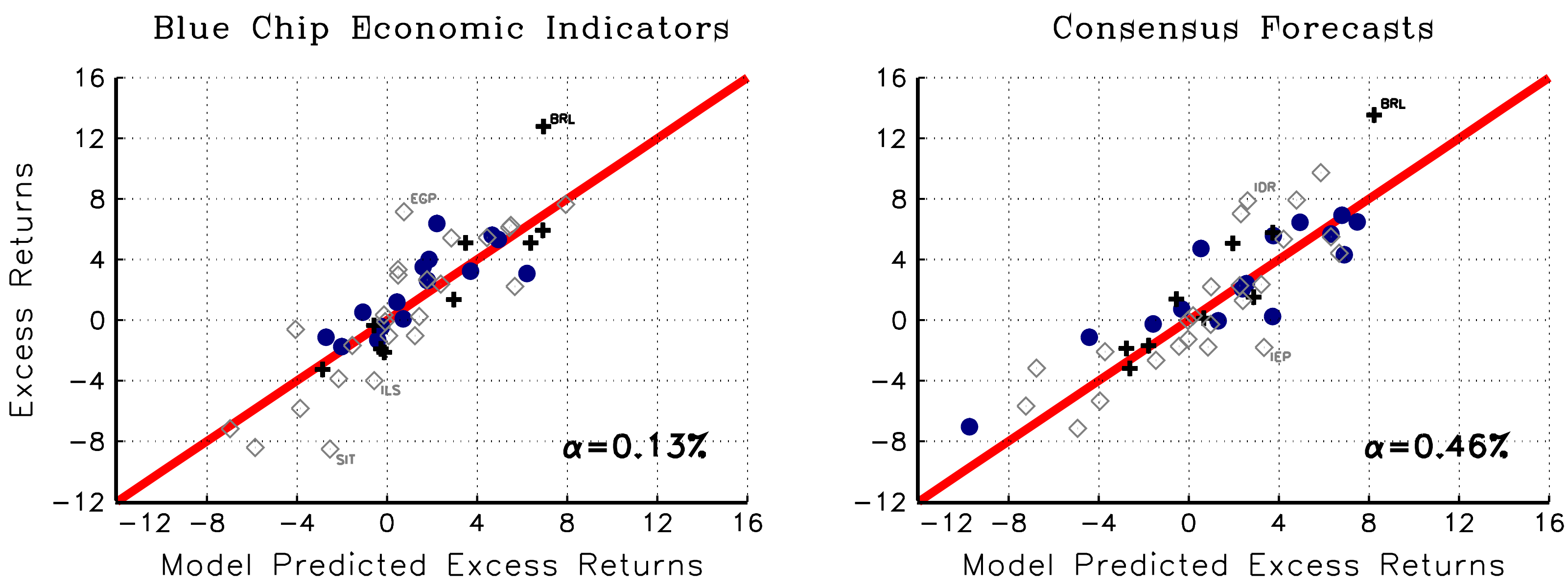

Figure 4: Pricing errors: individual excess returns

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 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 *Datastream* whereas international forecasts are collected from *Blue Chip Economic Indicators* and *Consensus Forecasts*.

Table 1: Portfolio sorted on past returns and proxies of uncertainty

This table presents currency portfolios sorted first into three buckets using past 1-month exchange rate returns, 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 traded over-the-counter. *Panel A* reports the excess 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 return differential between these momentum strategies is denoted as $u_h - u_l$. Excess returns are reported in percentage per annum. *Panel B* presents t-statistics for the null hypothesis of equal return differentials $u_h - u_l$ for 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	1.42	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 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			
	ca	if	ir	rg	ca	if	ir	rg
if	0.19				0.13			
ir	0.30	0.37			0.08	0.11		
rg	0.15	0.55	0.37		0.14	0.50	0.24	
fx	0.23	0.34	0.36	0.41	0.02	0.09	0.12	0.18

