Monetary Policy Predicts Currency Movements

Söhnke M. Bartram,* Mark Grinblatt,† and Yan Xu‡

Abstract

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Keywords: Money supply, monetary policy, currency prediction, inflation, real time data, point-in-time data, carry
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* Research Fellow, Centre for Economic Policy Research (CEPR), London, UK, and Professor of Finance, University of Warwick, Warwick Business School, Finance Group, Coventry CV4 7AL, United Kingdom. Phone: +44 (24) 7657 4168, Fax: +1 (425) 952 10 70. Email: s.m.bartram@wbs.ac.uk. Webpage: http://go.warwick.ac.uk/sbartram.
† Distinguished Research Professor, UCLA and NBER, 110 Westwood Plaza, Los Angeles CA 90095-1481, Phone: +1 (310) 825 2508, Email: <mark.grinblatt@anderson.ucla.edu>.
‡ Associate Professor of Finance, HKU Business School, Department of Finance, Hong Kong, Email: <yanxuj@hku.hk>.
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1 Introduction

Starting with Friedman (1961), macroeconomics has adopted the tenet that central bank monetary policy affects the economy at "long and variable lags." This tenet may apply to the level of real economic activity and the prices of consumption goods, but could it also hold for financial investments like currencies? The answer is clearly "yes" if information about past central bank policy is gradually dribbled out to investors. However, efficient markets theory rejects the notion that public information about central bank policy can affect future returns adjusted for risk.

We calibrate public information about monetary restrictiveness with a novel approach, using both a rarely used and a heretofore unanalyzed data set. Rather than employ revised, final estimates of macroeconomic variables, these data sets employ only information about macroeconomic conditions known at the time to currency traders. Each month, rolling sixty-month regressions fit a panel of historical M1 data to three major items reported by 16 OECD economies: GDP, exports, and imports (along with economy-specific and time fixed effects). The linear regression establishes international norms for its coefficients over the five-year historical period. Residuals per unit of M1 represent percentage deviations from international norms. Currencies with the most negative residuals per M1 unit in the regression's final month have relatively restrictive monetary policy and earn the highest returns over the next three years.

The effect is large: currencies of the 20% most restrictive central banks outperform those of the 20% least restrictive by an average of 29 bp in the regression's final month, which is concurrent with the restrictiveness signal. However, the same strategy earns an additional 42 bp in the subsequent month, which is entirely after the restrictiveness signal is publicly known. The delayed effect on monthly returns persists, and it is of similar magnitude in the 36 months following the restrictiveness signal. These spreads might derive from heretofore unknown sources of risk. However, they hurdle most adjustments for risk and anomaly characteristics used in the literature. The benchmarks include carry and momentum, as well as risk attributes tied to an optimal portfolio previously shown to eliminate the efficacy of known currency predictors.

Traders can exploit this central bank restrictiveness signal to earn abnormal profits relative to the literature's standard risk benchmarks. Presumably, more accurate signals about central bank restrictiveness from macroeconomic data revisions that traders learn later would earn even greater profits. However, a "crystal ball" that sees future revisions to the relevant macroeconomic variables generates a less profitable signal than the one from real time public information.

Inflation also reacts to the restrictiveness signal. The economies with the 20% most restrictive central banks tend to have significantly more inflation next month than the 20% with the least restrictive banks, controlling for past inflation as well as growth in M1 from the prior month. The former are also predicted to have the highest currency appreciation. Inflation should make currencies less attractive as investments, generating depreciation in many macroeconomic models. We find the opposite correlation between the predictions of inflation and concurrent currency returns—an outcome that may reflect central banks' efforts to dampen anticipated inflation.

In theory, currency returns and macroeconomic fundamentals are tightly linked (e.g., Berg and Mark, 2018; Cochrane, 2017; Ready et al., 2017; Gabaix and Maggiori, 2015; Hassan, 2013). Empirically, the link between the two is weak (Mark, 1995) or highly unstable (Fratzscher et al., 2015; Rossi, 2013). Obstfeld and Rogoff (2000) note the surprising lack of an observable relationship between macroeconomic fundamentals and currency returns. Our exchange rate signal is consistent with this literature, in that the signal is correlated with M1 but uncorrelated with M1's macroeconomic regressors: GDP, exports, and imports. However, the residual is derived from macroeconomic variables and thus represents a link between macroeconomic fundamentals and currency movements that has eluded prior research.

Exchange rate fluctuations have also been notoriously difficult to predict using economic models, a conclusion dating back to the time series analysis of Meese and Rogoff (1983). They find that a random walk better predicts exchange rates than any economic model, including those derived from uncovered interest rate parity, purchasing power parity (PPP), and flexible or sticky-price versions of monetary models. More recent work has found some predictability in the cross-section. Typical predictors, as summarized in Rossi (2013), include PPP deviations, inflation, output, and productivity. Rossi (2013) concludes that exchange rate predictability is sensitive to the choice of predictor, forecast horizon, sample period, forecasting model, and forecast evaluation method. However, other variables, like carry (Lustig et al., 2014, 2011), output gap (Colacito et al., 2020; Dahlquist and Hasseltoft, 2020), commodity prices (Bakshi and Panayotov, 2013; Chen and Rogoff, 2003), momentum (Asness et al., 2013; Menkhoff et al., 2012), net foreign investment (Jiang et al., 2023), and external trade imbalance (Gourinchas et al., 2017; Gourinchas and Rey, 2007) show some success at predicting currency returns.

Currency return predictability may also stem from other sources. These include market microstructure (Burnside et al., 2009), peso problems (Burnside et al., 2011a), and crash risk (Brunnermeier et al., 2008). Burnside (2012), Burnside et al. (2011b), Yu (2013) and Bartram et al. (2018) explain the efficacy of carry and other predictors as the outcome of non-rational behavior.

Our central bank restrictiveness signal predicts exchange rates better than other constructs in the literature. Returns to strategies formed from the signal are relatively orthogonal to risk measures proposed for currency returns. The orthogonality also applies to return spreads generated by predictor variables and used as factors. The one exception is interest rate spreads ("carry"). Restrictive monetary policy is associated with high interest rates. However, compared with our signal, carry's marginal predictive power is small, and our signal wins all horse races against carry.

2 Methodology, Sample, and Data

At the end of each month T, we use a 60-month panel prior to and including month T to estimate M1 as a linear function of GDP, exports, and imports, along with a cross-section of month T's regression residuals. The panel's predicted month T values for M1 represent international norms for M1, estimated from central banks' behavior over the prior 60 months. The underlying assumption is that historical periods encapsulating a full business cycle (here, 60 months) have "average" central banks supplying M1 quantities that meet the transactional need for money without being *relatively* expansionary or restrictive compared with other central banks. The working hypothesis is that the predicted M1 generates a stable exchange rate—just as r^* in macroeconomics represents an interest rate that leads to stable prices for goods and services and a healthy labor market. Non-zero residuals represent central banks that are more or less restrictive than the norm.

Thus, month T has a cross section of M1 predictions based on how OECD central banks typically supplied M1 in the prior 60 months given each economy's needs. These needs are assumed to be a linear function of the most recent values of GDP, exports, and imports known to traders and central banks in each of the 60 months. These three variables are selected because they have the broadest data coverage. The panel regression that estimates the linear function has an intercept that varies across economies (to capture unobserved sources of money demand, like the dollar's role as a reserve currency), as well as slope coefficients on GDP (GDP), Exports (X), and Imports (I) that do not vary across economies and that are assumed to be constant over the 60 months, facilitating estimation. However, because the methodology employs rolling panels, the slope coefficients (and cross-sectional vector of intercepts) change as the panel rolls forward.

Month T's money restrictiveness "signal," which is relevant to currency returns, is a scaling of the cross-section of residuals from the panel's last (i.e., 60^{th}) observation. The signal employs data that currency traders would have known at month T's end. Robustness tests examine whether better estimates about the economy's state from information known after month T—and thus known only with a "crystal ball"—improve or worsen signal efficacy.

The empirical analysis employs three steps, described first in brief and then in more detail.

- **Step 1**: For each month T, using $T-59, \ldots, T$, estimate the 60-month rolling panel regression

$$M1_{i,t} = \boldsymbol{a_i} + \boldsymbol{c_t} + \beta_{GDP} GDP_{i,t} + \beta_{EX} X_{i,t} + \beta_{IM} I_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $M1_{i,t}$ is the latest M1 value that is publicly known by month t's end, $t \in \{T-59, ..., T\}$ for economy i. $\boldsymbol{a_i}$ are economy fixed effect dummies, representing each economy's unobservable attributes (assumed to be stable over any 60 months), and $\boldsymbol{c_t}$ are month dummies representing time fixed effects. Data availability restricts us to the 16 OECD countries (including the U.S.) that report each month's most recent publicly known regressor values.

- **Step 2:** To obtain month T's signal, divide each element of the panel regression's last (i.e., month T) vector of residuals by month T's M1 for its respective economy and multiply by –1.
- **Step 3:** Identify any link of month T's signal to month T or later currency returns and inflation.

Step 1 (rolling regression) detail. Equation (1)'s variables follow processes that are close to random walks, so we estimate its slope coefficients with first differences: here, quarterly changes of the regression's variables because GDP applies to a quarter.[1] Equation (1)'s first difference necessarily omits economy fixed effects. We then substitute the first-difference regression's slope coefficients into a levels panel regression to obtain both the fixed effects for the economies and the panel's last-month residuals. We update each month as the rolling regression moves forward.

