Business Cycles and the Cross-Section of Currency Returns*

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Abstract

We show that business cycles are a key driver of currency excess returns: strong economies offer high returns while weak economies offer low or negative returns, which holds both in- and out-of-sample. Surprisingly, the returns stem primarily from spot exchange rate predictability and are uncorrelated with common currency strategies. Moreover, a business cycle factor that captures the spread in economic conditions across countries is priced in cross-sections of currency excess returns arising from carry, momentum and value strategies. We discuss the implications of these results for international macro-finance theory and for global investors seeking novel sources of currency portfolio diversification.

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1 Introduction

A growing body of research has documented that the cross-section of currency excess returns is predictable, which can be exploited using various investment strategies, including carry (Lustig and Verdelhan, 2007; Lustig, Roussanov, and Verdelhan, 2011; Menkhoff et al., 2012a), momentum (Menkhoff et al., 2012b; Asness, Moskowitz, and Pedersen, 2013), and value (Asness, Moskowitz, and Pedersen, 2013; Menkhoff et al., 2017).[1] Researchers have attempted to explain this predictability by theoretically and empirically investigating whether the returns generated by these currency investment strategies are compensation for risk.

Standard finance theory postulates that if investors are risk averse, the returns in excess of the risk-free rate reflect compensation for exposure to one or more underlying risk factors. In particular, a series of recent papers find evidence in support of a variety of risk factors, including 'global' exchange rate risk (Lustig, Roussanov, and Verdelhan, 2011; Colacito et al., 2016), unanticipated global volatility risk (Menkhoff et al., 2012a), downside risk (Lettau, Maggiori, and Weber, 2014), global imbalance risk (Della Corte, Riddiough, and Sarno, 2016), and correlation risk (Mueller, Stathopoulos, and Vedolin, 2016), among others.

Despite this progress, the literature provides limited empirical evidence to explain, from an economic perspective, why one currency is more or less risky than another. Instead, the loading of each currency (or basket of currencies) on the risk factor is treated as a free parameter in empirical estimation. Currencies' exposure to risk should, however, be driven by an underlying macroeconomic process. In the same way that a firm's level of risk is theoretically linked to firm fundamentals, a currency's riskiness should be a function of its underpinning macroeconomic fundamentals. Yet we have a limited understanding of whether or how currency risk premia are related to economic conditions across countries.[2]

Recent theoretical developments in macro-finance provide a new scope for understanding *why* currencies are risky. Much of this work centers on developing augmented consumption-

[1]While carry, momentum and value are well established currency investment strategies, several other strategies in the recent literature show predictability in currency markets. These include strategies which combine carry with other signals (Jordà and Taylor, 2012; Barroso and Santa-Clara, 2015), 'smart' carry (Bekaert and Panayotov, 2015), information in the volatility risk premium (Della Corte, Ramadorai, and Sarno, 2016), and optimal dynamic currency strategies (Maurer, Tô, and Tran, 2016).

[2]The few empirical papers that successfully document a link between macroeconomic fundamentals and currency premia include Lustig and Verdelhan (2007), who test the Consumption Capital Asset Pricing Model and find that consumption growth can account for currency excess returns, although the finding was later critiqued by Burnside (2011); Della Corte, Riddiough, and Sarno (2016), who find evidence that countries' net foreign assets are important determinants of currency premia, supporting the theory of Gabaix and Maggiori (2015); and Berg and Mark (2016), who propose a factor based on conditional skewness of the unemployment gap.

based models to account for currencies' conditional exposure to risk, for example, in a framework with long-run risk (Colacito and Croce, 2013), rare events (Farhi and Gabaix, 2016), or habit persistence (Verdelhan, 2010; Stathopoulos, 2017).[3] However, the development of these theories has been met with limited empirical interest in testing their implications for currency excess returns. This lack of interest may reflect, as Cochrane (2017) notes, that a horse-race between competing theories is difficult because they are inherently correlated: each theory tells an alternative 'economic parable' to provide insight into why investors dislike economic recessions. In other words, macro-finance theories share a central, but relatively unexplored, prediction that *business cycles* are a key driver of expected returns.

In this paper, we evaluate this general implication from the theoretical literature by investigating the relationship between business cycles and the cross-section of currency returns, and the properties of investment strategies that exploit the relationship. We provide structure for the analysis by presenting testable predictions, linking business cycles to currency excess returns, using a habit model of exchange rates. Within this framework, currencies of "strong" economies should generate higher currency excess returns than currencies of "weak" economies. A portfolio strategy that buys strong economy currencies and sells weak economy currencies should therefore generate positive average excess returns as compensation for risk.

The economic intuition is as follows: in bad times, consumption is close to the habit level and the domestic interest rate is low. In this case, the domestic investor is more risk averse than his foreign counterpart and demands a premium for holding foreign currency. A strategy which goes short the domestic currency and long the foreign currency should therefore generate positive excess returns. While the model provides structure and transparency for our empirical exercise, the results are not model dependent. Instead, they provide a general test of the broad class of models that include cyclical (or countercyclical) state variables to impose a link between business cycles and expected currency returns.

In our empirical work, we use the output gap – a common macroeconomic measure of business cycle conditions, defined as the percentage deviation in output from its long-run trend – to sort currencies into quintile portfolios at the end of each month. We measure the output gap using a standard Hodrick-Prescott (1980, HP) filter in our core results, but we also explore

[3]Other recent theories have focused on the *unconditional* source of heterogeneity to explain why countries with high *average* interest rates offer higher currency excess returns. Candidate sources of heterogeneity include: country size (Hassan, 2013), commodity intensity (Ready, Roussanov, and Ward, 2016), financial development (Maggiori, 2013) and trade-network centrality (Richmond, 2016). Our primary focus, however, is on the theoretical macro-finance literature explaining *conditional* time-varying exposure to risk.

various alternative filters in our robustness analysis. Using data from October 1983 onward, we find a strategy that goes long the highest output gap currencies and short the lowest output gap currencies – which we term the GAP strategy – produces desirable risk-adjusted returns and economically sizeable Sharpe ratios of up to 0.94 for a broad cross-section of 27 currencies and up to 0.70 for a smaller sample of major currencies. The results confirm the essence of the theoretical prediction that currency excess returns are higher for stronger economies, i.e. those in a more favorable state of the business cycle.[4]

We find the time-series correlation between the GAP strategy and the currency carry trade is essentially zero, and the correlations with other canonical currency investment strategies are also close to zero. Surprisingly, the performance of the GAP strategy stems almost entirely from the predictability of spot exchange rates, rather than from interest rate differentials: currencies with relatively high output gaps tend to appreciate over the subsequent month, while those with relatively low output gaps tend to depreciate. The observed predictability of spot exchange rates is a rare finding in this literature and accounts for the lack of correlation with standard currency strategies.

We then test empirically whether a business cycle risk factor explains the cross-section of currency excess returns in a standard asset pricing framework. This factor – termed the output gap (GAP) factor – is equivalent to the return from a strong-minus-weak strategy that buys the currencies of economies with strong output gaps and shorts the currencies of economies with weak output gaps, therefore capturing the cross-sectional spread in the state of business cycles across countries at each point in our sample. We find that the GAP factor explains a large fraction of the cross-sectional variation in currency excess returns, thus supporting a risk-based view of exchange rate determination that is based on business cycle conditions.

The pricing power of the GAP factor is not confined to portfolios sorted on output gaps, but also extends to other popular currency cross-sections, including portfolios sorted on carry (interest rate differentials), momentum and value, and provides better empirical performance in pricing these portfolios than other leading factors, such as the slope factor (Lustig, Roussanov, and Verdelhan, 2011) and volatility factor (Menkhoff et al., 2012a). Furthermore, risk factors that are successful in pricing carry trade portfolios, such as the slope factor of Lustig,

[4]While the output gap is a common measure of business cycle conditions in the macroeconomics literature, it has received comparatively little attention in financial economics. Cooper and Priestley (2009) provide a notable exception, finding that the output gap can help predict future stock returns for the United States and other G7 countries both in-sample and out-of-sample. In international macroeconomics, Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008) show that 'Taylor rule' models that incorporate output gap and inflation information display predictive power for spot exchange rate changes in time series regressions for three major exchange rates.

Roussanov, and Verdelhan (2011), are not able to explain the cross-section of portfolio returns sorted on output gaps, further signifying that business cycles provide a theoretically motivated but empirically novel source of risk in determining currency excess returns.

Our results on the relationship between business cycles and expected currency returns are obtained in-sample since our primary interest is to test the relationship using the most accurate measure of business cycle conditions. Nonetheless, we also find the *GAP* investment strategy can be successfully implemented out-of-sample, providing attractive returns and Sharpe ratios when conditioning purely on information available at the time of portfolio formation. We show this result using: Hamilton's (2016) detrending procedure with real-time industrial production data, the OECD's real-time measure of business cycle conditions, and a measure of real-time industrial production momentum. Furthermore, the lack of correlation between *GAP* returns and other canonical currency investment strategies implies that the *GAP* strategy offers tangible diversification benefits in a currency portfolio, for which we provide quantitative evidence. Specifically, adding the *GAP* strategy to a conventional menu of currency strategies – such as carry, momentum, value, and dollar strategies – substantially improves the risk-return trade-off faced by a currency investor.

It is also important to note that the theoretical literature in this area of research typically views its models of currency excess returns as a means to explain the profitability of the carry trade (see, for example Colacito and Croce, 2013; Farhi and Gabaix, 2016). Indeed, within the habit model, the trading strategy implied by the model should perfectly correlate with the carry trade since interest rates move with the (cyclical) state variable. We illustrate one channel for how the zero correlation between *GAP* and carry returns could be reconciled theoretically, by allowing for differences in long-run consumption growth rates across countries. This setup breaks the one-to-one relationship between interest rates and the strength of the economy, generating persistent differences in interest rates, consistent with the data.

Simulations of the model indicate that a zero correlation between *GAP* and carry returns occurs under standard parameter choices. Other mechanisms could generate the zero correlation, including variations in the subjective discount factor and asymmetric inflation risks as modeled, for example, in Jylhä and Suominen (2011). The key message, however, is that persistent interest-rate differentials are required to match carry returns, which are fundamentally different from *GAP* returns; hence, future theoretical work should seek to jointly account for both *GAP* and carry returns when modeling currency excess returns.

Overall, our contributions to the literature are fourfold. First, we show that a fundamental macroeconomic factor drives currency excess returns. Lustig and Verdelhan (2007) is the most closely related paper in this respect. They show a link between currency returns and U.S. consumption growth, instead we demonstrate a link between currency returns and relative output across countries. We thus provide the first evidence on the role of cyclical factors that are theoretically used to augment consumption growth in the literature. This result is obtained in a cross-sectional portfolio setting, which provides an intuitive measure of the economic value business cycle fluctuations have for predicting exchange rates. This is important since the vast majority of papers exploring the link between macroeconomic variables and exchange rate fluctuations either rely on purely statistical criteria or focus on time-series analysis using a limited number of currency pairs (Mark, 1995; Molodtsova, Nikolsko-Rzhevskyy, and Papell, 2008; Rossi, 2013, and the references therein).

Second, our finding that a business cycle risk factor is priced in cross sections of excess returns is notable, given the well-documented difficulty to explain asset returns with macroeconomic factors and the feeble link between exchange rates and economic fundamentals recorded in much empirical literature (Meese and Rogoff, 1983; Engel and West, 2005). Third, the excess returns generated from exploiting the predictive power of the output gap are primarily driven by the predictability of spot exchange rates rather than interest rate differentials, which contrasts with the implications of much international macro-finance theory (e.g., Verdelhan, 2010). While this is surprising, it provides useful guidance for future theory in this area of research, and we show that understanding these facts requires models that allow for persistent differences in interest rates across countries.

Finally, our findings provide a novel currency investment strategy that can be implemented successfully out-of-sample and provides diversification benefits when combined with other common currency strategies. This finding contributes to the burgeoning literature on cross-sectional foreign exchange market predictability (Lustig, Roussanov, and Verdelhan, 2011; Jordà and Taylor, 2012; Menkhoff et al., 2012b, 2017; Asness, Moskowitz, and Pedersen, 2013) and extends the literature on optimal currency asset allocation (e.g., Barroso and Santa-Clara, 2015).

In further analysis, we show, *inter alia*, that (i) the core results remain unchanged when using alternative measures of the output gap constructed with various detrending procedures; (ii) the results are robust when we depart from our base scenario of a U.S.-based investor and run calculations with alternative base currencies (taking the viewpoint of a Eurozone, British, Japanese, and Swiss investor, respectively); and (iii) transaction costs do not wipe out the returns from the GAP strategy either in- or out-of-sample.

The rest of the paper is structured as follows. Section 2 describes the framework that generates our hypotheses. Section 3 describes the data and construction of currency portfolios. In Section 4 we report results from implementing the *GAP* strategy, while in Section 5 we conduct cross-sectional asset pricing tests. Section 6 investigates whether and how the *GAP* strategy can be implemented out-of-sample and quantifies the diversification benefits from including the strategy in a broad currency portfolio. Section 7 provides a discussion of how the empirical results can be interpreted theoretically. Section 8 reports the results from further analysis and robustness checks. We conclude in Section 9.

2 Theoretical Motivation

A common feature of macro-finance models of asset pricing, including models with long-run risks, rare disasters, habit preference, and heterogeneous preferences, is that they essentially augment the Consumption Capital Asset Pricing Model to integrate one or more (unobservable) state variables that vary with business cycles to account for assets' exposure to risk (Cochrane, 2017). It is widely known that during bad times (e.g., in recession), risky assets generate negative returns, investors are more risk averse, and risk premia increase; therefore, risk-based theory attempts to predict these outcomes.

This feature of asset pricing models, linking business cycle and discount factors, is also common to the theoretical literature describing the evolution of currency excess returns. Farhi and Gabaix (2016), for example, present a rare "disasters" model in which a 'business cycle factor' is used to augment the baseline disasters model. Strong economies with high output gaps are predicted to have appreciated exchange rates and high interest rates, implying that stronger economies would generate a positive interest rate differential but a negative exchange rate return (since the output gap is mean reverting). Colacito and Croce (2013) present a two-economy general equilibrium model with long-run risks that accounts for the findings of Lustig, Roussanov, and Verdelhan (2011) that high interest rate currencies have the highest expected returns.

The state variable – the share of world consumption – varies cyclically with domestic productivity shocks. In 'good times' following a productivity shock, the domestic economy reduces its consumption as a share of world consumption and lends to the foreign economy. Weaker economies with rising shares of world consumption are predicted to offer higher currency returns to compensate for their exposure to global consumption shocks. In Verdelhan (2010), consumers are endowed with external habit preferences. A single state variable drives the model. This variable – surplus consumption – has been shown to vary with the output gap (Campbell, Pflueger, and Viceira, 2015). Investors in weak economies are more risk averse and thus require a high currency return to invest in strong economies.

We are thus motivated by the general macro-finance theoretical literature that either explicitly or implicitly links business cycles to currency excess returns. Therefore, although our contribution in this paper is empirical, we provide structure to our analysis by outlining *one set of hypotheses* from the literature. Specifically, we outline the predictions that arise from the external habit model of exchange rate determination, studied in, for example, Moore and Roche (2008, 2010, 2012), Verdelhan (2010) and Stathopoulos (2017).

The habit preferences model provides a convenient framework for expressing testable predictions for two main reasons. First, the theory provides a comparatively parsimonious model of the Stochastic Discount Factor (SDF). This feature allows us to make precise statements about the model's predictions on business cycles and the necessary ingredients required to reconcile our empirical findings with the model's predictions. Second, surplus consumption, the state variable in the habit framework, is widely recognized on both theoretical and empirical grounds to proxy for the business cycle (Campbell and Cochrane, 1999; Li, 2001; Campbell, Pflueger, and Viceira, 2015). We therefore view the model as providing a direct link between business cycles and currency excess returns.

Testable Predictions. The main elements of the habit model are outlined in the Appendix, and full details are in Verdelhan (2010). The framework is a symmetric two-country model in which the representative investor in each country is assumed to have external habit preferences (Campbell and Cochrane, 1999). The logarithm of consumption is assumed to follow a random walk with drift, while the log surplus consumption ratio (the cyclical state variable) is defined as a stationary AR(1) process with time-varying volatility. Under the standard no-arbitrage condition with complete markets, and assuming the SDF in each country is lognormally distributed, the expected log currency excess return r^e_{t+1} and interest rate differential $r^*_t - r_t$ can be shown to equal a function of the surplus consumption differential:

$$\mathbb{E}_t(r^e_{t+1}) = \zeta(s^*_t - s_t) \tag{1}$$

$$r^*_t - r_t = \iota(s^*_t - s_t) \tag{2}$$

where $\zeta > 0$, $\iota > 0$, s is the log surplus consumption ratio, and the asterisk denotes foreign country's variables.

Equation (1) indicates that investors can expect to earn high currency excess returns from investing in countries with high surplus consumption (high output gap). The intuition is simple: in bad times, a negative domestic consumption growth shock pushes consumption close to its habit level and the interest rate lower. In this case, the domestic investor is more risk averse than his or her foreign counterpart and demands a positive currency excess return (risk premium) for holding the foreign currency. Hence a strategy that is short in the domestic currency (weak economy) and long in the foreign currency (strong economy) should generate positive excess returns.