Table 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						
m	λ_{dol}		λ_m		λ_{ca}		R^2	λ_{dol}		λ_m		λ_{ca}		R^2
Panel A: macro uncertainty														
ca	0.13	[1.06]	**-0.64**	[-3.16]			34%	0.16	[1.25]	**-0.51**	[-3.03]			36%
if	0.12	[0.91]	0.14	[0.71]			26%	0.10	[0.72]	0.17	[0.97]			21%
ir	0.13	[1.04]	-0.25	[-1.28]			28%	0.10	[0.77]	-0.01	[-0.07]			20%
rg	0.12	[0.93]	0.26	[1.35]			42%	0.11	[0.82]	-0.08	[-0.51]			12%
fx	0.13	[1.01]	0.29	[1.24]			39%	0.11	[0.83]	-0.34	[-1.54]			34%
Panel B: (orthogonalized) macro uncertainty														
ca	0.12	[0.95]	**-0.74**	[-3.44]			32%	0.18	[1.39]	**-0.67**	[-3.76]			48%
if	0.14	[1.13]	-0.06	[-0.26]			33%	0.09	[0.71]	**0.42**	[2.13]			26%
ir	0.14	[1.09]	-0.41	[-1.91]			33%	0.10	[0.76]	-0.01	[-0.06]			19%
rg	0.13	[1.06]	0.31	[1.56]			36%	0.10	[0.74]	-0.20	[-1.05]			17%
fx	0.15	[1.16]	0.49	[1.91]			47%	0.11	[0.86]	-0.48	[-1.71]			41%
pc	0.13	[0.99]	0.24	[1.04]			36%	0.10	[0.77]	-0.28	[-1.21]			22%
Panel C: macro vs. (orthogonalized) current account uncertainty														
if	0.10	[0.77]	0.18	[0.92]	**-0.78**	[-3.62]	40%	0.18	[1.37]	0.36	[2.16]	**-0.78**	[-4.47]	52%
ir	0.12	[0.90]	-0.17	[-0.86]	**-0.65**	[-3.08]	35%	0.18	[1.39]	0.19	[1.46]	**-0.78**	[-3.91]	47%
rg	0.10	[0.80]	0.27	[1.40]	**-0.68**	[-3.36]	47%	0.20	[1.49]	0.18	[0.97]	**-0.78**	[-3.97]	49%
fx	0.12	[0.92]	0.23	[0.97]	**-0.65**	[-3.13]	45%	0.14	[1.09]	0.01	[0.04]	**-0.68**	[-4.18]	60%
pc	0.12	[0.90]	0.17	[0.74]	**-0.65**	[-3.17]	42%	0.18	[1.35]	0.05	[0.23]	**-0.69**	[-4.23]	54%

Table 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						
m	λ_{dol}		λ_m		λ_{ca}		R^2	λ_{dol}		λ_m		λ_{ca}		R^2
Panel A: macro uncertainty														
ca	0.13	[0.98]	**-0.67**	[-2.54]			32%	0.12	[0.89]	**-0.75**	[-2.77]			27%
if	0.11	[0.88]	0.10	[0.43]			39%	0.11	[0.86]	-0.07	[-0.41]			20%
ir	0.13	[0.96]	-0.10	[-0.50]			33%	0.12	[0.94]	0.09	[0.51]			24%
rg	0.15	[1.13]	0.29	[1.10]			39%	0.10	[0.78]	-0.25	[-1.19]			24%
fx	0.13	[1.04]	0.30	[1.33]			52%	0.10	[0.73]	-0.16	[-0.84]			38%
Panel B: (orthogonalized) macro uncertainty														
ca	0.13	[0.98]	**-0.70**	[-2.88]			39%	0.12	[0.93]	**-0.84**	[-3.23]			50%
if	0.14	[1.08]	-0.05	[-0.23]			34%	0.11	[0.83]	0.02	[0.10]			27%
ir	0.14	[1.04]	-0.21	[-1.05]			33%	0.11	[0.86]	0.09	[0.55]			35%
rg	0.16	[1.22]	0.26	[1.12]			32%	0.09	[0.70]	-0.23	[-1.28]			31%
fx	0.14	[1.08]	0.35	[1.61]			56%	0.10	[0.75]	-0.15	[-0.80]			43%
pc	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														
if	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%
ir	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%
rg	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%
fx	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%
pc	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 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 Ilzetzki, 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*.