We source regressor data for exports, imports, and GDP from the Original Release Data and Revisions (ORDR) Database of the OECD. The database contains real time data and the months (referred to as Editions or Vintages) when the specific data value is the most up-to-date value available to the public. Thus, May 2003's exports may have different values at the time it is first reported (say, July 2003) compared with later months when May 2003 exports are revised. We know all such dates. The values are seasonally adjusted (where available). GDP is reported for a quarter but can be revised in any month. In rare instances, quarterly GDP is in annualized units. We convert any annualized GDP values to quarterly equivalents by dividing the values by four.

[1] As Wooldridge (2010) shows, estimating first difference regressions is more appropriate than a conventional panel regression with fixed effects for processes that are close to random walks.

M1 is not in ORDR's database. We source monthly values for seasonally adjusted M1 from the archives of OECD's Main Economic Indicators (MEI) database. Every month has a separate archive file that specifies the file's creation date. Combining the archive files creates a real time database for the most recent M1 values known to market participants at each historical point in time. To the best of our knowledge, prior studies have not analyzed these data.[2]

We check for data entry errors by comparing point-in-time values with final vintage values for large differences, researching items of unusual magnitude, as well as data points that lead to short-term negative serial correlation. Data points extracted from these checks are matched against data from Bloomberg and other databases. We find two errors; both are corrected for statistical analysis, but their effects are innocuous without corrections.[3]

The constructed signal represents information that hedge funds could trade on. For each regressor, the signal's month t regression observation is the month t vintage value, which portrays the most recent information about economic activity preceding t. Thus, if April 2003's exports are first available in June 2003, while May's are available in July, the signal would use the June 2003 vintage of April 2003's exports for June's regression observation, and the July 2003 vintage of May 2003's export for July's observation. These would be the most recent export data available to both a trader and a central bank in the regression's observation month.[4]

In most cases, regressors are translated into U.S. Dollars at exchange rates as of the middle of the month the data item pertains to. If the month has an even number of days, we use the

[2] We treat the Euro area's macroeconomic fundamentals as if the Euro zone were one country by summing all regression variable values across Euro zone countries. Our sample starts after the Euro's introduction and the beginning of the ORDR database. Aggregate fundamentals for the changing composition of Euro area member states range from 11 to 19 countries depending on the observation month. No observations are omitted or winsorized.

[3] We verified with the OECD statistician that one data error, a Japan imports observation, was a decimal point misplacement entry mistake, and that traders accessing data feeds from multiple sources (e.g., the Japanese Ministry of Economy, Trade, and Industry) would have had the correct value at the time. The other data error, exports for Switzerland, had an observation date after the edition date. Consistent with the timing in earlier and later editions, we assigned this export observation to pertain to two months before the edition date.

[4] Data that traders knew at the time has successfully been used to demonstrate that profitable anomaly strategies can be implemented for U.S. and international stocks, and bonds (Bartram and Grinblatt, 2018, 2021; Bartram et al., 2024). More traditional data is prone to look ahead bias.

average of the rates on the two days closest to the middle of the month. Occasionally, when the month *t* vintage reports recent information from month $t - 1$, we use the exchange rate from month $t - 2$ to translate. To illustrate, assume May 2003's imports are first reported in ORDR's June 2003 edition. We would then convert imports into U.S. Dollars using the exchange rate at the middle of April 2003.[5] Employing exchange rates that are at least 2.5 months before the month *T* trade date negates any contribution to signal profitability from short-term reversals (or momentum) in exchange rates *per se*.

Step 2 (regression residual) detail. Each month *T* is associated with a panel regression employing the 60 months ending in month *T*. Currencies with fewer than four months of observation vectors reporting all four regression variables (out of 60) are omitted from $T - 59$ to *T*'s regression. The residual vector from each regression's last month, *T*, is scaled—dividing it by the negative of M1—to proxy for monetary restrictiveness in month *T*. This monetary restrictiveness signal can be implemented from public information known by month *T*'s end.

Appendix A motivates the functional form we use by presenting a simplified model of money demand for transactional use, which is linear in the regressors we employ. Central bank restrictiveness is the degree to which M1 is lower than transaction-based money demand. Not knowing the functional form that restrictiveness has with currency returns (Step 3), we generally sort currencies into restrictiveness quintiles. Parametric restrictiveness is explored later.

Step 3 (return correlation with signal) detail. The empirical analysis uses monthly data from central bank restrictiveness signals known by month *T*'s end to predict exchange rate changes. Changes in the exchange rate during the signal disclosure month *T* are referred to as "contemporaneous returns"; those in the following month $T + 1$ are referred to as "next-month returns." Following the literature (e.g., Chernov et al., 2023; Okunev and White, 2003), currency *i*'s month

[5] Results using beginning-of-month or end-of-month exchange rates are similar.

t return is the percentage difference between the spot exchange rate at month t's end, $f_{i,t}$, and the one-month forward exchange rate at month $t-1$'s end, $F_{i,t-1}$:

$$R_{i,t} = \frac{f_{i,t} - F_{i,t-1}}{F_{i,t-1}}. \tag{2}$$

F and f's units are expressed as dollars bought per unit of foreign currency. The strategy that earns this profit is a zero-cost investment in a forward contract. Unlike spot-only returns, currency returns from forward contracts are not distorted by cross-currency differences in the riskless time value of money or convenience yields, and expected currency returns from forwards are only affected by differences in currency risk premia. One can also compound these returns without concerns about biases from bid-ask bounce. The return's monthly ending price (a spot value) comes from a different market than the next month return's beginning price (a value from a forward contract).

Assuming covered interest parity and no convenience yield, the forward contract return is the spot currency return adjusted by the risk-free interest rates of the two currencies being exchanged. Since these rates are known, unanticipated changes in the forward currency return are entirely driven by unexpected changes in spot rates. For this reason, and expositional simplicity, we often refer to Equation (2)'s ratio as just the "currency return." (Prior literature sometimes refers to Equation (2) as the currency "excess return" because it approximates the spot return in excess of the risk-free rate difference under covered interest parity.)

We source daily spot exchange rates and daily one-month forward exchange rates from Datastream. Currency forward and spot prices are Datastream's mid-point exchange rate quotes. The data cover up to 16 currencies in each observation month, i.e., our data set is an unbalanced panel containing 2,469 currency-month observations over the period July 2001 to April 2020.[6]

[6] Regressions requiring non-missing values of various covariates are based on unbalanced panels that are slightly smaller (e.g., in Table 2). Signal regressions use 16 currencies, including the U.S. dollar, but employ currency fixed effects that help control for the U.S. economy's importance as a reserve currency. Return and return forecasting

Controls for risk and other FX return predictors. To control for known predictors of currency returns, we employ panel regressions and factor model time series regressions. The panels regress returns from currency forward contracts (Equation (2)) on quintile dummies for the signal (for expositional simplicity, reflected below as one variable rather than five), control variables, and month fixed effects, δ_t:

$$R_{i,t} = \gamma_0 Money\ Restrictiveness_{i,t-\tau} + \sum_{j=1}^{J} \gamma_j ControlVariable_{i,j,t-1} + \delta_t + e_{i,t}, \quad (3)$$

with τ denoting contemporaneous ($\tau = 0$) or next-month ($\tau = 1$) return analysis, respectively. Control variables include the percentage changes in money supply measures and other commonly used predictors of currency returns such as carry; currency momentum over the past 1, 3, and 12 months; a filter rule combination; dollar exposure; term spread; output gap; currency value; and Taylor Rule—all measured at the end of month $t-1$. Appendix B provides more detail on these controls. Driscoll and Kraay (1998) cross-sectional and time-series dependent robust standard errors are used to calculate t-statistics.[7] We require at least 10 currencies with non-missing data for the observation month to be included in the unbalanced panel.

For the panel regressions and factor model regressions, we sort currencies into equally weighted quintiles based on the contemporaneous or prior-month signals, with Quintile 5 representing the largest central bank restrictiveness signal. The extreme quintile difference in intercepts from factor model time series regressions are analogous to the panel regression's coefficients on the Quintile 5 dummy (as we omit Q1 for the panel's intercept). Factor models regress the time series of one-month returns (Equation (2)) of Quintile q in month t on contemporaneous risk factors:

regressions exclude the U.S. because, as numeraire currency, its return is zero by construction. Results using a currency index (as in Chernov et al., 2023) are similar to those from our use of the U.S. Dollar as numeraire. The 16 currencies are the U.S. Dollar, Euro, Pound Sterling, Japanese Yen, Australian Dollar, New Zealand Dollar, Canadian Dollar, Swiss Franc, Norwegian Krone, Swedish Krona, Czech Koruna, Hungarian Forint, South Korean Won, Iceland Krona, Turkish Lira, and Danish Kroner.

[7] Driscoll and Kraay (1998) standard errors have significantly better small sample properties than alternative estimators when cross-sectional or time series dependence is present with panel data.

$$R_{q,t} = \alpha_q + \sum_{k=1}^{K} \beta_{qk} RiskFactor_{k,t} + \varepsilon_{q,t}. \tag{4}$$

The risk factor models consist of one 2-factor model, five 1-factor models, and a 7-factor model combining all factors from each of the factor models. The 2-factor model contains the dollar and carry trade risk factors from Lustig et al. (2011).[8] The five 1-factor models contain a global imbalance factor (Della Corte et al., 2016), an output gap factor (Colacito et al., 2020), a sovereign risk factor (Della Corte et al., 2022), and two unconditional mean-variance efficient factors ("UMVE" and "UMVE-GE"), respectively. The last two were constructed and graciously provided to us by Chernov, Dahlquist, and Lochstoer (2023, 2024). Heteroscedastic-robust standard errors are used to calculate *t*-statistics (as residual serial correlation is negligible).