We are interested in these implications for a portfolio of currencies. It is easy to show (see Appendix) that generalizing Equation (1) to the case of a sufficiently large number of countries N, the portfolio return of an investment strategy that buys strong economy currencies and sells weak economy currencies is expected to generate a positive currency excess return equal to

$$r^e_{HML,t+1} = \zeta \underbrace{\left(\overline{s_{t,H}} - \overline{s_{t,L}}\right)}_{>0} + \gamma \underbrace{\left(\overline{\lambda(s_{t,L})} - \overline{\lambda(s_{t,H})}\right)}_{>0} \omega_{g,t+1} \tag{3}$$

where γ is the risk aversion coefficient, $\omega_{g,t+1}$ is the common shock to consumption growth across countries at time $t+1$, $\overline{s_{t,H}}$ ($\overline{s_{t,L}}$) is the average surplus consumption ratio in the 'high' ('low') portfolio at time t, and $\overline{\lambda(s_{t,H})}$ ($\overline{\lambda(s_{t,L})}$) is the average sensitivity ratio of currencies in the high (low) portfolio at time t. The average sensitivity of low surplus consumption countries is high since investors in these countries are more risk averse because consumption is close to habit. It can be seen from Equation (3) that returns are driven by surplus consumption ratios at time t and shocks to a common component ω_g at time $t+1$, with sensitivity to the shock being a function of relative surplus consumption ratios.

Given that surplus consumption depends on the state of the business cycle (Campbell and Cochrane, 1999; Li, 2001; Cochrane, 2017) one can empirically proxy a country's surplus consumption using a measure of business cycle conditions. Campbell, Pflueger, and Viceira (2015) highlight the strong empirical and theoretical relationship between the output gap and surplus consumption, which are perfectly correlated under realistic model assumptions. We use this framework to form our main testable hypothesis:

- *Currencies of countries with high output gaps ("strong" economies) should offer higher excess returns than currencies with low output gaps ("weak" economies). Thus, a portfolio* *that buys strong economy currencies and sells weak economy currencies, which we term the GAP strategy, should generate positive average excess returns as compensation for business cycle risk.*

The mechanism described above provides a single, transparent, channel through which business cycles affect currency returns. Our primary motivation in describing the model is to provide intuition for the link between business cycles and currency returns. Nonetheless, we acknowledge that other channels exist and our empirical exercise has implications for all currency models with cyclical (or countercyclical) risk factors. We leave to future work any attempt to distinguish between competing theories or disentangle their precise implications for a business cycle factor. Instead, we concentrate on providing the first empirical results on the link between business cycles and the cross-section of currency excess returns that can inform future theoretical and empirical work.

3 Data and Currency Portfolios

This section describes the main data employed in the empirical analysis. We also describe the construction of currency portfolios and the risk factors.

3.1 Data on Spot and Forward Exchange Rates

We collect daily spot and 1-month forward exchange rates vis-à-vis the U.S. dollar from Barclays and Reuters via Datastream. The empirical analysis uses monthly data obtained by sampling end-of-month rates from October 1983 to January 2016. Our sample comprises 27 countries: *Australia*, *Austria*, *Belgium*, Brazil, *Canada*, Chile, Czech Republic, *Germany*, *Finland*, *France*, Iceland, *Ireland*, *Italy*, *Japan*, Mexico, *Netherlands*, *New Zealand*, *Norway*, Poland, *Portugal*, South Korea, *Spain*, *Sweden*, *Switzerland*, Turkey, *United Kingdom*, and the *United States*. We call this sample 'all countries.'

Several currencies in this sample are pegged or subject to capital restrictions. Investors may not easily trade some of these currencies in large amounts even though quotes on forward contracts (deliverable or nondeliverable) are available. Hence, we also consider a subset of 19 countries, which we refer to as 'developed countries.' This sample includes the countries in italics in the above list. After the introduction of the euro in January 1999, we remove the Eurozone countries except for Germany, which we use to proxy for the Euro area.[5]

[5]The sample of developed countries is slightly larger than that used by Lustig, Roussanov, and Verdelhan

3.2 Data on Economic Activity

Turning to macroeconomic data, we use monthly data on industrial production, obtained from the OECD's *Original Release Data and Revisions Database.* For the main analysis we use the April 2016 vintage of data. The full series of monthly industrial production data begin at various dates across countries. The earliest start date is January 1960, and the sample runs until January 2016. We use the full sample to calculate various measures of the output gap for each country in the sample. Our benchmark measure is the standard HP filtered output gap, but we also estimate output gaps using the Baxter-King (1999) filter, a forecasting approach attributable to Hamilton (2016), a linear trend, and a quadratic trend.

The full sample contains revisions to the data, which is useful for forming the most accurate estimate of the output gap in each period. However, in part of the empirical analysis, we require *real-time* industrial production data to proxy investors' information set. We therefore collect monthly 'vintage' data of industrial production, available from December 1999 until January 2016.[6] Each monthly vintage dataset records the industrial production data available to an investor in that particular month. For example, in December 1999, the available U.S. industrial production data ran from January 1960 to October 1999. We thus assume that the industrial production data for November and December of 1999 were unknown to the investor in December 1999.

We also collect data on *Composite Leading Indicators* (CLIs) from the OECD's *Original Release Data and Revisions Database.* The CLIs are designed to capture (and indeed predict) turning points in industrial production by aggregating across a variety of country-specific macro-indicators, which are known to have a reasonably consistent relationship with the local business cycle. The underlying components of the CLI series are all passed through a variety of filters by the OECD prior to aggregation, including 'seasonal adjustment, outlier detection, trend-removal, smoothing and normalization' to maintain stable lead times and reduce the possibility of missing turning points in the cycle (OECD, 2016).

We collect vintage data for the 'amplitude-adjusted' CLI – the OECD's preferred CLI measure of business cycle conditions. The amplitude-adjusted series takes the average of the

(2011) and Menkhoff et al. (2012a). The full sample of countries instead comprises a smaller set of countries than those studies. Our data constraint for the sample of all countries is due to the availability of data from the OECD, discussed later in this section. For the smaller sample of developed countries, we also consider the smaller set of countries as in Lustig, Roussanov, and Verdelhan (2011) and Menkhoff et al. (2012a) and find qualitatively identical results.

[6]The dataset is available from February 1999, but the early months have unusually short samples. We therefore choose to begin the analysis using the December 1999 vintage.

filtered and detrended component series and then 'amplifies' the series to match the standard deviation of detrended industrial production. It can be interpreted as an output-gap-type cyclical measure of business cycle conditions in real time. Although the dataset begins in 2001, the majority of currencies in our sample only become available much later, and hence our monthly vintages run from April 2006 to January 2016.

3.3 Currency Excess Returns

We define spot and forward exchange rates at time t as $Spot_t$ and Fwd_t. Exchange rates are defined as units of U.S. dollars per unit of foreign currency such that an increase in $Spot_t$ indicates an appreciation of the foreign currency. The excess return on buying a foreign currency in the forward market at time t and selling in the spot market at time $t+1$ is computed as

$$RX_{t+1} = \frac{(Spot_{t+1} - Fwd_t)}{Spot_t}, \tag{4}$$

which is equivalent to the spot exchange rate return minus the forward premium

$$RX_{t+1} = \frac{Spot_{t+1} - Spot_t}{Spot_t} - \frac{Fwd_t - Spot_t}{Spot_t}. \tag{5}$$

According to the Covered Interest Parity (CIP) condition, the forward premium approximately equals the interest rate differential $(Fwd_t - Spot_t)/Spot_t \simeq i_t - i_t^*$, where i_t and i_t^* represent the U.S. and the foreign riskless rates respectively, over the maturity of the forward contract. Since CIP generally holds closely in the data at low frequency (e.g., Akram, Rime, and Sarno, 2008), the currency excess return is approximately equal to the exchange rate return (i.e., $(Spot_{t+1} - Spot_t)/Spot_t$) plus the interest rate differential relative to the United States (i.e., $i_t^* - i_t$). As a matter of convenience, throughout this paper we refer to $fd_t = (Spot_t - Fwd_t)/Spot_t = i_t^* - i_t$ as the forward discount or interest rate differential relative to the United States.[7]

3.4 GAP Portfolios

Motivated by the theoretical predictions described in Section 2, we construct the GAP strategy as follows. At the end of each period t, we sort currencies on the time-t output gap and allocate them to five portfolios. Portfolio 1 corresponds to the weakest countries with the lowest output gaps (output most below potential), whereas Portfolio 5 comprises the strongest countries with the highest output gap (output most above potential). We then compute the excess return for

[7] Due to large deviations from CIP caused by extreme market illiquidity, and consistent with other studies in the literature, we remove the Turkish lira from our sample between November 2000 and November 2001.

each portfolio as an equally weighted average of individual currency excess returns within the portfolio. We construct a GAP factor as the difference between Portfolio 5 (P_5) and Portfolio 1 (P_1). This approach is equivalent to a strong-minus-weak strategy that buys the currencies of strong economies (characterized by relatively high output gaps) and sells the currencies of weak economies (characterized by relatively low output gaps).

Our benchmark results are obtained using an in-sample measure of the output gap constructed using the HP filter over the full sample and ignoring real-time data considerations. The output gap is defined as the logarithm of the difference between actual (y_t) and 'potential' ($\bar{y}_t$) output. A country's potential output is not directly observable, and it therefore needs to be estimated. Numerous statistical methods have been proposed to measure potential output $\bar{y}_t$, with the principal aim being to split a country's output into cyclical and trend components. The trend component can be viewed as the economy's natural or potential growth path, from which growth cyclically deviates.

The cyclical component is thus a measure of these short-term deviations and serves as our empirical proxy for the output gap. The HP filter is the most common technique for extracting the output gap in the macroeconomics literature (see, e.g., Backus and Kehoe, 1992; Cooley and Hansen, 1989; Danthine and Girardin, 1989; Kydland and Prescott, 1990; Hansen, 1985). Specifically, the HP filter decomposes the logarithm of real output y_t, into a cyclical component (y_t^{cy}, output gap) and a trend growth component (y_t^{gr}, potential output), $y_t = y_t^{cy} + y_t^{gr}$.[8]

3.5 Carry Trade Portfolios

At the end of each month t, we allocate currencies to five portfolios on the basis of their forward discounts (or interest rate differential relative to the United States). This exercise implies that currencies with the lowest forward discounts (or lowest interest rate differential relative to the United States) are assigned to Portfolio 1, whereas currencies with the highest forward discounts (or highest interest rate differential relative to the United States) are assigned to Portfolio 5. We compute the excess return for each portfolio as an equally weighted average of the currency excess returns within that portfolio. The strategy that is long Portfolio 5 and short Portfolio 1 is referred to as CAR.

[8] One criticism of using the HP filter is the 'endpoint' problem. While the HP filter performs well in capturing peaks and troughs in the business cycle (see, e.g., Canova, 1994), the approach does not consider if the start and end points reflect similar points in the cycle, which can bias the first and last few data points. This feature is troublesome when the primary objective is to make policy recommendations or forecasts. The filter is hence more useful for characterizing business cycles in-sample, as we do, than forecasting out-of-sample. Nonetheless, we also apply the technique of Watson (2007) to mitigate endpoint concerns. The procedure requires estimating an AR(8) model to forecast and backcast the data by 12-quarters before applying the HP filter.

3.6 Currency Momentum Portfolios

At the end of each period t, we form five portfolios based on exchange rate returns over the previous month. We assign the 20% of all currencies with the lowest lagged exchange rate returns to Portfolio 1 and the 20% of all currencies with the highest lagged exchange rate returns to Portfolio 5. We then compute the excess return for each portfolio as an equally weighted average of the currency excess returns within that portfolio. A strategy long in Portfolio 5 (*winner currencies*) and short in Portfolio 1 (*loser currencies*) is denoted as MOM.

3.7 Value Portfolios

At the end of each period t, we form five portfolios based on the lagged five-year real exchange rate return as in Asness, Moskowitz, and Pedersen (2013). This measure of currency value is based on calculating a deviation from relative purchasing power parity. Specifically, relative inflation over a 5-year window vis-à-vis the United States is compared with the foreign exchange rate appreciation over the same period versus the U.S. dollar. To provide a more stable measure of the foreign exchange rate appreciation, Asness, Moskowitz, and Pedersen (2013) calculate the appreciation as today's FX rate minus the average FX rate observed 4.5 to 5.5 years earlier. If inflation growth in the foreign economy outpaced that in the U.S. but the U.S. dollar did not appreciate against the foreign currency by an offsetting amount, then the foreign currency is considered 'overvalued'.

To construct currency value portfolios, we collect monthly data on consumer price indices from the IMF's *International Financial Statistics* database beginning in October 1978 and also collect additional foreign exchange spot rate data from *Global Financial Data* beginning in April 1978, such that the first currency value signals are obtained in October 1983. We assign the 20% of all currencies with the highest lagged real exchange rate return to Portfolio 1 and the 20% of all currencies with the lowest lagged real exchange rate return to Portfolio 5. We compute the excess return for each portfolio as an equally weighted average of the currency excess returns within that portfolio. A strategy long in Portfolio 5 (*undervalued currencies*) and short in Portfolio 1 (*overvalued currencies*) is denoted as VAL.

4 The GAP Strategy: Properties and Performance

This section describes the properties of the excess returns from implementing the GAP strategy. Our benchmark is a standard cross-sectional portfolio sort, in which currencies are sorted into five bins (P_1, P_2, P_3, P_4, P_5) based on quintiles of the cross-sectional distribution of output gaps. Within each bin, currencies are equally weighted. We report results for the *GAP* portfolio that goes long in P_5 (strong economy currencies, i.e., the highest output gaps) and short in P_1 (weak economy currencies, i.e., the lowest output gaps).

In addition to the main *GAP* portfolio strategy, for robustness we also build alternative measures of the *GAP* portfolio with linear weights given by

$$w_{j,t+1} = c_t \left(x_{j,t} - \overline{x}_t \right), \tag{6}$$

where $x_{j,t}$ denotes the signal for currency j in month t (i.e., the output gap in that month for that currency) and $\overline{x}_t = N_t^{-1} \Sigma_{j=1}^{N_t} x_{j,t}$ denotes the *cross-sectional average* of this signal (across countries, N_t). c_t is a scaling factor such that the absolute sum of all portfolio weights equals unity, that is, $c_t = 1/\sum_j |x_{j,t} - \overline{x}_t|$. Currencies with a value of the signal above the cross-sectional mean receive positive portfolio weights, whereas currencies with a below-average value receive negative weights. The portfolio return rx^p is then given by $rx^p_{t+1} = \sum_{j=1}^{N_t} w_{j,t+1} rx_{j,t+1}$. In the implementation of this approach we rebalance the portfolios at the end of each month.

Finally, we also report returns of rank portfolios (Asness, Moskowitz, and Pedersen, 2013), where weights are given by

$$w_{j,t+1} = c_t \left(\text{rank}(x_{j,t}) - \sum_{j=1}^{N_t} \text{rank}(x_{j,t})/N_t \right). \tag{7}$$

The scaling factor c_t is analogous to the case of linear weights above (but uses ranks of signals instead of actual signals) and ensures that we are one dollar long and one dollar short as in Asness, Moskowitz, and Pedersen (2013). The procedures based on linear weights and rank portfolios are useful for a comparison with the P_5-P_1 *GAP* strategy because they are more conservative, assigning smaller weights to extreme output gaps. Given the relatively small number of assets in the currency cross-section, these strategies provide some reassurance that results from the main *GAP* strategy are not driven by just a few currencies.

In Panel A of Table 1, we present the average excess returns on the five output-gap-sorted portfolios, which monotonically increase from P_1 (-0.25% and -0.60% per annum) to P_5 (6.41% and 4.92% per annum) for both samples of countries.[9] The average excess returns of the *GAP* strategy are 6.66% and 5.52% for the two samples, which are statistically different from zero at the 1% level. The Sharpe ratio (*Sharpe*) is 0.82 for the sample of all countries and 0.68 for the sample of developed countries. The Sharpe ratios are comparable with carry trade strategies

[9]The portfolio returns are available online at http://www.stevenriddiough.com/research/.

and are larger than currency value and momentum strategies, suggesting the GAP strategy has highly appealing risk-adjusted returns in its own right.[10]

Further scrutiny of the results in Table 1 reveals the GAP strategy returns are mainly driven by predicting spot exchange rates (5.06% and 4.92% per annum, in the row denoted fx), whereas the interest rate differential contributes much less (1.60% and 0.60% per annum, in the row denoted ir). This finding is quite different from that observed with carry trade strategies in which returns are entirely driven by exploiting interest rate differentials across countries, and typically the exchange rate component of the excess return is negative.[11] The stark difference between the GAP strategy and the carry trade is visible in Figure 1, which plots the cumulative return from these two strategies as well as the cumulative returns from the exchange-rate and interest-rate components over the full sample.