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

Table 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 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 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 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 (2015). 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	[0.16]	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	[-2.73]	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	[-2.21]	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

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. $\widehat{\lambda} = T^{-1} \sum_{t=1}^{T} \widehat{\lambda}_t$. 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 $\widehat{\lambda}^* = T^{-1} \sum_{t=1}^{T} \widehat{\lambda}_t^*$.

4. We construct the bootstrapped standard error as $\sqrt{\sum_{i=1}^{R} (\widehat{\lambda}_i^* - \overline{\lambda}^*)^2 / (R-1)}$, where $\overline{\lambda}^*$ is the mean of $\widehat{\lambda}_i^*$.

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.

B Generalized method of moments

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

$$M_t = 1 - (h_t - \mu)' b, \tag{20}$$

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 $E[vech((h_t - \mu)(h_t - \mu)' - \Sigma_h)] = 0$. In sum, we work with the following vector valued function

$$g(z_t, \theta) = \begin{bmatrix} RX_t[1 - (h_t - \mu)' b] \\ h_t - \mu \\ vech((h_t - \mu)(h_t - \mu)' - \Sigma_h) \end{bmatrix}, \tag{21}$$

where $\theta' = [b' \;\; \mu' \;\; vech(\Sigma_h)']$ 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 (21), we will incorporate estimation uncertainty arising from μ and Σ_h into the standard errors of the factor prices λ.[29]

We estimate θ via a first-stage GMM estimator that minimizes $g_T'(\theta) W_T g_T(\theta)$, where $g_T(\theta) =$

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

$T^{-1}\sum_{t=1}^{T} g(z_t, \theta)$ 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

$$V_\theta = (a_T d_T)^{-1} a_T S_T a_T' [(a_T d_T)^{-1}]', \tag{22}$$

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

$$V_\lambda = \left(\frac{\partial\lambda}{\partial\theta'}\right) V_\theta \left(\frac{\partial\lambda}{\partial\theta'}\right)', \tag{23}$$

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

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

when $k = 2$.

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Internet Appendix to

"Macro Uncertainty and Currency Premia"

(not for publication)

Abstract

This appendix presents supplementary results not included in the main body of the paper.