Finally, we analyze monthly inflation rates—the growth rates of monthly Consumer Price Index (CPI) values from the July 2023 edition of the OECD MEI Archive. CPI is not seasonally adjusted because adjusted CPI is unavailable for most economies. These inflation rates are regressed on the central bank restrictiveness signal and other variables. The approach is similar to Equation (3) but with a different predictor variable on the regression's left side.

3 Results

3.1 Summary Statistics

Table 1 reports the time series average of the cross-sectional means, standard deviations, minima, maxima, and correlations of several monthly variables, both for the overall sample and (with cross-sectional means) for quintiles sorted by the signal.[9] It also includes time series averages of the extreme quintile spreads (equally weighted within quintiles), with *t*-statistics based on standard errors that are robust to heteroscedasticity. The variables include the contemporaneous and next-month forward returns (Equation (2)). These currency returns, expressed in percent per month, show the quintile of the highest central bank restrictiveness currencies outperforming the lowest

[8] Source: https://gsb-faculty.stanford.edu/hanno-lustig/files/2022/05/CurrencyPortfolios.xls.

[9] Appendix B defines all variables. Appendix C, which weights every observation equally, reports the distribution of these variables.

quintile by 29 bp per month in the month of the signal and by 42 bp in the month after the signal. These represent approximately 3–5% annualized return differences. The latter return spread is 5% statistically significant (t = 2.29).[10] While the extreme quintiles differ, the three middle quintiles have non-monotonic return patterns. For this reason, we mostly use quintile sorts to assess signal efficacy. However, we find similar results with parametric versions of the signal, as discussed later.

Table 1's contemporaneous and next-month return spreads have average correlations with the monetary restiveness signal of 0.07.[11] The percentage difference between forward and spot exchange rates, known as the carry trade control, has a far larger average correlation with the signal (0.38). Positive spreads between the extreme quintile values are also evident for most of Table 1's other variables, which consist of known or theorized predictors of currency returns. Indeed, around half of the variables have extreme signal quintile spreads that are significant.

3.2 Currency Returns (from Forward Contracts) and Central Bank Restrictiveness

Tables 2 and 3 study the relationship between central bank restrictiveness and currency returns. Panel A of each table studies contemporaneous returns, while Panel B focuses on next-month returns. Only Panel B assesses market efficiency, as traders can implement the signal at the end of month T and earn returns in month $T + 1$. Next-month returns are computed beginning the second trading day of month $T + 1$ to ensure that any time differences across the venues for trading different currencies allow the signal to be implemented. For comparison purposes with same-month returns, ending prices for next-month returns are the second trading day of month $T + 2$.

Table 2 reports findings from panel regressions with month fixed effects. Because its regressors have far more variation in the cross-section than in the time series, any correlation of our signal with returns must stem from their cross-sectional relationship. Table 3 analyzes factor model

[10] Although unreported, no similar effect exists for spot currency returns, which are complicated by interest rate differences. No money is used to purchase a forward contract, obviating the need for interest rate adjustments.

[11] While not reported in the table, the extreme quintile return spreads are positive 57% (contemporaneous return) and 55% (next-month return) of the time, respectively.

regressions, which are more commonly used in the currency literature to control for potential risk factors that influence these returns.

Panel Regressions. Table 2 employs quintile dummies for central bank restrictiveness. The controls are characteristics measured immediately prior to the return month. They include momentum over three past return horizons, carry, the change in M1 (or M2), a filter rule combination, dollar exposure, term spread, output gap, currency value, and the Taylor Rule.

At the 10% significance level, all but 3 of the 28 specifications of Table 2's first row show that the restrictiveness signal's extreme quintile alpha spread is significant, controlling either individually or jointly for other known or suspected determinants of exchange rates. Generally, Panel A's contemporaneous return coefficients on the Quintile 5 dummy are modestly smaller than the corresponding next-month return coefficients in Panel B. This is surprising. In an efficient market, we expect month $T + 1$ currency returns to be zero. However, Panel B shows that Q5 currencies outperform Q1 currencies next month by 28–47 bp per month, depending on the specification. Twelve of Panel B's 14 extreme quintile spreads exhibit 5% significance.

By contrast, observing significant extreme quintile spreads for the contemporaneous return is less surprising. Traders know the signal with certainty by month T's end, and much of the signal's components may be released by the middle of month T, generating some trader reaction. Traders may also have estimates or leaks from private sources about the signal's components, which they act on prior to month T's end, causing currencies to move within month T. Yet, these alpha spreads are modest in comparison to Panel B's next-month spreads.

The two specifications in Table 2 Panel B (Specifications 3 and 14), which have extreme quintile alpha spreads that just miss 5% significance, have our signal compete with carry as an explanation for returns. Whether carry accounts for the efficacy of our central bank restrictiveness signal or whether restrictiveness explains the carry effect requires more investigation. We explore this issue in more detail after studying factor models.

Factor Models. The intercepts or alphas in the factor models represent the abnormal returns of the central bank restrictiveness quintiles. We employ seven different factor models to assess whether factor exposures explain our results. Table 3 shows intercepts, slope coefficients (often omitted for brevity), and *t*-statistics from time series regressions of each quintile portfolio's monthly currency returns on the seven sets of risk factors. Table 3's two panels parallel Table 2's panels: Panels A's contemporaneous returns focus on the returns in the month the signal is obtained; Panel B's returns are from the month after observing the signal.

The factor models include Lustig et al.'s (LRV, 2011) two-factor model (a dollar factor and a carry factor), Della Corte et al.'s (2016) global imbalance factor, Colacito et al.'s (2020) output gap factor, Della Corte et al.'s (2022) sovereign risk factor, and Chernov et al.'s (2023, 2024) two unconditional mean-variance efficient (UMVE and UMVE-GE) factors, as well as the combination of these seven factors. In contrast to other security types, like stocks, the two UMVE portfolios are feasible for currencies because the number of time series observations far exceeds the number of currencies, facilitating estimation of means and covariances. If the stochastic process used to construct UMVE portfolios generates returns, a mean-variance optimized factor must price its components perfectly in large samples, even when estimated out of sample.[12]

Table 3 Panel B's next-month returns, like Table 2 Panel B, show large significant extreme quintile alpha spreads, while Panel A's returns exhibit modestly weaker and sometimes insignificant alpha spreads. Panel B's next-month spreads range from 30 to 45 bp per month. The least significant of these next-month spreads still attains 10% significance. However, the benchmark here, UMVE-GE, contains many currencies that we do not study, including all the emerging markets currencies it employs. The six other alpha spreads attain 5% significance, including the lowest alpha spread model: the 7-factor combination model that includes the UMVE-GE factor.

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[12] The only paper that we are aware attempts to price equity anomalies from out-of-sample mean-variance optimization is Grinblatt and Saxena (2018).

To investigate the effect of signal delay, Figure 1 plots the Q5–Q1 currency return spread for a signal received at lags varying from 0 to 36 months. The 0-month and 1-month signal lags have different returns from those in Table 1 because (for apples-to-apples comparisons across lags) the returns start 36 and 35 months later than the two returns spreads in Table 1. As the figure indicates, spreads do not weaken as the signal lag moves from 0 to 36 months. The cumulative effect is impressive, suggesting that a long-short strategy in one-month currency forwards, held for a year in the same basket of currencies, earns more than 3%, based solely on public information.

3.3 Carry vs. Central Bank Restrictiveness

Tables 1–3 show that the central bank restrictiveness signal is correlated with both contemporaneous and next-month returns. However, signal efficacy diminishes when we include carry or a carry factor as a control, in part because carry correlates with the signal. Table 4 runs horse races to help assess whether the signal's ability to predict next-month returns is attributable to carry. Panel A repeats the panel regression methodology of Table 2 Panel B. It reports coefficients on quintile dummies both for our signal and for carry to predict next-month returns. Thus, Panel A's regressors in Specification (1) are dummies for carry, central bank restrictiveness, and time fixed effects, while Specification (2) adds the full set of controls. Panel A's Q5 coefficients for central bank restrictiveness are about 2½ (Specification 1) to 3½ (Specification 2) times larger and far more statistically significant than the comparable Q5 coefficients for carry.

Table 4 Panel B employs the factor model methodology of Table 3 Panel B to run carry vs. central bank restrictiveness horse races. The first of four models repeats the 2-factor LRV row from Table 3 Panel B. The model below it runs the same regression but with carry as a single factor. For apples-to-apples comparisons, Table 4 Panel B's carry factor is the extreme quintile return spread from carry-sorted portfolios of the currencies we study. (Table 3's carry factor, by contrast, is from LRV, which employs currencies we do not study.) The bottom two factor models study alphas with quintiles sorted by the carry signal across its columns. Its restrictiveness factor is the extreme quintile return spread for central bank restrictiveness.

The first model shows (as did Table 3 Panel B) that the central bank restrictiveness signal generates an LRV-adjusted alpha spread of about 33 bp per month, which is significant at the 5% level. By comparison, Panel B's third model, which replaces the carry factor with the central bank restrictiveness factor, has a *negative* extreme quintile alpha spread for carry: –7 bp (t = – 0.37).