The properties of the returns from the GAP strategy are qualitatively identical when using linear weights and rank portfolios, which tend to further improve the Sharpe ratio for the sample of all countries. The main difference we observe is that linear weights and rank portfolios alter the risk profile of the strategy by producing more positively skewed excess returns and reducing the maximum drawdown of the strategy, which is expected since these portfolio construction schemes place less weight on the currencies in the corner portfolios.

The last three rows in Table 1 report a measure of turnover and the spread in both interest rate differentials and output gaps in each of the five output-gap-sorted portfolios. The turnover measure is slightly higher than reported in the literature for carry trade strategies but lower than momentum strategies (see, e.g., Menkhoff et al., 2012a,b). We note a tendency exists for interest rate differentials to increase as we move from P_1 to P_5, albeit nonmonotonically; however, the spread is rather low, consistent with the fact that the returns of the GAP strategy are not driven by interest rate differentials. Instead, the spread in output gaps is large as we move across portfolios: for the all countries sample it ranges from a 3.08% negative output gap in P_1 to 3.01% positive output gap in P_5.

Panel B of Table 1 presents statistics on the main currencies entering each portfolio. It is useful to examine the identity of the currencies that enter the portfolios and particularly the corner portfolios of the GAP strategy. The Swiss franc (CHF), a typical carry funding currency, appears frequently in both P_1 and P_5, as does the New Zealand dollar (NZD), a typical carry

[10]For example, for our sample of all (developed) countries, carry (CAR), momentum (MOM), and value (VAL) generate Sharpe ratios of 0.72 (0.55), 0.27 (0.15), and 0.20 (0.43), respectively.

[11]For comparison, we present the equivalent descriptive statistics for forward-premia-sorted (carry) portfolios in Table A.1 of the Internet Appendix.

investment currency. The results in Panel B reveal that the GAP strategy has no typical weak or strong currencies, which makes sense: output gaps are stationary cyclical deviations from long-run growth trends, and therefore weak and strong currencies change over our long sample as countries move in and out of booms and recessions.

Table 2 reports a battery of correlation coefficients between the returns from the GAP strategy and the returns from CAR, MOM, VAL, and a 'market' portfolio that is equally long in all currencies against the U.S. dollar, termed DOL.[12] The results are reported for both samples of all countries and developed countries and for both the full sample and two subsample periods of equal size. The main point arising from this table is that the returns of the GAP strategy are largely uncorrelated, not only with carry, but with all the standard currency portfolios. For example, during the full sample period the correlation ranges from -0.15 with DOL to 0.15 with MOM for the sample of all countries. This result tentatively suggests the GAP strategy contains novel economic information in its own right and is not a mechanical relabeling of an existing currency strategy or factor.[13]

Overall, the currencies of strong economies with relatively high output gaps have higher excess returns than currencies of weak economies with relatively low output gaps, consistent with the main hypothesis stated in Section 2. Surprisingly the returns are driven by the FX component and are uncorrelated with the returns of popular currency investment strategies. The finding also raises the tantalizing prospect, to which we turn, that business cycles contain novel pricing information for the cross-section of currency returns.

5 Asset Pricing Tests

This section presents cross-sectional asset pricing tests designed to assess whether a business cycle factor is priced in the cross section of currency returns.

Methodology. We denote the discrete excess returns on portfolio j in period t as RX_t^j. In the absence of arbitrage opportunities, risk-adjusted excess returns have a price of zero and satisfy the following Euler equation:

[12]The DOL factor was first proposed in the work of Lustig, Roussanov, and Verdelhan (2011). Verdelhan (2015) highlights the importance of DOL as a risk factor, while Lustig and Richmond (2015) find that exchange rate loadings on the DOL factor are related to a country's distance from the base country.

[13]We also calculate the correlation with the global imbalance factor of Della Corte, Riddiough, and Sarno (2016) and find that it is virtually zero.

$$E_t[M_{t+1}RX^j_{t+1}] = 0 \tag{8}$$

with an SDF linear in the pricing factors f_{t+1}, given by

$$M_{t+1} = 1 - b'\left(f_{t+1} - \mu\right) \tag{9}$$

where b is the vector of factor loadings, and μ denotes the factor means. This specification implies a beta pricing model in which the expected excess return on portfolio j is equal to the factor risk price λ times the risk quantities β^j. The beta pricing model is defined as

$$E[RX^j] = \lambda'\beta^j \tag{10}$$

where the market price of risk $\lambda = \Sigma_f b$ can be obtained via the factor loadings b. $\Sigma_f = E\left[\left(f_t - \mu\right)\left(f_t - \mu\right)'\right]$, is the variance-covariance matrix of the risk factors, and β^j are the regression coefficients of each portfolio's excess return RX^j_{t+1} on the risk factors f_{t+1}.

Risk Factors and Pricing Kernel. The recent literature on cross-sectional asset pricing in currency markets has considered a two-factor SDF. The first risk factor is the expected market excess return, approximated by the average excess return on a portfolio strategy that is long in all foreign currencies with equal weights and short in the domestic currency – the DOL factor. For the second risk factor, the literature has employed several return-based factors such as the slope factor (essentially CAR) of Lustig, Roussanov, and Verdelhan (2011) or the global volatility risk factor of Menkhoff et al. (2012a).

Following this literature, we start from a two-factor SDF with DOL as the first factor, and the second factor as the CAR factor of Lustig, Roussanov, and Verdelhan (2011), which has been proven to be very successful at pricing carry portfolios. We then augment this two-factor SDF with a business cycle factor, constructed as the P_5-P_1 excess return from the GAP strategy implemented above.

Test Portfolios. We consider three sets of test portfolios, increasing in the number of portfolios. We first consider the five output-gap-sorted portfolios, which constitute a small set of test assets for the purpose of asset pricing tests. Lewellen, Nagel, and Shanken (2010) show that a strong factor structure in test asset returns can give rise to misleading results in empirical work, and this outcome is especially the case in small cross-sections. Therefore, we also conduct asset pricing tests on: 10 portfolios sorted on currency value and momentum (i.e., out-of-sample test assets where the sorting variable is neither carry nor the output gap); and a larger cross-section of 20 portfolios which comprises the 5 portfolios sorted on output gap, plus 5 portfolios sorted on forward premia (carry), 5 portfolios sorted on momentum, and 5 portfolios sorted on value.

Cross-Sectional Regressions. Table 3 presents the cross-sectional asset pricing results, including estimates of factor loadings b and the market prices of risk λ. The factor loadings b are estimated via the Generalized Method of Moments (GMM) of Hansen (1982). To implement GMM, we use the pricing errors as a set of moments and a prespecified weighting matrix. Since the objective is to test whether the model can explain the cross-section of expected currency excess returns, we only rely on unconditional moments and do not employ instruments other than a constant and a vector of ones. The first stage GMM estimation used here employs an identity-weighting matrix, which tells us how much attention to pay to each moment condition. With an identity matrix, GMM attempts to price all currency portfolios equally well.

We report estimates of b and λ, and standard errors based on Newey and West (1987). The model's performance is evaluated using the cross-sectional R^2 and the HJ distance measure of Hansen and Jagannathan (1997), which quantifies the mean-squared distance between the SDF of a proposed model and the set of admissible SDFs. To test whether the HJ distance is statistically significant, we simulate p-values using a weighted sum of χ_1^2 distributed random variables (see, Jagannathan and Wang, 1996; Ren and Shimotsu, 2009). The p-values of the HJ distance measure are reported in brackets.

Starting from Panel A of Table 3, we ask whether a two-factor model including DOL and CAR portfolios can price the three sets of test assets described above. We focus our interest on the sign and the statistical significance of the market price of risk λ attached to the CAR factor and of the associated factor loading b.[14] We find that this SDF specification, which is known to be powerful at pricing carry portfolios, does not explain satisfactorily the cross-sectional variation of currency excess returns.

The only case where CAR enters with both a statistically significant factor loading and price of risk is for the broad cross-section of 20 assets, which is the only cross-section that includes carry portfolios. Yet, even in this case the R^2 is a modest 33%. Therefore, it seems

[14] In general, throughout the literature on currency asset pricing, DOL does not display a significant price of risk in cross-sectional tests, and the factor loadings of different portfolio returns do not show a significant spread. This finding occurs with our results as well.

plausible to argue that the statistical significance of CAR is due solely to its ability to price portfolios sorted on forward premia, and that an additional source of risk is missing in the SDF specification in order to price the GAP portfolios or broader cross sections of test assets.

Indeed, when augmenting the SDF specification with the GAP factor, we find that both the loading and the price of risk for the GAP factor enter with positive and statistically significant coefficients. Moreover, CAR remains significant in the cross section of assets that includes carry portfolios. The R^2 for the three-factor model including the DOL, CAR and GAP factors is substantially higher (in the range between 59% and 97%) than the two-factor specification that excludes GAP (where the range is between -17% and 33%). Further support in favor of the pricing power of the SDF specification that includes the GAP factor comes from the fact that the HJ distance is statistically insignificant in each of the asset pricing tests carried out.

In Table A.2 of the Internet Appendix we report cross-sectional asset pricing results for a linear two-factor SDF including just the DOL and GAP factors. The results confirm that the GAP factor is priced (the factor loadings and risk prices are always highly statistically significant) in each model and performs particularly well at explaining value and momentum portfolios, the latter being known to be especially difficult to explain using standard risk factors (e.g., Menkhoff et al., 2012b).[15]

Overall, the results corroborate the earlier evidence that business cycles provide a novel source of information in determining currency excess returns while, unlike existing factors, the pricing power of GAP extends beyond portfolios sorted on carry, and is detected in cross sections of test assets that include output gap-, momentum-, and value-sorted portfolios.

6 The GAP Strategy in Real Time

6.1 Out-of-sample results

The GAP strategy has so far been implemented in-sample, in that the output gap is constructed by applying the HP filter to revised industrial production data across the full sample for each country, which is clearly unavailable in real time. This unavailability is not a major concern, since we are primarily interested in testing the theoretical predictions described in Section 2 using the most accurate measure of the business cycle each period. In practice, however, the returns in Table 1 cannot be obtained in real time both because the data are revised and because

[15]In Table A.3 of the Internet Appendix we present analogous results to Table 3, replacing the CAR factor with the volatility factor of Menkhoff et al. (2012a). The results are qualitatively identical and confirm the benefit of including the GAP factor in a currency market SDF.

the standard two-sided HP filter is not purely backward looking since it uses observations at $t + i \ (i > 0)$ to construct the time-t output gap. A recursive setting would need to be used in real time, which assumes that only current and past states influence the current observation of the output gap, essentially a one-sided HP filter. But the latter is well known to produce much less precise estimations of the current output gap (see, e.g., Stock and Watson, 1999; Orphanides and Van Norden, 2002).[16]

Hamilton (2016) provides a quantitative analysis of the main drawbacks of the HP filter and suggests an alternative procedure for detrending output and measuring the output gap to achieve the objectives of the HP filter without the drawbacks. We use the Hamilton procedure in our out-of-sample analysis. Specifically, Hamilton (2016) proposes an alternative concept of the cyclical component of a trending series, defined as the difference between the value at date $t + h$ and the value that we would have expected based on its behavior through date t. Thus, he suggests estimating by OLS a regression of output at time $t + h$ on a constant and four lags of output as available at time t and then using the residuals to remove the trend; we follow Hamilton (2016) and set h equal to 24 (i.e., two years ahead relative to time t), implementing the procedure recursively conditioning only on data available at the time of sorting. The real-time data begin in December 1999. These vintage data mimic the industrial production data an investor could have used if implementing the GAP strategy in real time, accounting for both delays in data releases and revisions. Full details of these real-time 'vintage' industrial production data are described in Section 3.

Using the same data, we also consider a simpler measure of output gaps constructed using the one-year growth rate in industrial production, which we refer to as 'industrial production momentum.' The one-year growth rate in industrial production is, admittedly, a crude measure of the output gap because it essentially assumes potential output is a random walk with drift plus a stationary error term, so that the cycle (output gap) component can be recovered simply by differencing the time series of industrial production. However, this calculation has the benefit of simplicity and easy replicability.[17]

In Panel A of Table 4 we report the results from implementing the GAP strategy when forming portfolios on the basis of the Hamilton procedure and industrial production momentum. Owing to the removal of pre-euro currencies, the number of developed market currencies drops

[16] Indeed, when we apply a one-sided HP filter recursively estimated on revised data for industrial production, these drawbacks become clear as the predictability recorded in Table 1 vanishes out-of-sample.

[17] In related work, Dahlquist and Hasseltoft (2016) find a measure of industrial production growth generates positive currency returns, which the authors view as a way to profit from momentum in economic activity.

substantially post 1999, and therefore we concentrate on the larger sample of developed and emerging market currencies. Starting from the results using the Hamilton (2016) output gap series (left-hand side), we observe that, although the increase in returns from Portfolio 1 to Portfolio 5 is not monotonic, a substantial spread occurs in the returns of the two corner portfolios. The real-time GAP return is 4.16%, and the corresponding Sharpe ratio is 0.60.

The results are not driven, however, by the corner portfolios. Indeed, the linear and rank weighting techniques, which use the entire set of currencies each period, generate higher Sharpe ratios of 0.72 and 0.69, respectively. Once again, the predictive power stems mainly from spot rate predictability rather than interest rate differentials: approximately 90% of the total return is delivered from the FX component across the three sorting procedures.

On the right-hand side of Table 4, we report results sorting on one-year industrial production momentum. The results suggest the GAP strategy continues to perform well with statistically significant excess returns and respectable Sharpe ratios, albeit lower than those delivered by the Hamilton's procedure. For the real-time one-year growth rate, the Sharpe ratios are between 0.44 and 0.48 across the three sorting procedures, and again the returns stem from the predictability of spot exchange rates, consistent with our previous results.

We view these preceding results as conservative in at least two dimensions. First, the real-time industrial production data are assumed to arrive at month's end. Instead the data are released during the month, and hence our portfolio formation takes place with a short time lag. Second, investors have considerable information at their disposal. Conditioning on a broader set of variables, known to be related to the business cycle, would likely produce superior portfolio sorts. To explore this possibility, we extend the real-time analysis with an alternative measure of output gaps. Real-time estimates of the output gap produced by the OECD use a wide information set to produce composite leading indicators (CLIs). Therefore, in addition to the industrial production data, we employ the CLIs produced by the OECD to examine the implications of using real-time measures of the business cycle across countries.

In Table 5, we report the results when currencies are sorted each period by the real-time amplitude-adjusted CLI (described in Section 3). In the left-hand panel we report results based on the GAP strategy being implemented using the most recently released data point. The excess return (Sharpe ratio) of the GAP strategy is 6.40% (0.85) and is again driven entirely by spot predictability; in fact, the interest rate differential contributes negatively to the total return. Sharpe ratios are lower when using linear and rank weights, but they remain respectable and in the range recorded for earlier tests.

In the right-hand panel of Table 5, we again form portfolios by sorting currencies by the real-time amplitude-adjusted CLI. This time, however, we use the fact that CLIs are designed to forecast industrial production approximately two quarters ahead. We therefore sort currencies by the CLI observed six months earlier. For example, in December 2006, we sort countries by the measure of amplitude-adjusted CLI available in June 2006. This formation provides a more difficult real-time benchmark by requiring relatively stale information to have value when sorting currencies. Nonetheless, we again find the GAP strategy performs well. Indeed the GAP strategy has a comparable excess return of 5.51% and Sharpe ratio of 0.69, which reflects the currency composition across the two sorting procedures remaining quite similar (see Panel B of Table 5).

Overall, the results reported in this section suggest the out-of-sample GAP strategy performs well and displays the same basic properties as its in-sample counterpart, albeit with slightly less impressive investment performance, as one would expect. Across the alternative methods, the majority of the excess returns are derived from predicting the spot exchange rate component, suggesting the underlying drivers of the GAP strategy returns are different from carry and other popular currency strategies. This finding indicates that the GAP strategy may be a useful complement to other widely studied currency strategies, which we investigate next.

6.2 Combining GAP with other currency strategies

Taken together, the previous results suggest that the GAP strategy has creditable excess returns overall, low correlation with conventional currency strategies, and the appealing characteristic of strong predictive power for spot exchange rate returns. The importance of these features is twofold. First, a currency investor would likely gain substantial diversification benefits from adding GAP to a currency portfolio to enhance risk-adjusted returns. Second, a spot currency trader interested in forecasting exchange rate fluctuations (as opposed to currency excess returns) might value the signals provided by output gaps.

To better understand the value of the GAP strategy for a currency investor, we compute two optimal currency portfolios for an investor who uses up to five strategies – DOL, CAR, MOM, VAL and GAP. Specifically, consider a portfolio of N assets with covariance matrix Σ. The global minimum volatility portfolio (GMV) is the portfolio with the lowest return volatility, and it represents the solution to the following optimization problem: min $w'\Sigma w$ subject to the constraint that the weights sum to unity $w'\iota = 1$, where w is the $N \times 1$ vector of portfolio weights on the risky assets, ι is a $N \times 1$ vector of ones, and Σ is the $N \times N$ covariance matrix of the asset returns. The weights of the global minimum volatility portfolio are given by $w = \frac{\Sigma^{-1}\iota}{\iota'\Sigma^{-1}\iota}$.