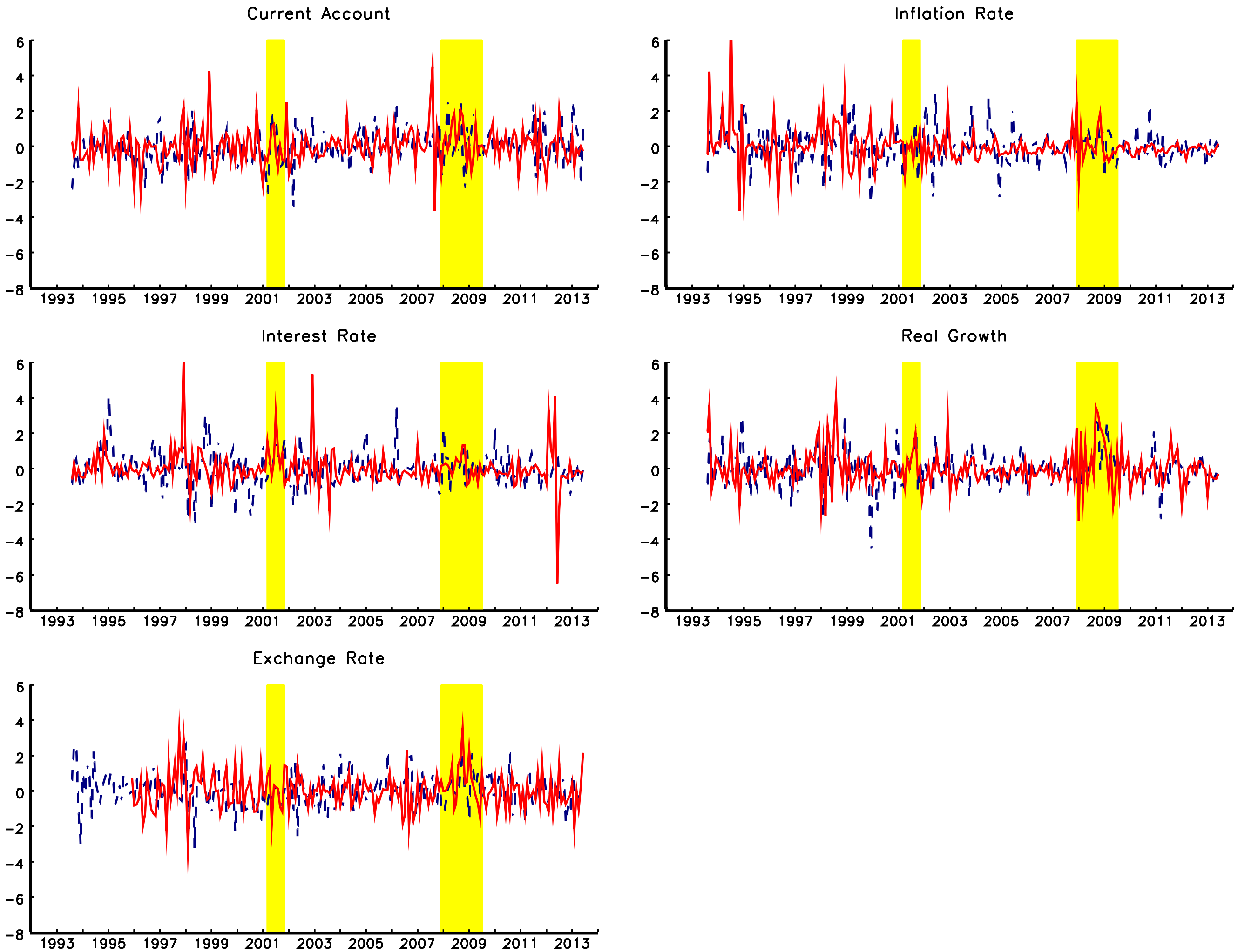

Figure IA.1: Macro uncertainty shocks

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 IA.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						
m	λ_{dol}		λ_m		λ_{ca}		R^2	λ_{dol}		λ_m		λ_{ca}		R^2
							Panel A: macro uncertainty							
ca	0.13	[1.06]	**-0.48**	[-2.71]			41%	0.15	[1.17]	**-0.46**	[-2.79]			32%
if	0.11	[0.90]	0.18	[0.94]			27%	0.10	[0.73]	0.10	[0.53]			22%
ir	0.13	[1.03]	-0.05	[-0.23]			23%	0.10	[0.75]	0.00	[0.01]			26%
rg	0.11	[0.88]	0.29	[1.50]			48%	0.11	[0.86]	-0.09	[-0.57]			18%
fx	0.14	[1.11]	0.35	[1.75]			33%	0.12	[0.91]	-0.43	[-1.77]			37%
							Panel B: (orthogonalized) macro uncertainty							
ca	0.12	[0.96]	**-0.67**	[-3.37]			46%	0.17	[1.32]	**-0.65**	[-3.73]			45%
if	0.15	[1.15]	-0.06	[-0.27]			35%	0.10	[0.73]	0.33	[1.62]			25%
ir	0.14	[1.14]	-0.46	[-1.95]			25%	0.10	[0.72]	0.05	[0.36]			25%
rg	0.13	[0.98]	0.31	[1.48]			32%	0.12	[0.90]	-0.20	[-1.01]			17%
fx	0.17	[1.34]	0.52	[2.60]			44%	0.13	[0.96]	-0.53	[-1.72]			43%
pc	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							
if	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%
ir	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%
rg	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%
fx	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%
pc	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 IA.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						
m	λ_{dol}		λ_m		λ_{ca}		R^2	λ_{dol}		λ_m		λ_{ca}		R^2
							Panel A: macro uncertainty							
ca	0.13	[1.03]	**-0.55**	[-2.67]			31%	0.17	[1.28]	**-0.64**	[-3.64]			44%
if	0.12	[0.90]	0.17	[0.83]			26%	0.09	[0.66]	0.15	[0.82]			18%
ir	0.14	[1.12]	-0.22	[-1.12]			21%	0.10	[0.79]	-0.05	[-0.37]			20%
rg	0.12	[0.95]	0.27	[1.25]			39%	0.10	[0.77]	-0.15	[-1.00]			16%
fx	0.13	[1.02]	0.35	[1.43]			39%	0.12	[0.92]	-0.40	[-1.81]			37%
							Panel B: (orthogonalized) macro uncertainty							
ca	0.12	[0.92]	**-0.68**	[-3.15]			33%	0.18	[1.35]	**-0.77**	[-4.04]			53%
if	0.14	[1.06]	0.02	[0.07]			29%	0.09	[0.71]	0.39	[1.79]			25%
ir	0.15	[1.21]	-0.41	[-1.80]			32%	0.11	[0.80]	-0.06	[-0.40]			21%
rg	0.14	[1.07]	0.32	[1.45]			33%	0.09	[0.69]	-0.27	[-1.46]			22%
fx	0.16	[1.20]	**0.54**	[2.26]			50%	0.13	[0.97]	-0.49	[-1.77]			39%
pc	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							
if	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%
ir	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%
rg	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%
fx	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%
pc	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 IA.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.