When carry is the only factor, the alpha spreads between the extreme quintiles of monetary restrictiveness are similar (31 bp, t = 2.02) to the LRV alpha spread. By contrast, carry's quintile alpha spread, controlling only for the central bank restrictiveness factor, is –8 bp, with a t-statistic of –0.45. In sum, the signal of central bank restrictiveness predicts future currency returns; the effect is weaker but significant or close to significant when carry is controlled for. However, the reverse is not true. Indeed, the carry effect is essentially absent when we control for central bank restrictiveness. This suggests that the relative restrictiveness of a central bank's money supply is a cleaner signal of future returns and may account for carry's ability to predict returns.

3.4 Monetary Restrictiveness as a Forecaster of Inflation

Money supply that exceeds transactional needs, as benchmarked by international monetary norms (i.e., loose monetary policy), depresses a currency's value. Here, we analyze whether our metric of monetary restrictiveness also forecasts inflation. Table 5's left-half specifications regress month t + 1's inflation rate on the quintile dummies attached to our month t signal and several controls. In lieu of central bank restrictiveness quintiles, Table 5's right half reports the coefficients of our signal's simplest inflation prediction, which is obtained in the first step of a two-step regression: regressing inflation only on quintiles formed from our signal without controls.

Table 5 reports coefficients and test statistics across 8 different specifications. All regressions include month fixed effects. In each of the regressions, the quintile of currencies with the highest central bank restrictiveness and, to an even larger extent, the month t inflation prediction of all quintile dummies for inflation in month t + 1—referred to as "Expected Inflation"—significantly predict inflation in month t + 1. Across all eight specifications, similar results obtain when using parametric central bank restrictiveness instead of the quintile dummies used.

Table 5 offers two insights. First, from Specifications 4 and 8, month t + 1's unexpected currency movements do not correlate with inflation once we control for either central bank restrictiveness or predicted inflation from central bank restrictiveness alone. Second, the central bank restrictiveness coefficients are positive, whether predicting currency returns (Panel B of Tables 2 and 3) or inflation (Table 5). Thus, predicted currency returns and inflation tend to move in the same direction even though appreciating currencies generate relatively cheaper imports.

Central banks with high expected next-month inflation tend to tighten M1's supply. The tightening supply causes inflation to diminish at some distant future date but creates a scarcity of M1 that causes the central bank's currency to appreciate. Thus, Table 5's regressions may only be picking up cross-sectional differences in what central banks perceive as a long-run problem requiring an immediate fix. Regression never establishes causation, and this conjecture has Table 5's causation arrow reversed.

3.5 More Accurate Signals of Central Bank Restrictiveness are Less Profitable

We now replace our signal of central bank restrictiveness with the entire dataset's latest (i.e., final) vintage, which is the July 2023 version of the ORDR and MEI archive. To distinguish it from our prior signal, we refer to it as the final vintage or "FV" signal. We assign quarterly GDP data to the middle of its observation quarter and linearly interpolate between adjacent months in order to obtain monthly GDP values. (Final vintage data for M1, exports, and imports are in monthly frequency and thus need no transformation.) For the FV signal, all regressors are translated into U.S. Dollars at exchange rates as of the middle of the observation month.

Final vintage data provide the economy's actual economic state, whereas data known to traders and central banks can only forecast the current economic state from recently publicized states of earlier periods. Surprisingly, however, lower profits emerge from having a crystal ball and being able to know revised values of GDP, exports, and imports as early as the beginning of month

T. For example, if we replace Table 2 Panel B's signal with the FV signal, all specifications have Q5 coefficients of 0.34 or below, and only two of the 14 are significant at the 10% level. Every one of these coefficients is below its sister value in Table 2 Panel B. If we replace Table 3 Panel B's signal with the FV signal, each alpha is below its sister value in Table 3 Panel B, with one exception: the LRV model, which is a virtual tie. With same-month returns, the FV signal is never significantly related to return; with Table 3's factor methodology, no specification hurdles the 5% significance threshold. (Tables showing these results are omitted for brevity.)

Why might the FV signal be less effective with contemporaneous than next-month returns? Also, why is the FV signal an inferior correlate of contemporaneous returns than our original signal? One hypothesis is that trader information is more salient to currency movements than more accurate information about the workings of the economy revealed later. Little is known about the FV signal in the month of the contemporaneous return. By contrast, the original signal is fully known to traders by the end of the contemporaneous return month. However, in the subsequent month, some revisions to macroeconomic fundamentals are publicly reported. Accordingly, part of the FV signal becomes known to traders in the next month, influencing returns in that month. The remaining puzzle for future theory is why our original signal of central bank restrictiveness predicts next month returns to any degree, let alone why it is the strongest pairing of signal and profitability among the many alternatives presented here.

3.6 Robustness

In addition to Table 2's regressions with quintile dummies, stratified by our central bank restrictiveness signal, we also run parametric regressions. To quantify the coefficients, we standardize the signal so it has a standard deviation of one. Results for Table 2 Panel B are similar to parametric regressors, with significant coefficients for all specifications and only Specification (3) (with the carry control) significant at the 10% but not the 5% level. Excluding Specification (3), the lowest coefficient implies that a one standard deviation increase in the monetary restrictiveness signal predicts a 17 bp higher return for the currency. (The table is omitted for brevity.)

4 Conclusion

We present evidence from OECD countries of predictable currency price movements. The predictability applies to currency returns from forward contracts expressed either as raw returns or as returns adjusted for commonly used risk factors and predictor variables. The currency movements occur both contemporaneously with the central bank restrictiveness signal and when implemented with a lag. The most effective signal is the one known to traders (which is based on preliminary values) rather than revised numbers for macroeconomic fundamentals. This is an unusual finding in that the final revised numbers more accurately reflect the true state of an economy.

Markets for currencies and currency derivatives are among the world's most liquid markets. The speed with which currency prices adjust to public information should be facilitated by the thousands of traders who participate in their price formation process. Their trades are aided by sophisticated information feeds and algorithms that help process information. Thus, our findings present an efficient markets anomaly that cannot be explained away by illiquidity, known risk factors, or market microstructure.

Traditional asset pricing theory has a difficult time explaining our findings as risk based. Its models of exchange rate premia generate unrealistically high interest rates (Hassan et al., 2013), volatility that is too low, and currency premia that face Backus and Smith's (1993) cyclicality puzzle. Tight monetary policy may predict high currency premia, but our data (and data of others) find that high premia tend to occur in good economic states. Theory says that premia should be lower in such states. While there may be undiscovered sources of risk premia that correlate with our signal, surmounting the many challenges summarized in Hassan et al. (2013) seems beyond asset pricing theory's capacity for now.

We have done our best to explore new sources of premia that could explain our findings but unfortunately have failed. The spreads in factor betas for the characteristic-based factors we analyzed, both within and separate from the paper's tables, suggest that the most restrictive monetary policies have riskier currencies—whether risk is measure by volatility, MSCI equity index beta, beta against a currency basket, the variance of unanticipated inflation, or any of the factors still prominent in the literature. However, irrespective of the risk model, the spread in factor betas across currencies is, given the factor premia, too small to explain our results.

So, we hope these findings spur further investigation into currency risk factors that have yet to be discovered. Alternatively, behavioral models may better explain our findings. If either approach turns out to resolve this anomaly, the paper will have at least spurred new discoveries.

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Figure 1: Decay of Signal Efficacy

The figure shows the quintile spread in currency returns between equally weighted portfolios of currencies with high and low central bank restrictiveness. The spread is shown for alternative lags of the signal between 0 and 36 months. The sample period is July 2009 to May 2020. All variables are defined in Appendix B.

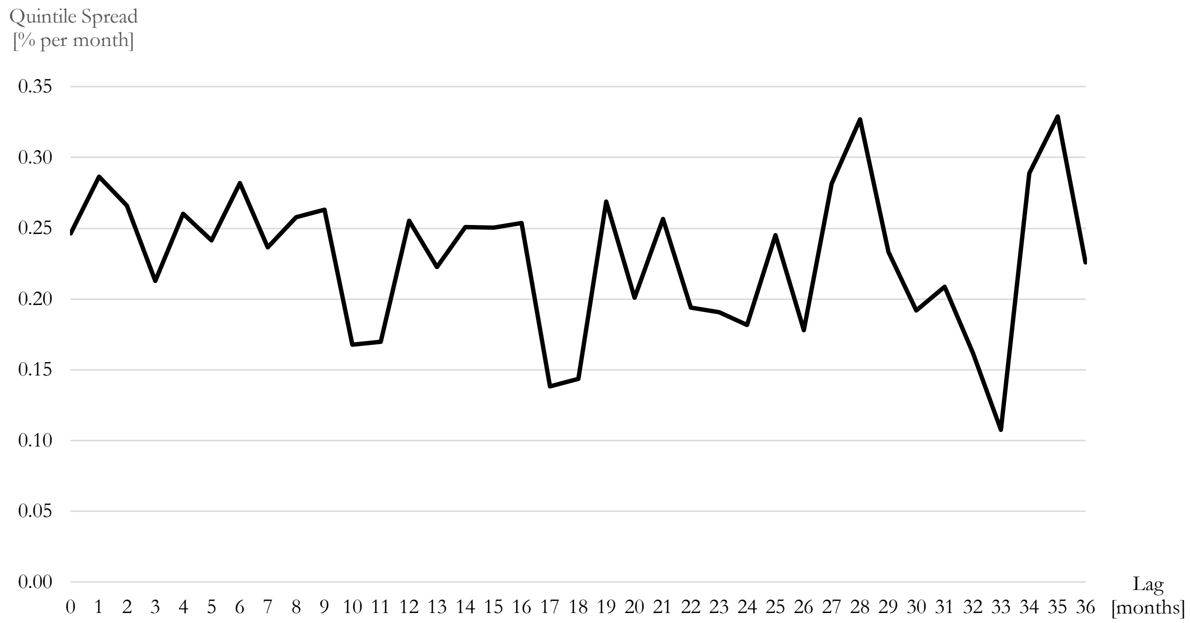

Table 1: Summary Statistics and Strategy Performance

The table reports the total number of panel observations as well as the time series averages and selected test statistics of monthly measures of central bank restrictiveness, currency returns, and various other variables. In particular, the table shows the time series average of each variable's cross-sectional means, standard deviations, minimums, maximums, and correlations with central bank restrictiveness. Time series averages are also reported for observations sorted each month into quintiles from low (Q1) to high (Q5) based on central bank restrictiveness. The right two columns show the time series average of each variable's extreme quintile spread, along with its associated *t*-statistic. The sample period is July 2006 to May 2020. Currency returns represent profit per unit of currency from 1-month forward contracts. Appendix B defines all variables.