The target return portfolio (TAR) is a portfolio with the lowest return volatility for a target return of 4% per annum, and it represents the solution to the global minimum volatility problem with the additional constraint that $w'\mu = 0.04$, where μ is the $N \times 1$ vector of expected strategy returns. We compute the optimal weights, using an expanding window where we use data between October 1983 and December 1999 (available in real time at December 1999) for the initial estimation of means, covariances, and optimal weights. We then move out-of-sample, using the industrial production data described in Section 3. We also construct a (suboptimal) portfolio that places the same weight on every strategy for each period (EWP). All three calculations – global minimum volatility, target return, and equally weighted portfolio – are consistent with an out-of-sample setting.

The results are reported in Table 6 for the case in which investors use all five strategies (DOL, CAR, MOM, VAL and GAP) in Panel A and the case in which the investor excludes the GAP strategy in Panel B. We report results for the full sample and out-of-sample period. The GAP strategy is computed out-of-sample using the real-time industrial production data, and hence the out-of-sample performance is reported between December 1999 and January 2016. Comparing the results in Panels A (with the GAP strategy) and B (without the GAP strategy) of Table 6 reveals that including the GAP strategy in the menu of strategies used by a currency investor delivers substantially higher excess returns and Sharpe ratios. For example, the Sharpe ratio of the minimum volatility and target return portfolios is 0.89 in the full sample. However, this number drops to between 0.42 and 0.78 if the investor is not given access to the GAP strategy and only employs the other four currency strategies.

In the case of the target return portfolio, the Sharpe ratio is also statistically higher at the 5% level based on Ledoit and Wolf (2008) p-values. The optimal weight assigned to the GAP strategy is economically significant and falls in the range between 20.0% and 25.4%. While the investment performance of the overall portfolios drops when moving out-of-sample, a clear improvement continues to be observed, including up to a 40% increase in the Sharpe ratio, when the GAP strategy is included. Overall, we view these findings as a confirmation of the value the GAP strategy adds when included in a currency portfolio, driven by its desirable correlation properties with existing currency-based strategies.

7 GAP and the Carry Trade: Theoretical Implications

The empirical analysis has so far revealed robust support for the hypothesis stated in Section 2: strong economy currencies generate higher expected returns both in-sample and out-of-sample and a business cycle factor is priced in the cross-section of currency returns. These findings provide support and guidance for the macro-finance literature that incorporates cyclical state variables (factors). But the theoretical macro-finance literature also typically views its models of currency excess returns as a way (in part) to explain carry trade returns (Colacito and Croce, 2013; Farhi and Gabaix, 2016). We have already observed, however, that the returns of the *GAP* strategy is virtually uncorrelated with carry trade returns.

In this section, we revisit the theoretical framework outlined in Section 2, to discuss possible reasons for this lack of correlation between *GAP* and carry, and consider how future theoretical developments may seek to reconcile the differences.

7.1 Asymmetric long-run interest rates

In the habit model, surplus consumption is persistent but stationary: a strong economy is thus unlikely to have *permanently* higher surplus consumption than its neighbor. Indeed, in the empirical analysis we find relatively little persistence in currencies entering the extreme output-gap-sorted portfolios. The New Zealand dollar, Norwegian krone, and Swiss franc all frequently enter *both* the highest and lowest output gap portfolios. In contrast, interest-rate-sorted portfolios are *highly* persistent. The Swiss franc and Japanese yen enter the low interest rate portfolio in over 80% of the sample months, while the Turkish lira, Brazilian real, and Mexican peso enter the high-interest-rate portfolio in most months they appear in the sample.

These empirical observations indicate that persistent interest rate differentials are required to explain carry trade returns. In Verdelhan's (2010) original habit model, the real interest rate in an economy is given by

$$\begin{aligned} r_t &= -\log(\beta) + \gamma g - \gamma(1-\theta)(s_t - \bar{s}) - \frac{\gamma^2\sigma^2}{2}(1+\lambda(s_t))^2 \\ &= \bar{r} - B(s_t - \bar{s}) \end{aligned} \tag{11}$$

where β is the time discount factor, γ is the parameter governing the curvature of the utility function, g is average consumption growth, θ is the AR(1) coefficient driving surplus consumption, $\bar{s} = log(\bar{S})$ is the steady-state surplus consumption ratio, and σ is the volatility of consumption growth. The function $\lambda(s_t)$ determines how habits are formed from past aggregate consumption, $\bar{r} = -\log(\beta) + \gamma g - \frac{\gamma^2\sigma^2}{2\bar{S}^2}$ and $B = \gamma(1-\theta) - \frac{\gamma^2\sigma^2}{\bar{S}^2}$. Interest rates are procyclical when $B < 0$. The interest rate is therefore a function of time-varying surplus consumption and fluctuates around a long-run level. Crucially, both countries are assumed to have the same long-run interest rate. The assumption is intuitive because it is unclear how a real interest rate differential could persist since capital flows should, *in the long run*, drive down the cost of borrowing in high real interest rate economies.

To generate this prediction, the parameters defining average real interest rates $(\beta, \gamma, g, \theta, \sigma, \bar{S})$ are assumed to be the same in both economies. Any asymmetry in these parameters would induce differences in long-run real interest rates. Evidence exists to suggest that, at least in the *medium run*, differences do persist. Engel and Rogers (2009), for example, provide empirical evidence that long-run consumption growth rates (g in the model) are persistently different across countries over long periods and may not converge due to differences in long-run income growth. If consumption growth differs in the two economies, it implies the real interest rate differential can be written as

$$r_t - r_t^* = \bar{r} - \bar{r}^* - B(s_t - s_t^*), \tag{12}$$

where the average interest rate differential $\bar{r} - \bar{r}^*$ is equal to $\gamma(g - g^*)$. Verdelhan (2010) argues that B can reasonably be expected to be negative, implying that when the domestic economy experiences bad times (recessions) and surplus consumption is low relative to foreign surplus consumption, the domestic interest rate decreases. But with $\bar{r} \neq \bar{r}^*$, high frequency changes in the state of the economy do not necessarily drive interest rate differentials.

Furthermore, given $E_t(\Delta q_{t+1}) = \mathbb{E}_t(r^e_{t+1}) + r_t - r_t^*$, the expected real exchange rate return is equal to

$$\begin{aligned} E_t(\Delta q_{t+1}) &= \frac{\gamma^2\sigma^2}{\bar{S}^2}(s_t^* - s_t) + (r_t - r_t^*) \\ &= (\bar{r} - \bar{r}^*) + \gamma(1-\theta)(s_t^* - s_t). \end{aligned} \tag{13}$$

The above expression suggests the expected exchange rate return is related to two components: (i) a static long-run interest rate differential $\bar{r} - \bar{r}^*$ (high interest rate currencies depreciate on average, which is true in the data), and (ii) the differential in surplus consumption ratios $s_t^* - s_t$ (high surplus consumption currencies appreciate on average). The standard carry trade strategy generates currency returns that are dominated by the static component in long-run interest rates: currencies that have persistently high interest rates or forward premia pay significantly higher expected excess returns than currencies with persistently low interest rates or forward premia (see e.g., Hassan and Mano, 2015). More importantly, Equation (13) suggests there is a separate predictive role for the state of the economy that is distinct from the static long-run differences in interest rates across countries.

7.2 Simulation

A natural question is to ask whether differences in consumption growth rates can quantitatively account for the lack of correlation between GAP and the currency carry trade. We investigate this question by simulating a version of the external habit model and provide evidence on the cross-sectional correlation; in this case, two currencies are sorted based on simulated surplus consumption and interest rate differentials.

In Table 7, we report the quarterly external-habit model parameters based on those commonly used in the literature (Wachter, 2006; Verdelhan, 2010; Campbell, Pflueger, and Viceira, 2015) that we adopt in the simulation. We are interested in understanding the extent to which currency sorts are correlated based on surplus consumption (the true unobservable state variable) and interest rates. In a symmetric model with no difference in long-run consumption growth rates, surplus consumption and interest rates move one to one, but this situation is not true in a model in which $g \neq g^*$.

The first economy is assumed to have economic growth of 0.5% per quarter (and a long-run real interest rate of 1.16% per annum). We vary the long-run consumption growth of the second economy between 0.5% (symmetry) and 1.0% per quarter (equating to 2% higher consumption growth per year). In Equation (11), long-run real interest rates are a linear function of the long-run consumption growth rate with coefficient γ. Setting $\gamma = 2.5$, a long-run consumption growth rate of 1% per quarter equates to a long-run real interest rate of 5% per annum higher in the second economy.

We view these values as consistent with evidence in the literature. For example, Engel and Rogers (2009) document, using survey data, that long-run expected consumption growth rates differ greatly across countries, with the differences averaging two or more percentage points per year and totaling 20%-25% over a ten-year horizon. Moreover, we find the cross-sectional difference (between P_5 and P_1) in average nominal (real) interest rates in our sample of all countries is indeed very large, equal to 13.09% (7.86%). A more conservative estimate using only two – instead of five – portfolios generates a cross-sectional difference in average nominal (real) interest rates of 6.64% (4.41%).

Figure 2 reports our key result. We rank the two economies in each period based on their interest rate and surplus-consumption ratio. If the procedure ranks the currencies equivalently we assign the period a value of 1. If the sorting procedure generates a different ranking, we assign the period a score of -1. Each bar represents the average value across 1,000 simulations of 30 years of quarterly data. We iterate by increasing the growth rate of the second economy from 0.5% by increments of 0.05% up to 1%. The graph indicates whether sorting countries (in strong and weak economies) on surplus consumption is the same as, or similar to, sorting countries by interest rates; it also indicates how the similarity in the sort changes as we move away from the perfectly symmetric benchmark with $g = g^* = 0.5\%$.

The result suggests interest rates and surplus consumption imply the same cross-sectional ranking only if growth rates are equal. The more long-run consumption growth rates differ, the less related the ranking implied by surplus consumption and interest rates. Put another way, different long-run growth rates across countries imply different real interest rates across countries, and the larger the difference in these growth rates, the less real interest rates are related to the state of the economy. In sum, depending on the magnitude of the average real interest rate differential, sorting currencies on output gaps could generate very different portfolios relative to carry portfolios sorted on interest rate differentials. It is therefore unsurprising that empirically the carry trade and the *GAP* strategy deliver uncorrelated portfolio returns.

Caveat. Long-run interest rate differentials may arise for reasons other than persistent consumption growth differentials; for example, they may be due to different subjective discount factors across countries (if certain cultures have greater propensity to save at a given interest rate), or because of asymmetric inflation risks and money supplies (Jylhä and Suominen, 2011). Our above discussion highlights one possible channel that is a quantitatively and empirically valid source of asymmetry. Primarily, we hope the discussion highlights the need for further research to shed light, both theoretically and empirically, on the causal factors that determine the persistence of long-run interest differentials which can help explain carry returns as a separate strategy and factor to *GAP* returns and the business cycle factor.

8 Further Analysis

8.1 Alternative Measures of Output Gap

Our benchmark result in Table 1 is obtained by constructing the *GAP* strategy sorting on the HP-filtered output gap. We also consider alternative measures of detrending industrial production to check whether the results are robust. In Tables A.4 to A.7 in the Internet Appendix we report results in the same format as Table 1, but we sort currencies on output gap measures obtained using a linear time trend, a quadratic time trend, the Baxter-King filter, and the Hamilton filtering procedure, respectively. The linear and quadratic time trends approximate potential output as a deterministic process, whereas the Baxter-King filter allow potential output to follow a stochastic trend. The Hamilton procedure was already used in Table 4, but it is now applied using the full sample period.[18]

The results suggest that, for each of these alternative output gap measures, the *GAP* strategy provides appealing Sharpe ratios, although they vary across specifications. Depending on the sample of countries and the portfolio strategy employed, the Sharpe ratio is in the range between 0.43 and 0.63 for the linear time trend (Table A.6), between 0.49 and 0.74 for the quadratic time trend (Table A.7), between 0.60 and 0.77 for the Baxter-King filter (Table A.8), and between 0.37 and 0.59 for the Hamilton procedure (Table A.9). The properties of the returns appear very similar as well. In particular, the bulk of the *GAP* excess return stems from the predictability of the cross-section of spot exchange rates rather than interest rate differentials.

8.2 Alternative Base Currencies

Up to now we have taken the perspective of a U.S. investor by calculating excess returns and building dollar-neutral portfolios. As a robustness check, we depart from this base scenario and run calculations with four alternative base currencies. Specifically, we construct the *GAP* strategy from the separate perspectives of Eurozone, British, Japanese, and Swiss investors.

The results are reported in Tables A.8 to A.11 in the Internet Appendix, and they indicate that excess returns from the *GAP* strategy have similar characteristics to the ones reported in Table 1. This outcome is reassuring since it makes clear that the United States does not play a key role in driving our results, which are qualitatively identical regardless of whether the currency portfolios are dollar-neutral or not. We conclude that our results are not specific to a U.S. investor.

[18] The Baxter-King band-pass filter is based on a frequency-domain approach that removes low-frequency components in a time series to isolate the component at business cycle frequency. We compute the output gap country by country, for each of the alternative filters.

8.3 Transaction Costs

The results reported till now do not consider transaction costs because our primary focus is on understanding the dynamics of currency excess returns and the relationship with relative output gaps in the cross-section of currencies. However, an interesting issue is whether the *GAP* strategy returns remain large after accounting for transaction costs. To examine this question, we compute *net* excess returns for *GAP* portfolios by adjusting for bid-ask spreads.[19] We report results for net excess returns for our benchmark result over the full sample period from 1983, using the HP filter (see Table A.12 in the Internet Appendix for comparison with results for gross returns in Table 1). The results suggest that the Sharpe ratios from the *GAP* strategy remain attractive even after accounting for transaction costs, equal to 0.62 and 0.52 for the two samples examined.

We also report out-of-sample results using the Hamilton detrending procedure on real-time data, industrial production momentum, and the OECD CLI data. These results further confirm that the performance of the *GAP* strategy remains attractive after costs, with Sharpe ratios in the range between 0.30 and 0.68 (see Table A.13 in the Internet Appendix for comparison with results for gross returns in Tables 4 and 5).

9 Conclusions

A fundamental challenge in asset pricing is to 'understand and measure the sources of macroeconomic risk driving asset prices' (Cochrane, 2005). Yet, a large literature in international macroeconomics and finance has attempted, with limited success, to establish any meaningful link between currency excess returns and macroeconomic fundamentals. In this paper, we provide evidence that business cycles are an important determinant of the cross-section of expected currency returns. Our primary result is that currencies issued by strong economies (high output gaps) command higher expected returns, which compensates more risk-averse investors in weak economies. This finding holds both in-sample and out-of-sample and is robust to a battery of tests. Moreover, we find that a business cycle risk factor that captures the spread in output gaps across countries is priced in the cross section of currency excess returns that includes portfolios sorted by carry, value and momentum.

[19]The bid-ask spread data available are for quoted spreads and not effective spreads. Because it is known that quoted spreads are much higher than effective spreads, we follow earlier work (e.g., Goyal and Saretto, 2009; Menkhoff et al., 2012a, 2017), and employ 50% of the quoted bid-ask spread as the actual spread. Even this number seems conservative: Gilmore and Hayashi (2011) find transaction costs due to bid-ask spreads are likely to be much lower than our 50% rule.

These findings are important for the broad theoretical literature seeking to explain the macroeconomic drivers of currency premia. A commonality among many macro-finance models is that business cycles are important for country-level discount factors. We identify a clear link between business cycles and currency excess returns that can help shape future theoretical advances. We also highlight a potential challenge associated with symmetric models in which all countries are assumed to have the same long-term interest rate. Explaining carry trade returns requires persistent interest rate differentials, which we highlight could be driven by long-run consumption growth differentials. Our results are also important for global investors: a strategy based on exploiting cross-country differences in business cycles is largely uncorrelated with popular currency investment strategies, including the carry trade, and therefore offers attractive diversification opportunities.

In future work, researchers could explore alternative sources of country-level asymmetry and seek to endogenize persistent differences in interest rates, perhaps linked to central banks' optimization problems. Empirical researchers may wish to explore alternative ways to measure business cycles, using richer financial and economic datasets, as a fruitful avenue to break new ground in exchange rate determination and predictability.

Appendix

The Habit Model of Currency Excess Returns

Preferences and consumption behavior. Consider a two-country world where the representative investor in each country is assumed to have external habit preferences:

$$U_t = \frac{(C_t - H_t)^{1-\gamma} - 1}{1-\gamma} = \frac{(S_t C_t)^{1-\gamma} - 1}{1-\gamma} \tag{A1}$$

where C_t is consumption, H_t is the time-varying 'habit' or subsistence level of consumption, and $S_t = (C_t - H_t/C_t)$ is the surplus consumption ratio. The curvature of the utility function is controlled by the parameter γ, which also determines risk aversion: $-C_t U''/U' = \gamma/S_t$.