	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. equity volatility risk													
ca	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%
if	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%
ir	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%
rg	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%
fx	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%
pc	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													
ca	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%
if	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%
ir	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%
rg	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%
fx	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%
pc	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 IA.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 IA.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*.

	Panel A: macro uncertainty						
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 IA.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 IA.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 $RX_t^i = \gamma_{t-1}^i \times (S_t^i - F_{t-1}^i)/S_{t-1}^i$ 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. 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*.

	standard deviation							range						
m	λ_{dol}		λ_m		λ_{ca}		R^2	λ_{dol}		λ_m		λ_{ca}		R^2
							Panel A: macro uncertainty							
consumption growth	0.11	[0.81]	0.16	[0.96]			21%	0.11	[0.80]	0.09	[0.52]			26%
investment growth	0.09	[0.71]	0.31	[1.76]			19%	0.10	[0.74]	0.30	[1.60]			19%
industrial production	0.12	[0.91]	-0.02	[-0.10]			19%	0.12	[0.90]	0.01	[0.05]			30%
wages	0.11	[0.85]	-0.16	[-0.93]			13%	0.10	[0.80]	-0.18	[-1.00]			20%
unemployment rate	0.12	[0.91]	0.22	[0.93]			20%	0.10	[0.75]	-0.05	[-0.25]			22%
budget balance	0.12	[0.94]	0.43	[1.85]			25%	0.10	[0.76]	-0.02	[-0.09]			29%
long-term interest rate	0.08	[0.54]	-0.12	[-0.51]			28%	0.08	[0.54]	-0.11	[-0.52]			30%
principal component	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							
consumption growth	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%
investment growth	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%
industrial production	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%
wages	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%
unemployment rate	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%
budget balance	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%
long-term interest rate	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%
principal component	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 IA.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 *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	CAR
	Blue Chip Economic Indicators							
mean	-1.57	-0.60	2.02	3.14	2.34	6.69	2.00	8.26
	[-1.00]	[-0.38]	[1.26]	[1.87]	[1.19]	[3.25]	[1.34]	[4.08]
median	-1.75	0.53	0.82	3.70	3.15	9.07	2.61	11.53
sdev	6.86	6.68	7.15	7.20	8.09	8.56	6.42	8.01
skew	0.33	-0.23	-0.02	-0.44	-0.70	-0.36	-0.43	-0.48
kurt	4.54	4.49	4.18	5.38	5.57	7.16	4.81	4.82
SR	-0.23	-0.09	0.28	0.44	0.29	0.78	0.31	1.03
SO	-0.37	-0.12	0.43	0.56	0.37	0.97	0.43	1.41
MDD	0.45	0.37	0.26	0.25	0.30	0.24	0.23	0.18
$AC(1)$	0.05	0.08	0.01	0.08	0.12	0.11	0.07	0.19
$freq$	0.19	0.31	0.35	0.36	0.31	0.17	0.28	0.36
	Consensus Forecasts							
mean	-0.99	-0.79	1.16	2.34	3.63	6.77	2.02	7.76
	[-0.63]	[-0.49]	[0.68]	[1.30]	[1.89]	[3.29]	[1.34]	[3.74]
median	-1.42	-0.94	0.62	1.67	3.53	8.03	2.49	9.97
sdev	7.03	7.02	7.02	7.48	7.73	8.39	6.34	8.43
skew	0.35	0.18	0.18	-0.13	-0.26	-0.13	0.04	-0.57
kurt	3.55	3.47	3.96	3.79	5.32	6.29	3.33	4.81
SR	-0.14	-0.11	0.17	0.31	0.47	0.81	0.32	0.92
SO	-0.25	-0.18	0.27	0.45	0.69	1.11	0.53	1.28
MDD	0.44	0.39	0.28	0.30	0.23	0.23	0.22	0.20
$AC(1)$	0.01	0.09	0.15	0.12	0.14	0.11	0.12	0.12
$freq$	0.21	0.31	0.33	0.33	0.30	0.16	0.28	0.37