			Standard	Correlation			Signal Quintiles					Q5–Q1	
	Observations	Mean	Deviation	with Signal (T)	Minimum	Maximum	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Average	*t-stat*
Central Bank Restrictiveness (*T*)	2,469	2.75	7.37	1.00	-0.27	28.7	-0.14	0.15	0.50	1.07	12.1	12.3	22.9
Currency Returns (*T*) (% per month)	2,505	-0.03	2.19	0.07	-4.16	4.16	-0.03	-0.04	-0.15	-0.17	0.26	0.29	1.61
Currency Returns (*T*+1) (% per month)	2,505	0.01	2.19	0.07	-4.12	4.19	-0.15	0.14	-0.10	-0.12	0.26	0.42	2.29
Carry Trade (*T*) * 100	2,505	0.10	0.29	0.38	-0.17	0.91	-0.04	0.00	0.05	0.21	0.29	0.33	18.2
1-Month Momentum (*T*) * 100	2,505	-0.09	2.18	0.07	-4.26	3.98	-0.08	-0.10	-0.20	-0.22	0.18	0.26	1.47
3-Months Momentum (*T*) * 100	2,505	-0.22	3.78	0.11	-7.53	6.74	-0.37	-0.26	-0.25	-0.63	0.42	0.79	2.41
12-Months Momentum (*T*) * 100	2,505	-0.56	7.43	0.12	-14.9	12.9	0.19	-1.27	-0.87	-1.84	0.98	0.79	1.21
Filter Rule Combination (*T*)	2,505	1.07	0.31	0.04	0.54	1.57	1.05	1.10	1.06	1.04	1.08	0.03	1.17
Dollar Exposures (*T*)	2,466	0.57	0.36	0.04	-0.18	1.19	0.46	0.53	0.60	0.58	0.69	0.23	7.16
Term Spread (*T*) * 100	2,435	0.27	1.30	-0.06	-2.18	2.68	0.26	0.31	0.32	0.22	0.22	-0.04	-0.42
Output Gap (*T*) * 100	2,418	-1.19	6.11	-0.13	-13.7	9.22	-2.43	-1.36	-0.57	-1.48	-0.47	1.96	4.32
Currency Value (*T*) * 100	2,505	-0.95	14.3	0.08	-30.4	24.8	2.00	-3.85	-3.29	-0.61	1.02	-0.98	-0.94
Taylor Rule (*T*) * 100	2,418	-0.32	3.15	-0.11	-6.64	5.12	-1.09	-0.49	-0.06	-0.32	0.17	1.26	5.25
Inflation Rate (*T*+1) * 100	2,505	0.21	0.41	0.11	-0.40	1.13	0.09	0.12	0.16	0.33	0.26	0.16	7.12
Growth in M1 (*T*) * 100	2,505	0.73	1.34	-0.05	-1.45	3.72	0.62	0.65	0.56	0.95	0.67	0.05	0.45

Table 2: Panel Regressions with Currency Returns

The table reports coefficients and test statistics from panel regressions of monthly currency returns from forward contracts on central bank restrictiveness and control variables. Panel A uses the contemporaneous currency return from the signal month (*t*) as the dependent variable. Panel B uses next month's (i.e., *t* + 1) currency return as the dependent variable. Across different specifications, regressions control for the change in M1, the carry trade, 1-month momentum, 3-month momentum, 12-month momentum, a filter rule, dollar exposures, term spread, output gap, currency value, the Taylor rule, and the growth in M2 in the month prior to the return. The table employs quintile dummies for central bank restrictiveness, i.e., Central Bank Restrictiveness Q2 to Q5, with Q1 omitted due to the regression intercept. Each month's quintiles are determined from sorts of currencies with non-missing values for all variables. All regressions include month fixed effects. Driscoll-Kraay (1998) cross-sectional and time series dependence-robust standard errors are used in calculating the *t*-statistics. The table also shows the number of observations and the adjusted R-squared. The sample period is July 2006 to May 2020. Currency returns represent profit per unit of currency from 1-month forward contracts. All variables are defined in Appendix B.

Panel A: Contemporaneous Returns (month *t*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Central Bank Restrictiveness Q5 (*t*)	0.326	0.326	0.184	0.330	0.343	0.366	0.327	0.338	0.327	0.326	0.354	0.320	0.317	0.219
	[1.72]	[1.71]	[0.98]	[1.68]	[1.70]	[1.88]	[1.69]	[2.02]	[1.72]	[1.72]	[1.86]	[1.70]	[1.67]	[1.36]
Central Bank Restrictiveness Q4 (*t*)	-0.077	-0.078	-0.198	-0.076	-0.082	-0.115	-0.077	-0.071	-0.075	-0.077	-0.091	-0.088	-0.093	-0.268
	[–0.47]	[–0.48]	[–1.27]	[–0.46]	[–0.49]	[–0.73]	[–0.46]	[–0.46]	[–0.46]	[–0.49]	[–0.57]	[–0.56]	[–0.59]	[–1.91]
Central Bank Restrictiveness Q3 (*t*)	-0.099	-0.099	-0.148	-0.096	-0.093	-0.115	-0.095	-0.093	-0.098	-0.099	-0.124	-0.102	-0.104	-0.167
	[–0.60]	[–0.59]	[–0.90]	[–0.56]	[–0.54]	[–0.70]	[–0.56]	[–0.60]	[–0.59]	[–0.60]	[–0.75]	[–0.62]	[–0.63]	[–1.05]
Central Bank Restrictiveness Q2 (*t*)	-0.022	-0.022	-0.042	-0.021	-0.022	-0.063	-0.012	-0.019	-0.021	-0.022	-0.054	-0.025	-0.028	-0.096
	[–0.16]	[–0.16]	[–0.30]	[–0.15]	[–0.16]	[–0.46]	[–0.09]	[–0.14]	[–0.15]	[–0.16]	[–0.41]	[–0.17]	[–0.20]	[–0.71]
Growth in M1 (*t*-1)		0.367												-0.198
		[0.15]												[–0.10]
Carry Trade (*t*-1)			48.10											43.78
			[1.31]											[1.09]
1-Month Momentum (*t*-1)				-1.488										1.155
				[–0.36]										[0.25]
3-Months Momentum (*t*-1)					-2.309									-1.430
					[–0.88]									[–0.35]
12-Months Momentum (*t*-1)						-2.315								-2.353
						[–1.70]								[–1.50]
Filter Rule Combination (*t*-1)							-0.245							0.134
							[–1.04]							[0.34]
Dollar Exposures (*t*-1)								-0.043						-0.030
								[–0.22]						[–0.15]
Term Spread (*t*-1)									1.642					3.018
									[0.35]					[0.59]
Output Gap (*t*-1)										0.037				-4.750
										[0.04]				[–1.09]
Currency Value (*t*-1)											-0.634			0.017
											[–0.99]			[0.02]
Taylor Rule (*t*-1)												0.787		9.587
												[0.39]		[1.11]
Growth in M2 (*t*-1)													5.200	4.293
													[1.24]	[1.01]
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors							Driscoll-Kraay							
Adjusted R-Squared	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58
Observations	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306

(continued)

Table 2: Panel Regressions with Currency Returns (continued)

Panel B: Next Month's Returns (month $t + 1$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Central Bank Restrictiveness Q5 (t)	0.426	0.426	0.278	0.430	0.449	0.471	0.430	0.438	0.426	0.426	0.452	0.420	0.415	0.319
	[2.23]	[2.23]	[1.45]	[2.19]	[2.22]	[2.41]	[2.20]	[2.63]	[2.23]	[2.23]	[2.41]	[2.22]	[2.17]	[1.90]
Central Bank Restrictiveness Q4 (t)	-0.007	-0.009	-0.137	-0.008	-0.011	-0.044	-0.006	-0.001	-0.005	-0.006	-0.022	-0.018	-0.025	-0.205
	[–0.04]	[–0.06]	[–1.01]	[–0.05]	[–0.07]	[–0.31]	[–0.04]	[–0.01]	[–0.04]	[–0.04]	[–0.15]	[–0.12]	[–0.17]	[–1.66]
Central Bank Restrictiveness Q3 (t)	0.059	0.060	0.007	0.058	0.063	0.042	0.061	0.066	0.059	0.059	0.035	0.057	0.053	-0.007
	[0.37]	[0.37]	[0.05]	[0.36]	[0.37]	[0.26]	[0.37]	[0.44]	[0.36]	[0.37]	[0.21]	[0.35]	[0.33]	[–0.04]
Central Bank Restrictiveness Q2 (t)	0.249	0.248	0.226	0.249	0.249	0.211	0.262	0.252	0.249	0.249	0.217	0.246	0.238	0.182
	[2.30]	[2.30]	[2.07]	[2.28]	[2.24]	[1.91]	[2.33]	[2.41]	[2.30]	[2.31]	[1.90]	[2.27]	[2.23]	[1.62]
Growth in M1 (t)		0.614												-0.012
		[0.25]												[–0.01]
Carry Trade (t)			50.68											45.538
			[1.39]											[1.14]
1-Month Momentum (t)				-1.306										2.066
				[–0.32]										[0.44]
3-Months Momentum (t)					-2.777									-2.060
					[–1.04]									[–0.50]
12-Months Momentum (t)						-2.373								-2.292
						[–1.72]								[–1.47]
Filter Rule Combination (t)							-0.301							0.093
							[–1.24]							[0.24]
Dollar Exposures (t)								-0.042						-0.037
								[–0.21]						[–0.18]
Term Spread (t)									1.636					3.033
									[0.35]					[0.59]
Output Gap (t)										-0.007				-5.165
										[–0.01]				[–1.18]
Currency Value (t)											-0.592			0.087
											[–0.92]			[0.11]
Taylor Rule (t)												0.746		10.488
												[0.38]		[1.20]
Growth in M2 (t)													5.284	4.376
													[1.28]	[1.02]
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors							Driscoll-Kraay							
Adjusted R-Squared	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58	0.58
Observations	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306	2,306