The logarithm of consumption in the domestic country is assumed to follow a random walk with drift

$$\Delta c_{t+1} = \quad g + \xi_{t+1} \quad \xi \sim \text{i.i.d. } \mathcal{N}(0, \sigma^2) \tag{A2}$$

where $c_t = \log(C_t)$, and g is the average consumption growth in the domestic economy. We assume the error term is comprised of both a common 'global' shock (ω_g) that determines the risk premia in the model, and an idiosyncratic shock (ω_i) that can be diversified away in a portfolio of multiple currencies

$$\xi_{t+1} = \omega_{g,t+1} + \omega_{i,t+1}, \quad \omega_g, \omega_i \sim \text{i.i.d. } \mathcal{N}(0, \frac{\sigma^2}{\sqrt{2}}) \text{ and } cov(\omega_g, \omega_i) = 0. \tag{A3}$$

Surplus consumption. The log surplus consumption ratio is defined as in Campbell and Cochrane (1999) and Verdelhan (2010) as a stationary AR(1) process with time-varying volatility

$$s_{t+1} = (1-\theta)\bar{s} + \theta s_t + \lambda(s_t)\xi_{t+1} \tag{A4}$$

where $\bar{s} = \log(\bar{S})$ is the steady-state surplus consumption ratio, θ is the persistence parameter, and $\lambda(s_t)$ is a sensitivity function determining how habits are formed from past aggregate consumption. The sensitivity function is chosen such that habits are predetermined around the steady-state level

$$\lambda(s_t, \bar{S}) = \begin{cases} \frac{1}{\bar{S}}\sqrt{1 - 2(s_t - \bar{s})} - 1, & \text{if } s_{max} \geq s_t \\ 0, & \text{otherwise} \end{cases} \tag{A5}$$

where $s_{max} = \bar{s} + (1 - \bar{S}^2)/2$ and $\bar{S} = \sigma\sqrt{\frac{\gamma}{1-\theta-\frac{B}{\gamma}}}$.[20]

Pricing kernel. Given the functional forms taken by preferences and the surplus consumption ratio, the Stochastic Discount Factor (SDF) or pricing kernel, $M_{t+1} = \beta\frac{U'_{t+1}}{U'_t}$ can be shown to equal[21]

[20] The definition of $\bar{S}$ follows Verdelhan's (2010) innovation of including the term B/γ to generate time-variation in interest rates, as it will become clear later.

[21] Augmenting the model with the output gap specification described in Section 8.1, the SDF can equivalently be written as $M_{t+1} = \beta e^{-\gamma(g-(1-\theta)(s_t-\bar{s})+\tau(1+\lambda(s_t))(y^{gap}_{t+1}-\phi y^{gap}_t))}$.

$$M_{t+1} = \beta \left(\frac{S_{t+1}}{S_t} \frac{C_{t+1}}{C_t} \right)^{-\gamma} = \beta e^{-\gamma(g-(1-\theta)(s_t-\bar{s})+(1+\lambda(s_t))(\Delta c_{t+1}-g))}. \tag{A6}$$

Under the standard no-arbitrage condition with complete markets, a single SDF can be shown to discount all returns equal to a price of 1 in both domestic and foreign markets, so that

$$1 = \mathbb{E}_t[M_{t+1}R_{t+1}], \qquad 1 = \mathbb{E}_t[M^*_{t+1}R^*_{t+1}] \tag{A7}$$

where the superscript $*$ refers to foreign country variables. If domestic and foreign investors are allowed to trade in each others' security, the condition also applies to foreign returns earned by the domestic investor, once the returns are converted back into the domestic currency. Thus $\mathbb{E}_t[M^*_{t+1}R^*_{t+1}] = \mathbb{E}_t[M_{t+1}R^*_{t+1}\frac{Q_{t+1}}{Q_t}]$, where Q_{t+1}/Q_t is the real exchange rate return, and Q_t is defined as the price of domestic currency per unit of foreign consumption.

Under complete markets it must therefore be the case that $M^*_{t+1} = M_{t+1}Q_{t+1}/Q_t$ and thus the exchange rate return can be defined in terms of the foreign and domestic SDFs

$$\frac{Q_{t+1}}{Q_t} = \frac{M^*_{t+1}}{M_{t+1}}. \tag{A8}$$

Then, assuming that pricing kernels are lognormally distributed delivers the familiar expression that the expected log currency excess return is related to the difference between domestic and foreign log SDFs:

$$\mathbb{E}_t(r^e_{t+1}) = \mathbb{E}\Delta q_{t+1} + r^*_t - r_t = \frac{1}{2}Var_t(m_{t+1}) - \frac{1}{2}Var_t(m^*_{t+1}) \tag{A9}$$

where $q_t = \log(Q_t)$ and $r_t = -\log(\mathbb{E}_t[M_{t+1}])$.[22]

Real interest differentials and surplus consumption. Within the model, the domestic real interest rate is equal to $R^f_t = 1/\mathbb{E}_t[M_{t+1}]$, which from Equation (A6) can be seen to equal

$$\begin{aligned} r_t &= -\log(\beta) + \gamma g - \gamma(1-\theta)(s_t - \bar{s}) - \frac{\gamma^2\sigma^2}{2}(1+\lambda(s_t))^2 \\ &= \bar{r} - B(s_t - \bar{s}) \end{aligned} \tag{A10}$$

where $\bar{r} = -\log(\beta) + \gamma g - \frac{\gamma^2\sigma^2}{2\bar{S}^2}$ and $B = \gamma(1-\theta) - \frac{\gamma^2\sigma^2}{\bar{S}^2}$; and thus interest rates are procyclical when $B < 0$.

Assume for simplicity that the representative investors in the domestic and foreign economies share the same risk aversion and time preference coefficients ($\gamma = \gamma^*$ and $\beta = \beta^*$), are exposed to the same variance and growth of consumption growth ($\sigma^2 = \sigma^{2^*}$, $g = g^*$), and experience the same persistence and steady-state level of surplus-consumption ($\theta = \theta^*$ and $\bar{S} = \bar{S}^*$). Then the foreign real interest rate is

$$\begin{aligned} r^*_t &= -\log(\beta) + \gamma g^* - \gamma(1-\theta)(s^*_t - \bar{s}) - \frac{\gamma^2\sigma^2}{2}(1+\lambda(s^*_t))^2 \\ &= \bar{r}^* - B(s^*_t - \bar{s}). \end{aligned} \tag{A11}$$

Thus the real interest rate differential between the domestic and foreign economies can be written as

[22] See Backus, Foresi, and Telmer (2001) and Verdelhan (2010) for full details.

$$r_t - r_t^* = -B(s_t - s_t^*), \tag{A12}$$

which is Equation (2) in the paper. As argued by Verdelhan (2010), B can reasonably be expected to be negative, implying that when the domestic economy experiences bad times and surplus consumption is low relative to foreign surplus consumption the domestic interest rate decreases.

Combining the expressions for the SDF in Equation (A6) and currency excess returns in Equation (A9), the log currency excess return can be seen to equal a function of the surplus consumption differential

$$\mathbb{E}_t(r_{t+1}^e) = \frac{\gamma^2\sigma^2}{\bar{S}^2}(s_t^* - s_t). \tag{A13}$$

where it is now clear that $\zeta = \frac{\gamma^2\sigma^2}{\bar{S}^2} > 0$ in Equation (1). It follows that a strategy which buys high surplus consumption currencies and sells low surplus consumption currencies is expected to generate a positive currency excess return. Furthermore, given $E_t(\Delta q_{t+1}) = \mathbb{E}_t(r_{t+1}^e) + r_t - r_t^*$, the expected real exchange rate return is equal to

$$\begin{aligned} E_t(\Delta q_{t+1}) &= \frac{\gamma^2\sigma^2}{\bar{S}^2}(s_t^* - s_t) + (r_t - r_t^*) \\ &= \gamma(1-\theta)(s_t^* - s_t). \end{aligned} \tag{A14}$$

Rearranging, it can be seen that the real exchange rate follows the process

$$\Delta q_{t+1} = \gamma(1-\theta)(s_t^* - s_t) + \gamma(1+\lambda(s_t))\xi_{t+1} - \gamma(1+\lambda(s_t^*))\xi_{t+1}^*. \tag{A15}$$

Using Equations (A12) and (A14), the currency return each period is therefore equal to

$$r_{t+1}^e = \frac{\gamma^2\sigma^2}{\bar{S}^2}(s_t^* - s_t) + \gamma(1+\lambda(s_t))\xi_{t+1} - \gamma(1+\lambda(s_t^*))\xi_{t+1}^*. \tag{A16}$$

In the empirical analysis we constructed portfolios of currencies sorted by output gaps (as a close proxy for surplus consumption). With a sufficiently large number of currencies (N) within a portfolio the idiosyncratic shocks will tend towards zero in the limit. That is, $\lim_{N\to\infty} \sum_{n=1}^{N} \frac{\omega_n}{N} = 0$. The portfolio return of the GAP strategy is therefore given by Equation (3).

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Table 1:

Output-Gap-Sorted Portfolios: Descriptive Statistics and Main Currencies Entering each Portfolio

PANEL A: Descriptive Statistics

	All Countries								*Developed Countries*							
	output-gap-sorted portfolios					**GAP**	**Linear**	**Rank**	*output-gap-sorted portfolios*					**GAP**	**Linear**	**Rank**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**($\mathbf{P_5}$-$\mathbf{P_1}$)**	**weights**	**weights**	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**($\mathbf{P_5}$-$\mathbf{P_1}$)**	**weights**	**weights**
mean (%)	-0.25	0.96	2.77	4.00	6.41	**6.66*** **	**2.99*** **	**5.39*** **	-0.60	1.24	1.97	2.41	4.92	**5.52*** **	**2.29*** **	**4.23*** **
fx (%)	*-2.34*	*-1.03*	*0.88*	*1.58*	*2.72*	*5.06*	*2.27*	*4.21*	*-1.17*	*0.43*	*0.98*	*1.41*	*3.75*	*4.92*	*2.01*	*3.79*
ir (%)	*2.09*	*1.99*	*1.89*	*2.41*	*3.69*	*1.60*	*0.73*	*1.18*	*0.57*	*0.81*	*0.99*	*1.00*	*1.17*	*0.60*	*0.28*	*0.44*
Sharpe	-0.02	0.11	0.27	0.43	0.71	**0.82**	**0.94**	**0.93**	-0.06	0.13	0.19	0.25	0.54	**0.68**	**0.70**	**0.68**
std (%)	10.18	9.09	10.12	9.32	9.05	8.14	3.19	5.79	10.25	9.63	10.44	9.57	9.08	8.12	3.26	6.18
mdd (%)	42.5	34.2	23.9	23.6	24.4	9.0	4.8	7.4	44.2	34.2	30.4	29.0	24.4	9.0	5.5	8.6
skew	-0.06	-0.47	-0.28	-0.27	-0.28	0.01	0.11	0.22	-0.01	-0.11	-0.18	-0.08	-0.04	0.25	0.27	0.46
kurt	4.49	4.72	4.75	4.39	3.97	4.32	4.27	4.64	4.60	4.32	4.19	4.91	3.22	5.39	4.69	5.22
ac(1)	0.03	0.09	0.08	0.00	0.11	0.03	0.10	0.12	0.05	0.07	0.06	-0.01	0.12	0.08	0.11	0.13
t/o (%)	44.5	58.0	66.7	59.9	44.4				40.0	57.5	70.7	58.4	41.5			
fp (%)	2.23	2.03	1.80	2.45	4.15				0.50	0.99	1.03	1.17	1.10			
gap (%)	-3.08	-0.96	0.11	1.17	3.01				-2.57	-0.84	0.11	0.98	2.51			

PANEL B: Main Currencies Entering each Portfolio (and percentage of sample in the portfolio)

	All Countries				*Developed Countries*			
	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest
$\mathbf{P_1}$	CHF (26%)	NZD (26%)	NOK (24%)	SEK (20%)	CHF (27%)	NZD (27%)	NOK (27%)	JPY (22%)
$\mathbf{P_2}$	GBP (31%)	DEM (27%)	AUD (26%)	CAD (23%)	GBP (34%)	DEM (25%)	AUD (24%)	CAD (24%)
$\mathbf{P_3}$	GBP (29%)	CAD (22%)	DEM (22%)	MXN (18%)	GBP (20%)	DEM (18%)	AUD (15%)	CHF (14%)
$\mathbf{P_4}$	DEM (28%)	CAD (26%)	GBP (24%)	SEK (23%)	GBP (29%)	CAD (27%)	DEM (26%)	AUD (22%)
$\mathbf{P_5}$	NOK (26%)	NZD (25%)	JPY (24%)	CHF (19%)	NOK (30%)	NZD (29%)	JPY (27%)	SEK (22%)

The table presents descriptive statistics for currency portfolios sorted by country-level output gaps (Panel A) and the main currencies entering each portfolio (Panel B). The output trend is estimated using a Hodrick-Prescott filter. In Panel A, currency portfolios are split between those containing *all* countries and a smaller sub-sample of *developed* countries. Portfolios are rebalanced monthly with strong (weak) economy currencies entering P_5 (P_1). We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components. The superscripts *, **, *** represent significance of the GAP portfolios at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition we report the Sharpe ratio (*Sharpe*), standard deviation (*std*), maximum drawdown (*mdd*), skewness (*skew*), kurtosis (*kurt*), and first-order autocorrelation coefficient (*ac(1)*). We also report the average turnover (*t/o*), forward premium (*fp*) and output gap (*gap*) for each portfolio. *GAP* is a portfolio long P_5 and short P_1. Linear and rank weights are portfolios with positions in every currency, in which the weights are calculated based on relative output gaps (see Section 4 for further details). In Panel B we report the main currencies entering the five output-gap-sorted portfolios. The percentage of months in the sample in which a currency enters a portfolio is reported in parentheses. The sample runs from October 1983 to January 2016. The data is described in Section 3.

Table 2:

Currency Portfolio Correlations

	All Countries					Developed Countries			
					1983 - 2016				
	GAP	CAR	MOM	VAL		**GAP**	CAR	MOM	VAL
CAR	0.05				*CAR*	-0.06			
MOM	0.15	-0.10			*MOM*	0.15	-0.11		
VAL	0.14	-0.16	-0.02		*VAL*	0.23	-0.09	-0.04	
DOL	-0.15	0.00	-0.11	-0.16	*DOL*	-0.14	0.17	-0.08	-0.18
					1983 - 1999				
	GAP	CAR	MOM	VAL		**GAP**	CAR	MOM	VAL
CAR	0.14				*CAR*	0.12			
MOM	0.17	-0.03			*MOM*	0.19	-0.03		
VAL	0.05	0.19	-0.08		*VAL*	0.10	0.25	-0.11	
DOL	-0.07	-0.08	-0.07	-0.26	*DOL*	-0.02	-0.08	-0.08	-0.28
					2000 - 2016				
	GAP	CAR	MOM	VAL		**GAP**	CAR	MOM	VAL
CAR	-0.06				*CAR*	-0.26			
MOM	0.14	-0.18			*MOM*	0.10	0.21		
VAL	0.24	-0.56	0.06		*VAL*	0.37	0.43	0.02	
DOL	-0.25	0.09	-0.15	-0.06	*DOL*	-0.27	0.44	-0.09	-0.09

The table presents correlations between currency portfolio returns. The portfolios are rebalanced monthly based on output gaps (GAP), forward premia (CAR), momentum (MOM) and value (VAL). The DOL portfolio is an equally weighted portfolio with a long position in every currency against the US dollar. In each panel, portfolios are split between those containing *all* countries and a smaller sub-sample of *developed* countries. We report full sample correlation coefficients and sub-samples for the first half (1983-1999) and second half (2000-2016) of the sample. The sample runs from October 1983 to January 2016. The data is described in Section 3.

Table 3:
Cross-Sectional Asset Pricing Tests

Panel A: All Countries

	2 Pricing Factors $(DOL + CAR)$						**3 Pricing Factors** $(DOL + CAR + GAP)$							
	Factor Loadings (b)		**Risk Prices** (λ)		**Model Fit**		**Factor Loadgings** (b)			**Risk Prices** (λ)			**Model Fit**	
	DOL	CAR	DOL	CAR	R^2	HJ_{dist}	DOL	CAR	GAP	DOL	CAR	GAP	R^2	HJ_{dist}
5 Test Portfolios (output gap)	0.25	1.63	0.02	0.23*	0.05	0.26 [0.03]	0.38*	0.08	0.92***	0.02	0.02	0.07***	0.89	0.11 [0.17]
10 Test Portfolios (value, momentum)	0.24	0.07	0.02	0.01	-0.17	0.21 [0.38]	0.64*	0.41	2.63**	0.02	0.07	0.20**	0.94	0.09 [1.00]
20 Test Portfolios (output gap, carry, value, momentum)	0.25	0.49**	0.02	0.07***	0.33	0.31 [0.90]	0.40	0.45**	1.02***	0.02	0.07***	0.08***	0.80	0.23 [0.99]

Panel B: Developed Countries

	2 Pricing Factors $(DOL + CAR)$						**3 Pricing Factors** $(DOL + CAR + GAP)$							
	Factor Loadings (b)		**Risk Prices** (λ)		**Model Fit**		**Factor Loadgings** (b)			**Risk Prices** (λ)			**Model Fit**	
	DOL	CAR	DOL	CAR	R^2	HJ_{dist}	DOL	CAR	GAP	DOL	CAR	GAP	R^2	HJ_{dist}
5 Test Portfolios (output gap)	0.68	-2.40	0.01	-0.31	0.13	0.18 [0.17]	0.41	-0.71	0.70**	0.01	-0.09	0.06***	0.97	0.04 [0.17]
10 Test Portfolios (value, momentum)	0.32	-0.74	0.01	-0.09	0.15	0.20 [0.45]	0.55**	-0.60	1.98**	0.01	-0.08	0.15***	0.77	0.14 [0.92]
20 Test Portfolios (output gap, carry, value, momentum)	0.10	0.30*	0.01	0.04**	0.15	0.33 [0.87]	0.21	0.34**	0.84***	0.01	0.04**	0.06***	0.59	0.27 [0.95]

The table presents cross-sectional asset pricing results for three sets of test portfolios. The SDF is constructed as a linear combination of DOL and CAR (2 Pricing Factors, left-hand-side) and DOL, CAR and GAP (3 Pricing Factors, right-hand-side). We report Generalized Method of Moments (GMM) one-step estimates of factor loadings on the pricing kernel (*b's*) and prices of factor risk (*λ's*). The superscripts *, **, *** represent significance of the coefficients at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition, we report goodness-of-fit statistics for each model including the R^2 statistic and the Hansen-Jagannathan distance statistic (HJ) with simulated p-values in brackets. The HJ statistic measures the distance between the estimated pricing kernel and the efficient set of permissible pricing kernels. A p-value less than 5% indicates the null hypothesis that the pricing kernel is efficient can be rejected at the 95% confidence level. The test assets are split between those containing *all* countries (Panel A) and a smaller sub-sample of *developed* countries (Panel B). The sample runs from October 1983 to January 2016. The data and factor construction are described in Section 3.