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

Table IA.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 IA.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 IA.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 IA.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 *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	[1.65]	-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 IA.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 IA.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	[-1.21]	0.18	[1.46]	-1.29	[-2.56]	-0.39	[-1.85]	0.89	0.29	(0.37)
if	0.01	[0.22]	-0.66	[-2.48]	-0.89	[-3.13]	0.19	[1.61]	-0.58	[-2.33]	-0.83	[-3.70]	0.74	0.33	(0.03)
ir	-0.03	[-0.56]	0.23	[0.36]	-0.92	[-2.64]	0.18	[1.60]	0.16	[0.25]	-0.89	[-3.26]	0.67	0.34	(0.01)
rg	0.00	[0.05]	0.61	[2.21]	-1.05	[-3.20]	0.19	[1.68]	0.47	[1.97]	-0.97	[-3.78]	0.74	0.33	(0.03)
fx	-0.02	[-0.34]	0.11	[0.31]	-0.89	[-2.89]	0.18	[1.56]	0.23	[0.70]	-0.90	[-3.83]	0.67	0.33	(0.06)
pc	-0.02	[-0.27]	-0.12	[-0.42]	-0.83	[-2.82]	0.18	[1.50]	-0.06	[-0.23]	-0.82	[-3.62]	0.67	0.34	(0.03)
	Panel B: Consensus Forecasts														
ca	-0.03	[-0.60]	-1.12	[-3.77]	-0.20	[-0.77]	0.18	[1.41]	-1.12	[-4.12]	-0.26	[-1.07]	0.88	0.21	(0.72)
if	-0.02	[-0.33]	0.74	[1.55]	-0.55	[-1.69]	0.17	[1.46]	0.76	[1.50]	-0.58	[-2.15]	0.58	0.30	(0.05)
ir	0.00	[-0.04]	-1.01	[-2.07]	-0.48	[-2.32]	0.18	[1.44]	-1.01	[-2.26]	-0.48	[-2.38]	0.68	0.30	(0.06)
rg	0.06	[0.91]	1.18	[2.61]	-1.43	[-3.14]	0.17	[1.28]	0.83	[2.25]	-1.15	[-3.47]	0.66	0.27	(0.34)
fx	-0.03	[-0.54]	-0.93	[-2.03]	-0.23	[-0.89]	0.15	[1.24]	-0.93	[-2.27]	-0.29	[-1.17]	0.59	0.33	(0.05)
pc	0.04	[0.68]	0.38	[1.02]	-0.92	[-2.57]	0.17	[1.33]	0.29	[0.80]	-0.89	[-3.16]	0.53	0.29	(0.16)

Table IA.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}		λ_m		λ_{fliq}		R^2	HJ	
							Panel A: Blue Chip Economic Indicators								
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)