Table 3: Factor Model Time Series Regressions

The table reports intercepts, slope coefficients, and *t*-statistics from time series regressions of monthly portfolio currency returns from forward contracts on alternative sets of risk factors from the month of the return. Currencies are sorted each month into quintiles based on central bank restrictiveness and combined into equally weighted portfolios. Panel A's signal is contemporaneous with the currency return; Panel B's signal is from the month prior to the return. The table reports averages and regression statistics separately for each of the five portfolios, Q1 to Q5, and for the corresponding times series of return spreads between the currencies with the highest (Q5) and lowest (Q1) central bank restrictiveness quintiles. The table shows results for seven distinct factor models. Risk factors are alternatively the dollar risk factor and the carry trade risk factors from Lustig et al. (2011), a global imbalance factor (Della Corte et al., 2016), an output gap factor (Colacito et al., 2020), a sovereign risk factor (Della Corte et al., 2022), the two UMVE factors from Chernov et al. (2023, 2024), and a combination of all seven factors. Heteroscedastic-robust standard errors are used in calculating the *t*-statistics. The table also shows the number of observations and R-squared. The sample period is July 2006 to May 2020. Currency returns represent profit per unit of currency from 1-month forward contracts. All variables are defined in Appendix B.

Panel A: Contemporaneous Returns

	Signal Quintile											
	Q1 (low)		Q2		Q3		Q4		Q5 (high)		Q5-Q1	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
LRV 2-Factor Model												
Intercept	0.012	[0.12]	0.016	[0.14]	-0.149	[–1.58]	-0.195	[–1.42]	0.234	[1.62]	0.223	[1.38]
Dollar Factor	1.031	[15.4]	1.292	[14.3]	1.367	[19.8]	1.374	[13.7]	1.511	[12.7]	0.479	[3.57]
Carry Factor	-0.165	[–3.57]	-0.236	[–4.50]	-0.028	[–0.59]	0.096	[1.13]	0.081	[0.80]	0.246	[2.17]
R-Squared	0.67		0.72		0.82		0.71		0.74		0.29	
Observations	167		167		167		167		167		167	
Global Imbalance Factor												
Intercept	0.002	[0.01]	-0.016	[–0.08]	-0.108	[–0.53]	-0.111	[–0.49]	0.325	[1.35]	0.323	[1.89]
Output Gap Factor												
Intercept	-0.032	[–0.17]	-0.036	[–0.18]	-0.146	[–0.68]	-0.158	[–0.65]	0.270	[1.04]	0.302	[1.75]
Sovereign Risk Factor												
Intercept	-0.006	[–0.04]	0.000	[0.00]	-0.120	[–0.56]	-0.178	[–0.72]	0.281	[1.09]	0.287	[1.63]
CDL UMVE Currency Factor												
Intercept	-0.046	[–0.27]	-0.043	[–0.21]	-0.145	[–0.67]	-0.165	[–0.67]	0.254	[0.98]	0.300	[1.73]
CDL UMVE-GE Currency Factor												
Intercept	-0.019	[–0.11]	-0.003	[–0.02]	-0.166	[–0.75]	-0.194	[–0.76]	0.185	[0.67]	0.204	[1.11]
7-Factor Combination Model												
Intercept	0.020	[0.21]	0.054	[0.51]	-0.111	[–1.21]	-0.151	[–1.23]	0.214	[1.55]	0.194	[1.35]

(continued)

Table 3: Factor Model Time Series Regressions (continued)

Panel B: Next Month's Returns

	Signal Quintile											
	Q1 (low)		Q2		Q3		Q4		Q5 (high)		Q5-Q1	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
LRV 2-Factor Model												
Intercept	-0.107	[–1.04]	0.170	[1.64]	-0.101	[–1.02]	-0.163	[–1.28]	0.228	[1.67]	0.335	[2.10]
Dollar Factor	1.017	[14.2]	1.262	[15.3]	1.491	[24.5]	1.318	[13.8]	1.500	[14.7]	0.483	[4.15]
Carry Factor	-0.214	[–4.18]	-0.149	[–3.10]	-0.070	[–1.46]	0.128	[1.68]	0.076	[0.86]	0.290	[2.81]
R-Squared	0.63		0.75		0.83		0.73		0.75		0.32	
Observations	167		167		167		167		167		167	
Global Imbalance Factor												
Intercept	-0.129	[–0.78]	0.175	[0.91]	-0.065	[–0.29]	-0.067	[–0.30]	0.325	[1.38]	0.454	[2.67]
Output Gap Factor												
Intercept	-0.154	[–0.90]	0.148	[0.74]	-0.095	[–0.41]	-0.107	[–0.46]	0.275	[1.08]	0.429	[2.40]
Sovereign Risk Factor												
Intercept	-0.133	[–0.79]	0.178	[0.92]	-0.073	[–0.32]	-0.132	[–0.56]	0.280	[1.10]	0.413	[2.30]
CDL UMVE Currency Factor												
Intercept	-0.165	[–0.99]	0.137	[0.68]	-0.104	[–0.44]	-0.107	[–0.46]	0.258	[1.01]	0.424	[2.33]
CDL UMVE-GE Currency Factor												
Intercept	-0.128	[–0.72]	0.172	[0.83]	-0.119	[–0.50]	-0.159	[–0.64]	0.191	[0.70]	0.319	[1.74]
7-Factor Combination Model												
Intercept	-0.073	[–0.70]	0.210	[2.20]	-0.097	[–0.96]	-0.115	[–1.03]	0.226	[1.70]	0.299	[1.99]

Table 4: Central Bank Restrictiveness vs. Carry

The table reports results from panel regressions (Panel A) and factor model time series regressions (Panel B) using central bank restrictiveness and carry characteristics or factors formed from the characteristics. Panel A shows coefficients and test statistics from panel regressions of next month's (i.e., $t + 1$) currency returns from forward contracts on central bank restrictiveness, carry, and control variables. Regressions use non-parametric versions of central bank restrictiveness and carry, employing quintile dummies Q2 to Q5, with Q1 omitted due to the regression intercept. Each month's quintiles are determined from sorts of currencies with non-missing values for all variables. All specifications include month fixed effects. Specification (2) also includes the following parametric controls: the change in M1, 1-month momentum, 3-month momentum, 12-month momentum, a filter rule, dollar exposure, term spread, output gap, currency value, the Taylor rule, and the growth in M2. Driscoll-Kraay (1998) cross-sectional and time series dependence-robust standard errors are used to calculate t-statistics. Panel B reports results from time series regressions of monthly portfolio currency returns from forward contracts on alternative sets of risk factors. Currencies are sorted each month into quintiles based on, alternatively, central bank restrictiveness and carry, and combined into equally weighted portfolios. The panel contains intercepts, slope coefficients, t-statistics, and regression statistics for each of the five portfolios, Q1 to Q5, and for the corresponding extreme quintile spreads in the coefficients. The table shows results for 1- and 2-factor models. The dollar risk factor and the carry trade risk factors are constructed for our currencies following Lustig et al. (2011). The central bank restrictiveness factor is the return spread between the fifth and first portfolio of equal weighted currencies sorted by the central bank restrictiveness signal in the prior month. Heteroscedastic-robust standard errors are used in calculating the t-statistics. Both panels also show the number of observations and (adjusted) R-squared. The sample period is July 2006 to May 2020. Currency returns are profit per unit of currency from 1-month forward contracts. All variables are defined in Appendix B.