Table 4:

Output-Gap Portfolios Sorted on Real-Time Industrial Production: Descriptive Statistics and Main Currencies Entering each Portfolio

PANEL A: Descriptive Statistics

	Forecasted Trend								*Industrial Production Momentum*							
	real-time output-gap-sorted portfolios					**GAP**	**Linear**	**Rank**	*real-time output-gap-sorted portfolios*					**GAP**	**Linear**	**Rank**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**($\mathbf{P_5}$-$\mathbf{P_1}$)**	**weights**	**weights**	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**($\mathbf{P_5}$-$\mathbf{P_1}$)**	**weights**	**weights**
mean (%)	1.67	1.24	-0.02	4.97	5.82	**4.16******	**2.11******	**3.71******	1.00	2.23	2.03	2.41	4.79	**3.78*****	**1.42*****	**2.47*****
fx (%)	*-0.78*	*-0.78*	*-1.51*	*2.83*	*2.89*	*3.67*	*1.84*	*3.38*	*-1.07*	*0.07*	*0.00*	*0.01*	*2.43*	*3.49*	*1.38*	*2.27*
ir (%)	*2.45*	*2.02*	*1.49*	*2.14*	*2.94*	*0.49*	*0.26*	*0.33*	*2.07*	*2.17*	*2.03*	*2.40*	*2.36*	*0.29*	*0.03*	*0.20*
Sharpe	0.18	0.13	0.00	0.49	0.57	**0.60**	**0.72**	**0.69**	0.11	0.26	0.21	0.24	0.46	**0.48**	**0.45**	**0.44**
std (%)	9.34	9.35	9.04	10.08	10.15	6.90	2.92	5.41	9.30	8.54	9.60	10.06	10.45	7.83	3.14	5.66
mdd (%)	21.5	24.8	29.7	14.8	14.8	10.2	4.8	6.9	22.5	15.0	20.8	21.2	16.5	11.3	7.2	10.4
skew	-0.17	-0.88	-0.59	-0.44	-0.27	0.18	0.27	0.05	-0.28	-0.10	-0.59	-0.26	-0.45	0.17	-0.20	-0.27
kurt	4.28	6.64	5.05	4.83	3.28	2.81	3.27	3.53	4.00	4.21	5.18	4.09	4.35	5.40	4.82	5.27
ac(1)	-0.01	0.08	0.06	0.10	0.07	0.04	-0.04	-0.07	0.00	-0.02	0.08	0.06	0.06	-0.13	-0.07	-0.08
t/o (%)	20.9	40.6	44.2	43.6	22.3				34.8	54.1	54.3	55.9	35.0			
fp (%)	2.41	2.00	1.60	2.16	2.89				2.12	2.07	2.03	2.37	2.42			
gap (%)	-1.72	-0.58	0.12	0.83	2.24				-4.06	-0.59	1.66	3.93	8.29			

PANEL B: Main Currencies Entering each Portfolio (and percentage of sample in the portfolio)

	Forecasted Trend				*Industrial Production Momentum*			
	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest
$\mathbf{P_1}$	NOK (68%)	GBP (28%)	JPY (28%)	KRW (25%)	NOK (48%)	GBP (40%)	JPY (29%)	SEK (23%)
$\mathbf{P_2}$	GBP (54%)	MXN (37%)	AUD (25%)	KRW (21%)	GBP (38%)	MXN (26%)	CAD (25%)	DEM (24%)
$\mathbf{P_3}$	CAD (36%)	JPY (36%)	MXN (32%)	SEK (28%)	MXN (41%)	NZD (29%)	DEM (28%)	CAD (26%)
$\mathbf{P_4}$	DEM (41%)	BRL (28%)	SEK (25%)	CAD (24%)	PLN (31%)	DEM (27%)	CAD (25%)	MXN (24%)
$\mathbf{P_5}$	CZK (60%)	PLN (54%)	CHF (31%)	TRY (29%)	CZK (49%)	PLN (44%)	KRW (43%)	TRY (28%)

The table presents descriptive statistics for currency portfolios sorted by real-time country-level output gaps (Panel A) and the main currencies entering each portfolio (Panel B). The output trend is estimated using either a forecasting equation (*Forecasted Trend*, left-hand-side) or as a random walk (*Industrial Production Momentum*, right-hand-side). Portfolios are rebalanced monthly with strong (weak) economy currencies entering P_5 (P_1). We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components. The superscripts *, **, *** represent significance of the GAP portfolios at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition we report the Sharpe ratio (*Sharpe*), standard deviation (*std*), maximum drawdown (*mdd*), skewness (*skew*), kurtosis (*kurt*), and first-order autocorrelation coefficient (*ac(1)*). We also report the average turnover (*t/o*), forward premium (*fp*) and output gap (*gap*) for each portfolio. *GAP* is a portfolio long P_5 and short P_1. Linear and rank weights are portfolios with positions in every currency, in which the weights are calculated based on relative output gaps (see Section 4 for further details). In Panel B we report the main currencies entering the five output-gap-sorted portfolios. The percentage of months in the sample in which a currency enters a portfolio is reported in parentheses. The sample runs from October 1983 to January 2016. The data is described in Section 3.

Table 5:

Output-Gap Portfolios Sorted on Real-Time Leading Indicator: Descriptive Statistics and Main Currencies Entering each Portfolio

PANEL A: Descriptive Statistics

Amplitude Adjusted CLI

	real-time output-gap-sorted portfolios P_1	P_2	P_3	P_4	P_5	**GAP** (P_5-P_1)	**Linear weights**	**Rank weights**
mean (%)	-2.00	-0.32	1.85	-1.81	4.40	**6.40*** **	**1.52***	**2.81***
fx (%)	*-5.25*	*-1.92*	*-0.08*	*-3.25*	*2.19*	*7.44*	*1.91*	*3.48*
ir (%)	*3.25*	*1.60*	*1.93*	*1.44*	*2.20*	*-1.04*	*-0.40*	*-0.66*
Sharpe	-0.17	-0.03	0.18	-0.17	0.43	**0.85**	**0.48**	**0.51**
std (%)	11.50	9.46	10.53	10.95	10.34	7.53	3.16	5.49
mdd (%)	33.5	29.2	21.7	29.7	27.2	11.7	7.2	11.6
skew	-0.42	-0.20	-0.36	-0.80	-0.65	-0.20	-0.15	-0.27
kurt	3.83	3.78	4.74	4.69	6.36	4.91	4.90	3.21
ac(1)	-0.05	0.02	0.02	0.01	0.24	-0.03	-0.01	0.09
t/o (%)	23.9	40.5	36.0	36.5	26.4			
fp (%)	3.25	1.60	1.85	1.44	2.20			
gap (%)	-2.82	-1.14	0.04	1.32	3.04			

Lagged Amplitude Adjusted CLI

	real-time output-gap-sorted portfolios P_1	P_2	P_3	P_4	P_5	**GAP** (P_5-P_1)	**Linear weights**	**Rank weights**
mean (%)	-1.49	0.66	-1.20	-0.05	4.02	**5.51****	**1.35***	**2.62***
fx (%)	*-4.39*	*-1.06*	*-3.07*	*-1.54*	*1.62*	*6.01*	*1.57*	*2.98*
ir (%)	*2.91*	*1.71*	*1.87*	*1.49*	*2.40*	*-0.50*	*-0.22*	*-0.36*
Sharpe	-0.13	0.07	-0.11	0.00	0.40	**0.69**	**0.44**	**0.47**
std (%)	11.82	9.92	10.78	10.51	10.05	7.98	3.05	5.55
mdd (%)	30.5	22.9	32.3	27.9	20.3	9.4	7.6	11.2
skew	-0.08	0.19	-0.92	-0.81	-0.88	-0.47	-0.73	-0.65
kurt	3.92	4.01	6.10	4.52	5.83	3.52	3.97	3.50
ac(1)	-0.11	-0.03	0.11	0.07	0.18	0.06	0.11	0.08
t/o (%)	23.9	41.1	36.1	36.1	25.5			
fp (%)	2.91	1.71	1.80	1.49	2.40			
gap (%)	-2.93	-1.06	0.20	1.59	3.49			

PANEL B: Main Currencies Entering each Portfolio (and proportion of sample in the portfolio

Amplitude Adjusted CLI

	1st	2nd	3rd	4th
P_1	BRL (50%)	CZK (32%)	TRY (31%)	NZD (26%)
P_2	CAD (35%)	AUD (29%)	JPY (27%)	SEK (23%)
P_3	AUD (44%)	GBP (42%)	CAD (38%)	DEM (31%)
P_4	PLN (38%)	KRW (30%)	CHF (28%)	AUD (22%)
P_5	NZD (41%)	MXN (37%)	KRW (30%)	BRL (23%)

Lagged Amplitude Adjusted CLI

	1st	2nd	3rd	4th
P_1	BRL (46%)	CZK (32%)	NZD (31%)	TRY (26%)
P_2	AUD (33%)	CAD (32%)	JPY (28%)	SEK (24%)
P_3	GBP (43%)	AUD (42%)	CAD (36%)	DEM (30%)
P_4	PLN (38%)	CHF (32%)	KRW (31%)	DEM (22%)
P_5	NZD (38%)	MXN (38%)	BRL (29%)	KRW (25%)

The table presents descriptive statistics for currency portfolios sorted by real-time country-level composite leading indicators (Panel A) and the main currencies entering each portfolio (Panel B). The leading indicator is measured as the latest datapoint (*Amplitude Adjusted CLI*, left-hand-side) or with a six-month lag (*Lagged Amplitude Adjusted CLI*, right-hand-side). Portfolios are rebalanced monthly with strong (weak) economy currencies entering P_5 (P_1). We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components. The superscripts *, **, *** represent significance of the GAP portfolios at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition we report the Sharpe ratio (*Sharpe*), standard deviation (*std*), maximum drawdown (*mdd*), skewness (*skew*), kurtosis (*kurt*), and first-order autocorrelation coefficient (*ac(1)*). We also report the average turnover (*t/o*), forward premium (*fp*) and output gap (*gap*) for each portfolio. *GAP* is a portfolio long P_5 and short P_1. Linear and rank weights are portfolios with positions in every currency, in which the weights are calculated based on relative output gaps (see Section 4 for further details). In Panel B we report the main currencies entering the five output-gap-sorted portfolios. The percentage of months in the sample in which a currency enters a portfolio is reported in parentheses. The sample runs from October 1983 to January 2016. The data is described in Section 3.

Table 6:
Optimal Currency Portfolios Including and Excluding the GAP Strategy

PANEL A: Currency Portfolios Including GAP						
	GMV	**TAR**	**EWP**	**GMV**	**TAR**	**EWP**
	Full Sample			*Out-of-Sample*		
mean (%)	3.33***	3.36***	3.69***	2.80***	2.61***	2.86***
Sharpe	**0.89**	**0.89****	**1.01**	**0.77**	**0.72****	**0.84**
std (%)	3.74	3.78	3.66	3.65	3.64	3.41
mdd (%)	5.9	6.0	5.7	6.5	6.2	5.6
skew	-0.26	-0.13	-0.33	-0.26	-0.11	-0.09
kurt	5.31	4.77	7.52	4.02	3.29	3.85
ac(1)	0.18	0.17	0.15	0.24	0.18	0.24
$\bar{w}_{GAP}$ *(%)*	**22.2**	**25.4**	**20.0**	**20.9**	**20.7**	**20.0**

PANEL B: Currency Portfolios Excluding GAP						
	GMV	**TAR**	**EWP**	**GMV**	**TAR**	**EWP**
	Full Sample			*Out-of-Sample*		
mean (%)	2.98***	2.36***	3.47***	2.35**	1.94**	2.53***
Sharpe	**0.78**	**0.42**	**0.90**	**0.62**	**0.51**	**0.72**
std (%)	3.85	5.56	3.84	3.76	3.83	3.53
mdd (%)	10.4	28.0	5.5	7.8	8.8	7.3
skew	-0.25	0.83	-0.22	-0.34	-0.16	-0.23
kurt	5.43	12.21	6.60	4.36	3.70	4.10
ac(1)	0.17	0.11	0.15	0.22	0.15	0.24

The table presents descriptive statistics for optimal currency portfolios that combine DOL, CAR, MOM and VAL portfolios and also includes (Panel A) or excludes (Panel B) the GAP portfolio. GMV is a portfolio that minimizes portfolio volatility and is constructed by initially estimating means, covariances and optimal portfolio weights between 1983-1999 and calculating out-of-sample returns over the following month. The weights are then rebalanced monthly to incorporate new data within an expanding window. TAR minimizes portfolio variance for a target return of 4% per annum. EWP is a portfolio with equal weight in each currency portfolio. $\bar{w}_{GAP}$ is the average weight allocated to the GAP strategy. We also report summary statistics for the annualized mean return, Sharpe ratio (*Sharpe*), standard deviation (*std*), maximum drawdown (*mdd*), skewness (*skew*), kurtosis (*kurt*) and first-order autocorrelation coefficient (*ac(1)*). The full-sample runs from October 1983 to January 2016, and the out-of-sample period is from December 1999 to January 2016. The superscripts on the mean returns *, **, *** represent significance of the portfolios at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. The superscripts on the Sharpe ratios in Panel A *, **, *** reflect the Sharpe ratio being statistically different from that obtained without the GAP strategy according to Ledoit and Wolf (2008) p-values. The data is described in Section 3.

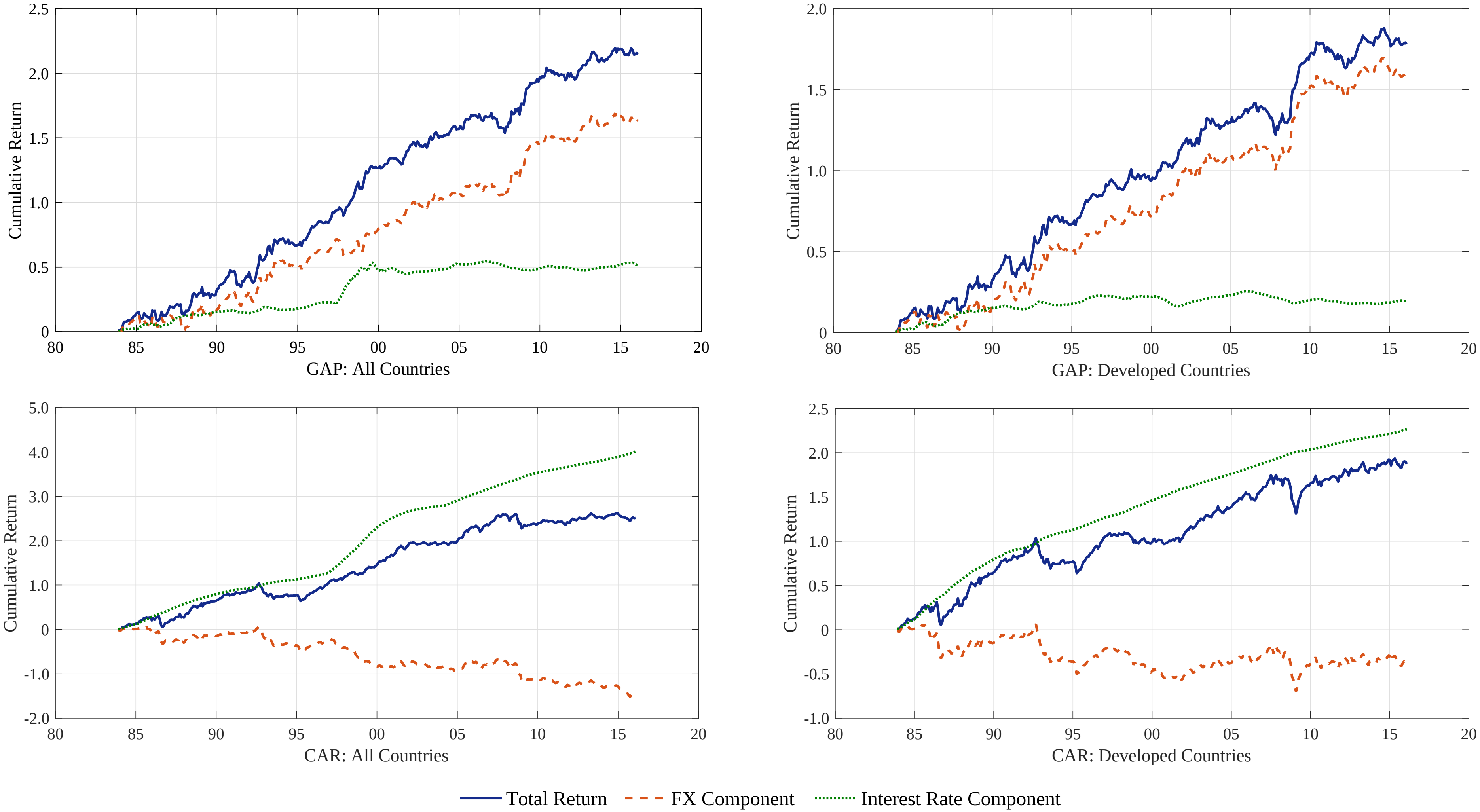
Table 7:
Simulation Parameters

Simulation Parameters	
Parameter Choices	
$g(\%)$	0.50
$g^*(\%)$	[0.50-1.00]
σ (%)	0.51
$\bar{r}$ (%)	0.34
γ	2.50
θ	0.99
B	-0.01
ρ	0.15
Implied Parameters	
β	0.99
S_{bar}	0.07
S_{max}	0.11

The table presents the parameters we use in the simulation of the two-economy habit model. We set consumption growth (g) in the home country equal to 0.5% and adjust the foreign country consumption growth rate (g^*) between 0.5% and 1.0%, increasing in increments of 0.05%. Details of the simulation are reported in Section 7 and graphical output from the simulation is presented in Figure 2.