Panel A: Panel Regressions

	(1)	(2)
Central Bank Restrictiveness Q5 (t)	0.292	0.291
	[1.59]	[1.78]
Central Bank Restrictiveness Q4 (t)	-0.087	-0.199
	[–0.60]	[–1.62]
Central Bank Restrictiveness Q3 (t)	0.018	-0.027
	[0.12]	[–0.18]
Central Bank Restrictiveness Q2 (t)	0.227	0.162
	[2.09]	[1.38]
Carry Q5 (t)	0.119	0.078
	[0.53]	[0.35]
Carry Q4 (t)	0.030	0.038
	[0.14]	[0.18]
Carry Q3 (t)	-0.088	-0.123
	[–0.53]	[–0.80]
Carry Q2 (t)	-0.145	-0.214
	[–1.02]	[–1.51]
Controls for all other variables	No	Yes
Month Fixed Effects	Yes	Yes
Standard Errors	Driscoll-Kraay	
Adjusted R-Squared	0.58	0.58
Observations	2,306	2,306

(continued)

Table 4: Central Bank Restrictiveness vs. Carry (continued)

Panel B: Factor Model Regressions

	Signal Quintile											
	Q1 (low)		Q2		Q3		Q4		Q5 (high)		Q5-Q1	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Central Bank Restrictiveness Portfolios												
Intercept	-0.122	[–1.37]	0.170	[2.07]	-0.104	[–1.48]	-0.153	[–1.72]	0.209	[2.48]	0.331	[2.41]
Dollar Factor	0.778	[14.80]	0.961	[19.26]	1.118	[33.86]	1.027	[24.86]	1.116	[31.78]	0.339	[5.39]
Carry Factor	-0.174	[–4.61]	-0.151	[–4.42]	-0.037	[–1.17]	0.144	[2.87]	0.217	[4.88]	0.391	[5.39]
R-Squared	0.74		0.84		0.91		0.86		0.90		0.48	
Observations	167		167		167		167		167		167	
Intercept	-0.173	[–1.02]	0.106	[0.53]	-0.177	[–0.79]	-0.221	[–1.04]	0.136	[0.60]	0.309	[2.02]
Carry Factor	0.087	[1.41]	0.171	[1.94]	0.338	[3.46]	0.488	[6.83]	0.591	[5.98]	0.504	[6.35]
R-Squared	0.01		0.03		0.10		0.20		0.24		0.36	
Observations	167		167		167		167		167		167	
Carry Portfolios												
Intercept	0.085	[0.89]	-0.097	[–1.26]	-0.067	[–0.82]	0.059	[0.69]	0.020	[0.17]	-0.065	[–0.37]
Dollar Factor	0.870	[15.49]	0.972	[19.52]	1.090	[24.78]	1.137	[23.44]	0.931	[13.43]	0.060	[0.61]
Restrictiveness Factor	-0.273	[–4.88]	-0.159	[–3.35]	-0.086	[–1.66]	0.120	[2.15]	0.398	[4.35]	0.671	[5.49]
R-Squared	0.73		0.83		0.87		0.89		0.80		0.36	
Observations	167		167		167		167		167		167	
Intercept	-0.125	[–0.73]	-0.330	[–1.73]	-0.329	[–1.63]	-0.214	[–1.03]	-0.204	[–1.05]	-0.079	[–0.45]
Restrictiveness Factor	0.242	[2.68]	0.415	[4.61]	0.559	[4.70]	0.793	[6.42]	0.948	[8.15]	0.706	[6.59]
R-Squared	0.06		0.15		0.20		0.32		0.44		0.36	
Observations	167		167		167		167		167		167	

Table 5: Panel Regressions with Next Month's Inflation Rate

The table shows coefficients and test statistics from panel regressions of the monthly percentage inflation rate on central bank restrictiveness and control variables. Across different specifications, inflation in month $t + 1$ is regressed against prior month values of central bank restrictiveness, the inflation rate, the growth rate in M1, the currency return in month $t + 1$, and the predicted inflation rate in month $t + 1$ (from Specification (1)). The table employs quintile dummies for central bank restrictiveness, i.e., central bank restrictiveness Q2 to Q5, with Q1 omitted due to the regression intercept. Each month's quintiles are determined from sorts of currencies with non-missing values for all variables. All regressions include month fixed effects. Driscoll-Kraay cross-sectional and time series dependence-robust standard errors are used to calculate t-statistics. The table also shows the number of observations and the adjusted R-squared. The sample period is July 2006 to May 2020. Currency returns represent profit per unit of currency from 1-month forward contracts. All variables are defined in Appendix B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Central Bank Restrictiveness Q5 (t)	0.157	0.123	0.123	0.123				
	[5.93]	[5.55]	[5.49]	[5.44]				
Central Bank Restrictiveness Q4 (t)	0.225	0.178	0.176	0.176				
	[6.25]	[6.27]	[6.16]	[6.14]				
Central Bank Restrictiveness Q3 (t)	0.079	0.069	0.069	0.069				
	[4.16]	[3.99]	[4.01]	[4.00]				
Central Bank Restrictiveness Q2 (t)	0.027	0.023	0.023	0.023				
	[1.57]	[1.55]	[1.54]	[1.52]				
Inflation Rate (t)		0.218	0.216	0.216		0.221	0.219	0.219
		[4.95]	[4.97]	[5.00]		[4.97]	[4.98]	[5.01]
Growth Rate in M1 (t)			0.005	0.005			0.006	0.006
			[0.85]	[0.85]			[0.96]	[0.96]
Currency Return (t+1)				0.001				0.000
				[0.14]				[0.06]
Expected Inflation Rate (t+1)					0.728	0.532	0.528	0.528
					[6.26]	[5.70]	[5.66]	[5.67]
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors				Driscoll-Kraay				
Adjusted R-Squared	0.22	0.25	0.25	0.25	0.21	0.25	0.25	0.25
Observations	2,351	2,351	2,351	2,351	2,351	2,351	2,351	2,351

Appendix A: Simple Transaction Based Model of Money Demand

We motivate the regression that measures central bank restrictiveness by initially focusing on demand for money in an autarchic economy with money only used to facilitate the autarchic economy's consumption. We then add money's use to facilitate exports and imports. The varying size and mix of transactions explain money demand differences across economies.

M1 Demand with One Transaction Type. Holding currency or demand deposits is costly. Hence, demand for M1 (here, *D*) comes from its convenience in transactions. Let *C* represent aggregate transaction volume, expressed in units of some numeraire good. Assume a logarithmic utility reward *U* from having a given amount of money *D* for transaction volume *C*. Specifically,

$$U = uC\, ln(D - a\,),$$

with *u* denoting a parameter for money's convenience and *a* denoting a shift parameter. Letting *p* denote the money price of the numeraire good, the utility reduction *R* from holding *D* units of money is assumed to be linear:

$$R = r\,\frac{D}{p}. \tag{C1}$$

The first order condition $\frac{\partial U}{\partial D} = \frac{\partial R}{\partial D}$ determines money demand as

$$D = \frac{u}{r}pC + a. \tag{C2}$$

Thus, money demand depends only on (nominal) transaction volume *pC*, the benefit cost ratio of money u/r, and the shift parameter *a*.

Multiple Transaction Types. Money-facilitated transactions come from many sources. For example, money facilitates the sale of domestic output to domestic consumers, but some output is also exported to foreigners. Likewise, domestic consumers may purchase imports. Different transaction components, like exports and imports, can have different benefit to cost ratios, generating different money demand coefficients for those components. Since money demand is the sum of the money demanded from each component, generalizing Equations (C1) and (C2) to isolated decisions about money demand for each component leads to a linear equation for optimal money demand, with as many regressors as there are components. Our data allow study of three major components: output for domestic purchases, exports (output for foreign purchases), and imports.

Domestic money is likely to be more useful to foreign purchasers than to domestic purchasers of the same domestic output. This is partly because foreigners need to obtain currency that is not their own and implement a foreign currency transaction to buy these exports. It is also because the cost of acquiring credit or other money substitutes that facilitate purchases of domestic output is generally greater when the purchaser lives abroad. Imports may generate positive or negative demand for domestic money. At the margin, imports foster sales of the domestic currency to acquire the foreign currency needed to import, but also the offsetting need to post domestic currency as collateral in financial transactions that facilitate imports. (Negative money demand from imports is induced by multiplying the arguments inside the logarithmic function by –1.)

In sum, letting Y be output for domestic consumption, investment, and government expenditure, X be exports, I be imports (all measured in units of goods or services), p^* be the price of the consumption good in the foreign country, and f be the exchange rate expressed as units of domestic currency that can be bought for one foreign currency unit, the model's aggregate demand for the domestic currency will be the linear function

$$D = D_Y + D_X + D_I = a + b_Y pY + b_X pX + b_I f p^* I \qquad \text{(C3)}$$

with b_Y and b_X likely positive (the latter likely larger), and b_I likely negative or smaller than b_Y. In Equation (C3), the coefficients on (nominal) output sold domestically, exports, and imports are

$$b_Y = \frac{u_Y}{r_Y} \qquad b_X = \frac{u_X}{r_X} \qquad b_I = \frac{u_I}{r_I}.$$

Since GDP is determined by Y, X, and I, we can substitute GDP for Y in empirical estimation and obtain the same prediction of M1 demand.

Appendix B: Variable Definitions

The table reports the names and definitions of all variables.