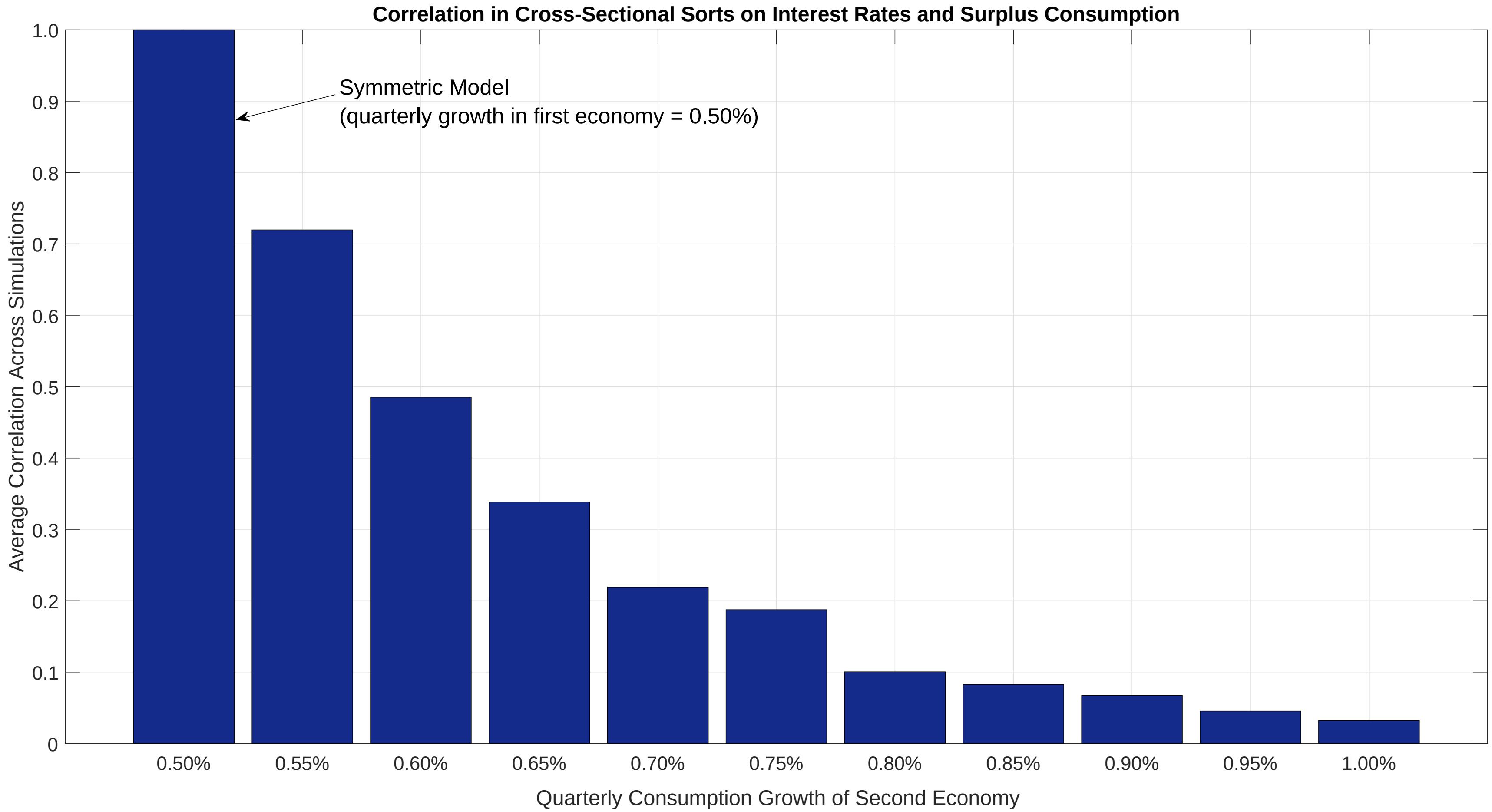
Figure 1:

Cumulative Returns to GAP and CAR Portfolios



The figure presents the total cumulative return (– solid blue line) to a zero-cost investment in either the GAP portfolio (top-panel) or the CAR portfolio (bottom-panel). The total return is decomposed between the cumulative interest rate (:: dotted green line) and FX (- - dashed orange line) components. The sample runs from October 1983 to January 2016. The data is described in Section 3.

Figure 2:
The Impact of Asymmetric Consumption Growth



The figure presents the results from a simulation of two habit economies which are identical except for an asymmetry in their long-run consumption growth. The habit-model is presented in the Appendix and a generalization is presented in Section 7. The first economy is assumed to have economic growth of 0.5% per quarter. We vary the long-run consumption growth of the second economy between 0.5% (symmetric model) and 1.0% per quarter. We rank the economies each period based on their interest rate and surplus-consumption ratio. If the procedure ranks the currencies equivalently we assign the period a value 1, otherwise we assign the period a value -1. Each bar represents the average value across $1,000$ simulations over 30 years of quarterly data.

SUPPLEMENTARY APPENDIX
BUSINESS CYCLES AND THE CROSS-SECTION OF CURRENCY RETURNS

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NOT FOR PUBLICATION

Table A.1:

Forward-Premia-Sorted Portfolios: Descriptive Statistics and Main Currencies Entering each Portfolio

PANEL A: Descriptive Statistics

All Countries

	forward-premia-sorted portfolios					**CAR**	**Linear**	**Rank**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	$\mathbf{(P_5\text{-}P_1)}$	**weights**	**weights**
mean (%)	-0.63	1.02	3.88	2.83	7.17	**7.80*** **	**3.98*** **	**5.79*** **
fx (%)	*1.58*	*1.35*	*2.54*	*-0.40*	*-3.05*	*-4.63*	*-2.96*	*-3.62*
ir (%)	*-2.20*	*-0.33*	*1.34*	*3.22*	*10.22*	*12.43*	*6.93*	*9.41*
Sharpe	-0.06	0.11	0.42	0.29	0.68	**0.72**	**0.88**	**0.73**
std (%)	9.80	9.30	9.23	9.72	10.49	10.87	4.50	7.98
mdd (%)	54.0	32.6	23.2	27.8	19.9	19.8	11.2	19.1
skew	0.26	-0.09	-0.29	-0.48	-0.63	-0.93	-0.72	-0.74
kurt	3.80	3.73	5.12	4.85	5.56	5.30	4.68	4.59
ac(1)	0.00	0.06	0.06	0.07	0.19	0.16	0.18	0.16
t/o (%)	18.2	25.1	29.1	23.8	12.9			
fp (%)	-2.15	-0.32	1.25	3.25	10.94			
gap (%)	-0.04	0.02	0.08	-0.05	0.30			

Developed Countries

	forward-premia-sorted portfolios					**CAR**	**Linear**	**Rank**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	$\mathbf{(P_5\text{-}P_1)}$	**weights**	**weights**
mean (%)	-0.66	0.61	3.60	2.15	5.14	**5.81*** **	**2.45*** **	**4.23*** **
fx (%)	*1.67*	*1.14*	*2.85*	*0.10*	*0.45*	*-1.22*	*-0.80*	*-1.39*
ir (%)	*-2.33*	*-0.53*	*0.75*	*2.05*	*4.69*	*7.03*	*3.25*	*5.63*
Sharpe	-0.07	0.07	0.40	0.22	0.45	**0.55**	**0.56**	**0.52**
std (%)	9.61	9.24	9.02	9.79	11.42	10.60	4.41	8.19
mdd (%)	52.7	37.1	23.2	27.8	20.0	19.8	11.2	19.1
skew	0.27	-0.08	-0.03	-0.33	-0.15	-0.87	-0.71	-0.76
kurt	3.60	3.53	4.45	4.35	4.21	5.28	4.44	5.25
ac(1)	0.01	0.05	0.08	0.05	0.12	0.11	0.09	0.11
t/o (%)	14.9	28.2	38.5	22.8	12.7			
fp (%)	-2.38	-0.47	0.77	2.33	4.50			
gap (%)	-0.02	-0.05	0.20	-0.09	0.19			

PANEL B: Main Currencies Entering each Portfolio (and percentage of sample in the portfolio)

All Countries

	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest
$\mathbf{P_1}$	CHF (85%)	JPY (81%)	DEM (25%)	CZK (19%)
$\mathbf{P_2}$	DEM (62%)	CAD (48%)	SEK (34%)	GBP (26%)
$\mathbf{P_3}$	NOK (38%)	GBP (36%)	KRW (31%)	CAD (26%)
$\mathbf{P_4}$	AUD (54%)	NZD (46%)	MXN (31%)	GBP (29%)
$\mathbf{P_5}$	TRY (47%)	BRL (34%)	MXN (27%)	NZD (27%)

Developed Countries

	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest
$\mathbf{P_1}$	CHF (85%)	JPY (81%)	DEM (18%)	NLG (11%)
$\mathbf{P_2}$	DEM (58%)	CAD (26%)	NLG (25%)	SEK (22%)
$\mathbf{P_3}$	CAD (32%)	SEK (25%)	NOK (20%)	GBP (19%)
$\mathbf{P_4}$	GBP (46%)	NOK (42%)	SEK (30%)	CAD (29%)
$\mathbf{P_5}$	NZD (74%)	AUD (55%)	ITL (24%)	NOK (19%)

The table presents descriptive statistics for currency portfolios sorted by forward premia (Panel A) and the main currencies entering each portfolio (Panel B). In Panel A, currency portfolios are split between those containing *all* countries and a smaller sub-sample of *developed* countries. Portfolios are rebalanced monthly with high (low) forward premia currencies entering P_5 (P_1). We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components. The superscripts *, **, *** represent significance of the CAR portfolios at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition we report the Sharpe ratio (*Sharpe*), standard deviation (*std*), maximum drawdown (*mdd*), skewness (*skew*), kurtosis (*kurt*), and first-order autocorrelation coefficient (*ac(1)*). We also report the average turnover (*t/o*), forward premium (*fp*) and output gap (*gap*) for each portfolio. *CAR* is a portfolio long P_5 and short P_1. Linear and rank weights are portfolios with positions in every currency, in which the weights are calculated based on relative forward premia (see Section 4 for further details). In Panel B we report the main currencies entering the five forward-premia-sorted portfolios. The percentage of months in the sample in which a currency enters a portfolio is reported in parentheses. The sample runs from October 1983 to January 2016. The data is described in Section 3.

Table A.2:
Cross-Sectional Asset Pricing Tests: DOL and GAP

Panel A: All Countries

	2 Pricing Factors ($DOL + GAP$)					
	Factor Loadings (b)		**Risk Prices** (λ)		**Model Fit**	
	DOL	GAP	DOL	GAP	R^2	HJ_{dist}
5 Test Portfolios (output gap)	0.38*	0.92***	0.02	0.07***	0.89	0.11 [0.30]
10 Test Portfolios (value, momentum)	0.60**	2.45**	0.02	0.19***	0.85	0.10 [0.97]
20 Test Portfolios (output gap, carry, value, momentum)	0.41*	1.09***	0.02	0.08***	0.47	0.29 [0.89]

Panel B: Developed Countries

	2 Pricing Factors ($DOL + GAP$)					
	Factor Loadings (b)		**Risk Prices** (λ)		**Model Fit**	
	DOL	GAP	DOL	GAP	R^2	HJ_{dist}
5 Test Portfolios (output gap)	0.26	0.73***	0.01	0.05***	0.95	0.05 [0.82]
10 Test Portfolios (value, momentum)	0.44*	2.07**	0.01	0.16***	0.85	0.17 [0.88]
20 Test Portfolios (output gap, carry, value, momentum)	0.28	0.80***	0.02	0.06***	0.39	0.30 [0.91]

The table presents cross-sectional asset pricing results for three sets of test portfolios. The SDF is constructed as a linear combination of DOL and GAP factors. We report Generalized Method of Moments (GMM) one-step estimates of factor loadings on the pricing kernel (*b's*) and prices of factor risk (*λ's*). The superscripts *, **, *** represent significance of the coefficients at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition, we report goodness-of-fit statistics for each model including the R^2 statistic and the Hansen-Jagannathan distance statistic (HJ) with simulated p-values in brackets. The HJ statistic measures the distance between the estimated pricing kernel and the efficient set of permissible pricing kernels. A p-value less than 5% indicates the null hypothesis that the pricing kernel is efficient can be rejected at the 95% confidence level. The test assets are split between those containing *all* countries (Panel A) and a smaller sub-sample of *developed* countries (Panel B). The sample runs from October 1983 to January 2016. The data and factor construction are described in Section 3.

Table A.3:
Cross-Sectional Asset Pricing Tests: DOL, VOL and GAP

Panel A: All Countries

	2 Pricing Factors $(DOL+VOL)$						**3 Pricing Factors** $(DOL+VOL+GAP)$							
	Factor Loadings (b)		**Risk Prices** (λ)		**Model Fit**		**Factor Loadgings** (b)			**Risk Prices** (λ)			**Model Fit**	
	DOL	VOL	DOL	VOL	R^2	HJ_{dist}	DOL	VOL	GAP	DOL	VOL	GAP	R^2	HJ_{dist}
5 Test Portfolios (output gap)	0.41*	2.83	0.02	0.03	-0.06	0.26 [0.00]	0.67**	4.80*	0.97***	0.02	0.06	0.07***	0.98	0.05 [0.71]
10 Test Portfolios (value, momentum)	0.41	2.58	0.02	0.03	-0.13	0.21 [0.26]	0.62*	-0.58	2.53**	0.02	-0.01	0.20***	0.86	0.09 [0.99]
20 Test Portfolios (output gap, carry, value, momentum)	0.09	-3.67	0.02	-0.05***	0.11	0.35 [0.97]	0.27	-3.35	1.08***	0.02	-0.04**	0.08***	0.63	0.28 [0.99]

Panel B: Developed Countries

	2 Pricing Factors $(DOL+VOL)$						**3 Pricing Factors** $(DOL+VOL+GAP)$							
	Factor Loadings (b)		**Risk Prices** (λ)		**Model Fit**		**Factor Loadgings** (b)			**Risk Prices** (λ)			**Model Fit**	
	DOL	VOL	DOL	VOL	R^2	HJ_{dist}	DOL	VOL	GAP	DOL	VOL	GAP	R^2	HJ_{dist}
5 Test Portfolios (output gap)	1.20	25.68	0.02	0.31	0.65	0.13 [0.95]	0.64	9.34	0.59	0.02	0.11	0.06***	0.98	0.03 [0.95]
10 Test Portfolios (value, momentum)	0.47**	6.77**	0.02	0.08***	0.76	0.13 [0.95]	0.52**	4.51	1.03	0.02	0.06	0.09	0.87	0.10 [0.98]
20 Test Portfolios (output gap, carry, value, momentum)	0.20	-0.23	0.02	0.00	-0.01	0.35 [0.78]	0.26	-1.67	0.88***	0.02	-0.02	0.06***	0.44	0.30 [0.95]

The table presents cross-sectional asset pricing results for three sets of test portfolios. The SDF is constructed as a linear combination of DOL and VOL (2 Pricing Factors, left-hand-side) and DOL, VOL and GAP (3 Pricing Factors, right-hand-side). We report Generalized Method of Moments (GMM) one-step estimates of factor loadings on the pricing kernel (b*'s*) and prices of factor risk (λ*'s*). The superscripts *, **, *** represent significance of the coefficients at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition, we report goodness-of-fit statistics for each model including the R^2 statistic and the Hansen-Jagannathan distance statistic (HJ) with simulated p-values in brackets. The HJ statistic measures the distance between the estimated pricing kernel and the efficient set of permissible pricing kernels. A p-value less than 5% indicates the null hypothesis that the pricing kernel is efficient can be rejected at the 95% confidence level. The test assets are split between those containing *all* countries (Panel A) and a smaller sub-sample of *developed* countries (Panel B). The sample runs from October 1983 to January 2016. The data and factor construction are described in Section 3.