Variable	Definition
Panel A: Country/Currency Characteristics	
1–Month Momentum (*t*)	Currency return (in percent per month) from month *t*–1 to *t*, where the currency return is the log difference between the one-month forward exchange rate of month *t*–1 and the spot exchange rate of month *t* (see e.g., Menkhoff et al., 2012). Data are from Datastream.
3–Month Momentum (*t*)	Cumulative currency return (in percent per month) from month *t*–3 to *t*, where the currency return is the log difference between the one-month forward exchange rate of month *t*–1 and the spot exchange rate of month *t* (see e.g., Menkhoff et al., 2012). Data are from Datastream.
12–Month Momentum (*t*)	Cumulative currency return (in percent per month) from month *t*–12 to *t*, where the currency return is the log difference between the one-month forward exchange rate of month *t*–1 and the spot exchange rate of month *t* (see e.g., Asness et al., 2013). Data are from Datastream.
Carry Trade (*t*)	Difference between one-month forward exchange rate in month *t* and spot exchange rate in month *t*, divided by the spot exchange rate in month *t*. Variable is in percent per month. Data are from Datastream.
Central Bank Restrictiveness (*t*)	Negative scaled residual from regressing narrow money (M1) on prior periods' GDP, exports, and imports using 60-months rolling panel regressions.
Currency Return (*t*)	Difference between one-month forward exchange rate in month *t*–1 and spot exchange rate of month *t*, divided by the one–month forward exchange rate in month *t*–1 (see e.g., Lustig et al., 2014). Variable is in percent per month. Data are from Datastream.
Currency Value (*t*)	At the end of each month *t*, we calculate each currency's real exchange rate return (RER) over the prior five years. The log RER is given by qt = –st + pkt – pt where s denotes the exchange rate (in foreign currency units per USD), pk denotes the price level in country k, and p denotes the U.S. price level. All variables are in logs. Following Asness et al. (2013), we calculate the lagged five–year (5y) real exchange rate return as Δ(5y)qt = qt – qt – 5y = –Δ(5y) st + π(5y),k – π(5y) (e.g., Menkhoff et al., 2017). Real time data on Consumer Price Indices to calculate real exchange rates are from OECD's Original Release Data and Revisions Database.
Dollar Exposures (*t*)	At the end of each month *t*, for each currency, the change in the exchange rate is regressed on a constant, the interest rate differential with the United States, the carry factor, the interaction between interest rate differential and carry factor, and the dollar factor using a 60–months rolling window. The carry factor is the average change in exchange rates between high interest rate countries and low interest rate countries based on quintiles. The dollar factor is the average change in exchange rates across all currencies. Dollar Exposure is the estimated beta on the dollar factor from this rolling regression.
Expected Inflation Rate (*t*)	Predicted percentage change in consumer price index from month *t*–1 to *t* from regression of inflation in month *t* on central bank restrictiveness in month *t*– 1 (alternatively parametrically or non-parametrically).
Exports (*t*)	Exports of goods and services in constant prices and in local currency in month *t*. Data are from ORDR.
Filter Rule Combination (*t*)	At the end of each month *t*, currencies are ranked from low to high based on each of the 354 moving average rules, which calculate the difference between short–run (SR) and long–run (LR) moving averages of currency returns, where SR ranges from 1–12 months and LR ranges from 2–36 months. The Filter Rule Combination is the overall sum of ranks for each currency of all these 354 strategies (e.g., Okunev and White, 2003). Variable is deflated by 1,000.
Growth in M1 (*t*)	Difference in M1 between month *t* and month *t*–1, divided by M1 in month *t*–1. Data are from MEI Archive.
Growth in M2 (*t*)	Difference in M2 between month *t* and month *t*–1, divided by M2 in month *t*–1. Data are from GFD.
Imports (*t*)	Imports of goods and services in constant prices and in local currency in month *t*. Data are from ORDR.
Inflation Rate (*t*)	Difference in consumer price index between month *t* and month *t*–1, divided by consumer price index in month *t*–1. Data are from MEI Archive.
Narrow Money M1 (*t*)	Narrow money (monetary aggregates) in local currency in month *t*. Data are from MEI archive.
Broad Money M2 (*t*)	Broad money (monetary aggregates) in local currency in month *t*. Data are from GFD.
Output Gap (*t*)	At the end of each month *t*, each country's output gap is calculated from detrending the monthly industrial production index (IPI) for each country. Specifically, the residuals from a regression of IPIt on a constant and IPIt–13, IPIt–14, ..., IPIt–24 (corresponding to p=12 and h=24 in Hamilton (2018)) are a measure of detrended output gap (e.g., Colacito et al., 2020). Real time data on industrial production are from ORDR.
Taylor Rule (*t*)	At the end of each month *t*, we calculate the Taylor Rule as 1.5 times inflation and 0.5 times the output gap, which is calculated following the procedure in the Output Gap variable. Real time data on CPI to calculate inflation and real time data on industrial production are from ORDR.
Term Spread (*t*)	At the end of each month *t*, we calculate the difference between a country's long-term interest rates and short-term interest rates (e.g., Ang and Chen, 2010). Short-term rates are three months interest rates (interbank or Treasury bills) and long-term rates are ten year (or if unavailable five year) Government bond rates. Data are from Datastream.
GDP (*t*)	Total GDP in current prices and in local currency in month *t*. Data are from ORDR.

(continued)

Appendix B: Variable Definitions (continued)

Variable	Definition
Panel B: Currency Factors	
Carry Factor (t)	At the end of each month t, currencies are sorted into five quintiles (Q1 to Q5) from low to high based on forward discounts relative to the U.S. Dollar and combined into equally weighted portfolios. The Carry Factor goes long portfolio Q5 and short Q1 (e.g., Lustig et al., 2011).
Dollar Factor (t)	At the end of each month t, currencies are sorted into five quintiles (Q1 to Q5) from low to high based on forward discounts relative to the U.S. Dollar and combined into equally weighted portfolios. The Dollar Risk Factor is the average of these portfolio returns (e.g., Lustig et al., 2011).
Global Imbalance Factor (t)	At the end of each month t, currencies are sorted into six portfolios using sequential sorts based on net foreign asset position and external liabilities in domestic currency and combined into equally weighted portfolios. The Global Imbalance Factor is the return difference between portfolio 5 and portfolio 1 (Della Corte et al., 2016).
Output Gap Factor (t)	At the end of each month t, currencies are sorted into quintiles (Q1 to Q5) from low to high based on the output gap and combined into equally weighted portfolios. The output gap is calculated from detrending the monthly industrial production index (IPI) for each country. Specifically, the residuals from a regression of IPIt on a constant and IPIt–13, IPIt–14, ..., IPIt–24 (corresponding to p=12 and h=24 in Hamilton (2018)) are a measure of detrended output gap. The procedure is implemented recursively conditioning on data available at the time of sorting. The Output Gap Factor goes long portfolio Q5 and short Q1 (e.g., Colacito et al., 2020). Real time data on industrial production are from ORDR.
Restrictiveness Factor (t)	At the end of each month t, currencies are sorted into five quintiles (Q1 to Q5) from low to high based on Central Bank Restrictiveness and combined into equally weighted portfolios. The restrictiveness factor goes long portfolio Q5 and short Q1.
Sovereign Risk Factor (t)	At the end of each month t, currencies are sorted into terciles from low to high based on the lagged CDS spread and combined into equally weighted portfolios. CDS spreads are obtained from USD-denominated CDS contracts written on foreign debts with a tenor of five years (Della Corte et al., 2022). The Sovereign Risk Factor is the return difference between portfolio 3 and portfolio 1. Data on CDS contracts are from Markit.
UMVE Currency Factor (t)	Return in month t of the unconditional mean–variance efficient (UMVE) portfolio of currencies (e.g. Chernov et al., 2023).
UMVE-GE Currency Factor (t)	Return in month t of the unconditional mean–variance efficient (UMVE-GE) portfolio of currencies (e.g. Chernov et al., 2024).

Appendix C: Summary Statistics

The table reports summary statistics of all variables. The sample period is July 2006 to May 2020. All variables are defined in Appendix B.

		Standard				Percentiles							
	Mean	Deviation	Skewness	Kurtosis	Minimum	1st	5th	25th	Median	75th	95th	99th	Maximum
Central Bank Restrictiveness (*t*)	2.75	8.32	4.26	20.9	-6.08	-0.27	-0.14	0.04	0.40	1.20	15.1	45.9	55.4
Currency Returns (*t*)	-0.13	3.48	-28.7	799	-26.5	-10.19	-5.56	-1.94	-0.09	1.75	5.01	9.25	21.4
Carry Trade (*t*)	0.10	0.31	233	1,395	-0.88	-0.39	-0.25	-0.04	0.01	0.19	0.75	1.20	3.48
1-Month Momentum (*t*)	-0.09	3.45	-72.8	788	-28.5	-10.3	-5.38	-1.86	-0.02	1.89	5.18	8.03	16.7
3-Months Momentum (*t*)	-0.22	6.04	-90.6	857	-52.6	-17.9	-9.89	-3.28	0.10	3.20	8.57	13.4	29.0
12-Months Momentum (*t*)	-0.56	11.8	-43.5	514	-78.4	-31.3	-20.4	-7.41	-0.21	6.64	17.5	28.2	36.3
Filter Rule Combination (*t*)	1.07	0.32	0.00	0.00	0.36	0.42	0.53	0.82	1.07	1.31	1.58	1.68	1.75
Dollar Exposures (*t*)	0.56	1.12	-0.72	1.89	-1.77	-1.47	-1.34	-0.76	1.06	1.38	1.81	1.94	2.07
Term Spread (*t*)	0.27	1.80	-31.2	930	-15.7	-4.20	-2.47	-0.64	0.18	1.21	3.13	5.17	12.0
Output Gap (*t*)	-1.16	7.87	-68.3	655	-39.8	-26.6	-17.0	-3.83	0.07	2.99	8.97	16.4	42.6
Currency Value (*t*)	-0.95	22.8	31.2	246	-79.2	-42.6	-34.2	-19.1	-3.19	15.2	39.6	50.4	64.8
Taylor Rule (*t*)	-0.30	4.03	-57.0	637	-20.4	-13.1	-8.14	-1.76	0.24	1.79	5.10	9.44	22.0
Inflation (*t*)	0.21	0.49	183	1,740	-1.54	-0.83	-0.48	-0.08	0.18	0.39	1.02	1.83	6.30