Table A.4:

Output-Gap-Sorted Portfolios: Descriptive Statistics and Main Currencies Entering each Portfolio (Linear Time Trend)

PANEL A: Descriptive Statistics

	All Countries								*Developed Countries*							
	output-gap-sorted portfolios					**GAP**	**Linear**	**Rank**	*output-gap-sorted portfolios*					**GAP**	**Linear**	**Rank**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	$(\mathbf{P_5}$-$\mathbf{P_1})$	**weights**	**weights**	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	$(\mathbf{P_5}$-$\mathbf{P_1})$	**weights**	**weights**
mean (%)	0.51	2.04	4.80	3.39	3.71	**3.20*** **	**1.44*** **	**2.11*** **	-1.01	1.73	2.78	3.85	2.86	**3.87*** **	**1.84*** **	**3.30*** **
fx (%)	*-1.58*	*-0.14*	*1.73*	*0.19*	*2.28*	*3.86*	*1.57*	*2.18*	*-1.23*	*0.75*	*1.86*	*2.08*	*2.23*	*3.46*	*1.64*	*2.63*
ir (%)	*2.09*	*2.17*	*3.07*	*3.20*	*1.44*	*-0.65*	*-0.13*	*-0.07*	*0.22*	*0.98*	*0.92*	*1.77*	*0.63*	*0.42*	*0.21*	*0.66*
Sharpe	0.06	0.22	0.48	0.37	0.37	**0.44**	**0.51**	**0.43**	-0.11	0.20	0.26	0.37	0.30	**0.56**	**0.63**	**0.60**
std (%)	8.94	9.12	9.97	9.24	9.92	7.21	2.83	4.92	9.06	8.83	10.86	10.35	9.5	6.9	2.9	5.5
mdd (%)	37.1	31.8	26.2	22.3	19.1	17.4	7.4	9.9	46.5	31.8	26.2	22.3	19.1	11.3	6.5	7.6
skew	-0.10	-0.10	-0.42	-0.43	-0.35	-0.09	-0.07	-0.25	0.01	0.05	-0.40	-0.17	-0.01	0.12	-0.11	-0.34
kurt	3.66	4.64	5.35	4.25	5.57	7.93	6.39	5.99	3.47	4.05	4.88	4.61	3.63	4.60	6.94	7.43
ac(1)	0.06	0.05	0.09	0.09	0.04	0.13	0.10	0.06	0.08	0.07	0.11	0.02	0.01	0.08	-0.05	-0.05
t/o (%)	11.5	21.6	29.1	24.4	15.3				8.4	16.9	26.6	18.3	11.2			
fp (%)	2.14	2.17	3.35	3.30	1.51				0.13	1.15	0.94	1.93	0.57			
gap (%)	-11.84	-2.86	2.71	6.91	14.72				-10.73	-2.53	2.95	7.05	14.72			

PANEL B: Main Currencies Entering each Portfolio (and percentage of sample in the portfolio)

	All Countries				*Developed Countries*			
	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest
$\mathbf{P_1}$	JPY (41%)	CHF (39%)	NOK (29%)	SEK (29%)	CHF (45%)	JPY (43%)	DEM (26%)	NOK (26%)
$\mathbf{P_2}$	DEM (52%)	AUD (43%)	GBP (39%)	NZD (37%)	AUD (52%)	CAD (34%)	DEM (33%)	GBP (28%)
$\mathbf{P_3}$	MXN (34%)	NLG (30%)	AUD (29%)	DEM (24%)	GBP (32%)	NLG (31%)	CAD (25%)	SEK (20%)
$\mathbf{P_4}$	FRF (40%)	GBP (31%)	ITL (26%)	CAD (22%)	FRF (38%)	GBP (37%)	NZD (31%)	DEM (27%)
$\mathbf{P_5}$	NOK (52%)	JPY (44%)	PLN (26%)	SEK (20%)	NOK (51%)	JPY (44%)	CHF (27%)	SEK (19%)

The table presents descriptive statistics for currency portfolios sorted by country-level output gaps (Panel A) and the main currencies entering each portfolio (Panel B). The output trend is estimated using a linear time trend. In Panel A, currency portfolios are split between those containing *all* countries and a smaller sub-sample of *developed* countries. Portfolios are rebalanced monthly with strong (weak) economy currencies entering P_5 (P_1). We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components. The superscripts *, **, *** represent significance of the GAP portfolios at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition we report the Sharpe ratio (*Sharpe*), standard deviation (*std*), maximum drawdown (*mdd*), skewness (*skew*), kurtosis (*kurt*), and first-order autocorrelation coefficient (*ac(1)*). We also report the average turnover (*t/o*), forward premium (*fp*) and output gap (*gap*) for each portfolio. *GAP* is a portfolio long P_5 and short P_1. Linear and rank weights are portfolios with positions in every currency, in which the weights are calculated based on relative output gaps (see Section 4 for further details). In Panel B we report the main currencies entering the five output-gap-sorted portfolios. The percentage of months in the sample in which a currency enters a portfolio is reported in parentheses. The sample runs from October 1983 to January 2016. The data is described in Section 3.

Table A.5:

Output-Gap-Sorted Portfolios: Descriptive Statistics and Main Currencies Entering each Portfolio (Quadratic Time Trend)

PANEL A: Descriptive Statistics

	All Countries								*Developed Countries*							
	output-gap-sorted portfolios					**GAP**	**Linear**	**Rank**	*output-gap-sorted portfolios*					**GAP**	**Linear**	**Rank**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	$\mathbf{(P_5\text{-}P_1)}$	**weights**	**weights**	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	$\mathbf{(P_5\text{-}P_1)}$	**weights**	**weights**
mean (%)	0.27	1.99	3.08	4.21	4.83	**4.56*** **	**2.28*** **	**3.49*** **	-0.27	1.96	2.07	3.76	3.46	**3.73*** **	**1.99*** **	**3.05*** **
fx (%)	*-1.04*	*-0.16*	*0.02*	*1.54*	*1.75*	*2.80*	*1.49*	*2.16*	*-0.67*	*1.19*	*0.72*	*2.72*	*2.09*	*2.76*	*1.47*	*2.33*
ir (%)	*1.31*	*2.15*	*3.06*	*2.67*	*3.08*	*1.76*	*0.79*	*1.33*	*0.39*	*0.77*	*1.35*	*1.04*	*1.37*	*0.97*	*0.52*	*0.72*
Sharpe	0.03	0.21	0.32	0.49	0.51	**0.60**	**0.74**	**0.66**	-0.03	0.20	0.19	0.40	0.38	**0.49**	**0.65**	**0.53**
std (%)	10.05	9.58	9.76	8.66	9.53	7.56	3.07	5.27	10.26	9.70	10.80	9.30	9.1	7.7	3.1	5.7
mdd (%)	38.9	28.5	31.1	24.8	21.5	18.3	4.7	11.5	43.3	33.8	31.1	24.8	21.5	18.3	4.7	11.5
skew	-0.23	-0.21	-0.07	-0.51	-0.15	-0.68	-0.19	-0.40	-0.30	-0.18	0.17	-0.02	-0.03	-0.59	-0.06	-0.15
kurt	4.23	4.58	4.29	4.50	5.02	6.29	4.98	5.00	4.32	4.15	3.88	4.15	4.25	5.53	4.63	4.58
ac(1)	0.03	0.10	0.00	0.05	0.10	-0.06	0.03	-0.02	0.05	0.09	0.00	0.06	0.07	-0.08	-0.01	-0.03
t/o (%)	20.0	32.9	44.3	33.8	19.7				17.5	28.2	39.8	29.7	17.8			
fp (%)	1.17	2.04	3.15	2.87	3.35				0.20	0.96	1.20	1.14	1.34			
gap (%)	-8.41	-3.35	-0.22	2.59	7.78				-8.21	-3.83	-1.44	1.81	6.73			

PANEL B: Main Currencies Entering each Portfolio (and percentage of sample in the portfolio)

	All Countries				*Developed Countries*			
	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest
$\mathbf{P_1}$	SEK (30%)	DEM (30%)	JPY (30%)	NOK (24%)	SEK (32%)	JPY (30%)	DEM (27%)	NOK (26%)
$\mathbf{P_2}$	NZD (30%)	GBP (25%)	FRF (22%)	CAD (20%)	NZD (34%)	GBP (26%)	CHF (24%)	DEM (21%)
$\mathbf{P_3}$	MXN (27%)	AUD (24%)	CHF (23%)	CAD (18%)	GBP (23%)	CAD (23%)	CHF (20%)	AUD (16%)
$\mathbf{P_4}$	AUD (29%)	CHF (29%)	NZD (28%)	GBP (26%)	AUD (35%)	NZD (26%)	CAD (25%)	CHF (23%)
$\mathbf{P_5}$	NOK (41%)	SEK (31%)	GBP (23%)	JPY (23%)	NOK (42%)	SEK (29%)	JPY (28%)	DEM (24%)

The table presents descriptive statistics for currency portfolios sorted by country-level output gaps (Panel A) and the main currencies entering each portfolio (Panel B). The output trend is estimated using a quadratic time trend. In Panel A, currency portfolios are split between those containing *all* countries and a smaller sub-sample of *developed* countries. Portfolios are rebalanced monthly with strong (weak) economy currencies entering P_5 (P_1). We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components. The superscripts *, **, *** represent significance of the GAP portfolios at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition we report the Sharpe ratio (*Sharpe*), standard deviation (*std*), maximum drawdown (*mdd*), skewness (*skew*), kurtosis (*kurt*), and first-order autocorrelation coefficient (*ac(1)*). We also report the average turnover (*t/o*), forward premium (*fp*) and output gap (*gap*) for each portfolio. *GAP* is a portfolio long P_5 and short P_1. Linear and rank weights are portfolios with positions in every currency, in which the weights are calculated based on relative output gaps (see Section 4 for further details). In Panel B we report the main currencies entering the five output-gap-sorted portfolios. The percentage of months in the sample in which a currency enters a portfolio is reported in parentheses. The sample runs from October 1983 to January 2016. The data is described in Section 3.

Table A.6:

Output-Gap-Sorted Portfolios: Descriptive Statistics and Main Currencies Entering each Portfolio (Baxter-King Filter)

PANEL A: Descriptive Statistics

	All Countries								*Developed Countries*							
	output-gap-sorted portfolios					**GAP**	**Linear**	**Rank**	*output-gap-sorted portfolios*					**GAP**	**Linear**	**Rank**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**($\mathbf{P_5}$-$\mathbf{P_1}$)**	**weights**	**weights**	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**($\mathbf{P_5}$-$\mathbf{P_1}$)**	**weights**	**weights**
mean (%)	-0.44	2.45	2.39	3.72	5.97	**6.41*** **	**2.35*** **	**4.49*** **	-0.93	1.99	2.30	2.20	4.69	**5.62*** **	**2.12*** **	**3.67*** **
fx (%)	*-2.34*	*0.65*	*0.49*	*1.23*	*1.92*	*4.26*	*1.35*	*2.94*	*-1.57*	*1.21*	*1.10*	*1.26*	*3.57*	*5.14*	*1.95*	*3.29*
ir (%)	*1.90*	*1.80*	*1.90*	*2.49*	*4.06*	*2.15*	*1.01*	*1.55*	*0.64*	*0.78*	*1.20*	*0.94*	*1.12*	*0.49*	*0.17*	*0.37*
Sharpe	-0.04	0.26	0.26	0.39	0.68	**0.77**	**0.70**	**0.76**	-0.09	0.20	0.22	0.23	0.54	**0.70**	**0.65**	**0.60**
std (%)	10.15	9.50	9.33	9.51	8.82	8.31	3.35	5.91	9.85	10.07	10.37	9.45	8.7	8.1	3.2	6.1
mdd (%)	49.0	28.8	26.1	24.6	21.8	23.0	8.3	13.1	53.5	28.8	33.3	24.6	21.8	23.0	8.3	13.1
skew	-0.08	0.06	-0.21	-0.29	-0.61	0.07	0.06	-0.02	0.16	0.02	0.06	-0.12	-0.35	-0.19	0.03	-0.09
kurt	3.94	3.83	4.32	4.22	5.00	4.25	3.81	3.64	3.51	4.62	4.40	3.54	4.27	4.52	3.75	3.52
ac(1)	0.08	0.09	0.04	0.07	0.18	0.13	0.16	0.13	0.03	0.01	0.09	0.07	0.14	0.08	0.05	0.03
t/o (%)	10.0	21.8	29.8	23.1	11.6				9.5	21.7	34.2	22.5	10.5			
fp (%)	1.91	1.87	1.75	2.38	4.81				0.55	1.00	1.08	1.11	1.07			
gap (%)	-2.75	-0.84	0.18	1.30	3.01				-2.34	-0.84	0.12	1.02	2.47			

PANEL B: Main Currencies Entering each Portfolio (and percentage of sample in the portfolio)

	All Countries				*Developed Countries*			
	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest
$\mathbf{P_1}$	NZD (28%)	JPY (25%)	NOK (25%)	CHF (24%)	JPY (29%)	NZD (29%)	NOK (26%)	CHF (24%)
$\mathbf{P_2}$	GBP (32%)	DEM (28%)	AUD (23%)	CHF (23%)	GBP (32%)	DEM (29%)	CAD (24%)	AUD (23%)
$\mathbf{P_3}$	SEK (23%)	GBP (23%)	DEM (21%)	CAD (19%)	GBP (18%)	SEK (17%)	AUD (17%)	CHF (15%)
$\mathbf{P_4}$	GBP (31%)	SEK (25%)	AUD (23%)	CHF (23%)	GBP (35%)	AUD (25%)	SEK (23%)	CHF (21%)
$\mathbf{P_5}$	CAD (26%)	NZD (24%)	NOK (23%)	JPY (23%)	NZD (30%)	JPY (28%)	NOK (27%)	CAD (25%)

The table presents descriptive statistics for currency portfolios sorted by country-level output gaps (Panel A) and the main currencies entering each portfolio (Panel B). The output trend is estimated using a Baxter-King filter. In Panel A, currency portfolios are split between those containing *all* countries and a smaller sub-sample of *developed* countries. Portfolios are rebalanced monthly with strong (weak) economy currencies entering P_5 (P_1). We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components. The superscripts *, **, *** represent significance of the GAP portfolios at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition we report the Sharpe ratio (*Sharpe*), standard deviation (*std*), maximum drawdown (*mdd*), skewness (*skew*), kurtosis (*kurt*), and first-order autocorrelation coefficient (*ac(1)*). We also report the average turnover (*t/o*), forward premium (*fp*) and output gap (*gap*) for each portfolio. *GAP* is a portfolio long P_5 and short P_1. Linear and rank weights are portfolios with positions in every currency, in which the weights are calculated based on relative output gaps (see Section 4 for further details). In Panel B we report the main currencies entering the five output-gap-sorted portfolios. The percentage of months in the sample in which a currency enters a portfolio is reported in parentheses. The sample runs from October 1983 to January 2016. The data is described in Section 3.

Table A.7:

Output-Gap-Sorted Portfolios: Descriptive Statistics and Main Currencies Entering each Portfolio (Forecasted Trend)

PANEL A: Descriptive Statistics

All Countries

	output-gap-sorted portfolios					**GAP**	**Linear**	**Rank**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**($\mathbf{P_5}$-$\mathbf{P_1}$)**	**weights**	**weights**
mean (%)	1.10	2.01	2.59	2.95	5.23	**4.13*** **	**1.85*** **	**3.15*** **
fx (%)	*-1.63*	*0.09*	*0.41*	*0.88*	*2.05*	*3.68*	*1.78*	*2.81*
ir (%)	*2.73*	*1.92*	*2.19*	*2.08*	*3.18*	*0.45*	*0.07*	*0.34*
Sharpe	0.11	0.23	0.27	0.31	0.55	**0.54**	**0.59**	**0.58**
std (%)	9.95	8.87	9.59	9.56	9.52	7.61	3.12	5.42
mdd (%)	34.1	29.4	29.8	32.7	23.2	37.7	6.4	17.3
skew	-0.07	-0.39	-0.13	-0.35	-0.38	-0.29	-0.18	-0.31
kurt	4.70	5.29	3.96	4.09	4.76	5.50	6.51	5.02
ac(1)	0.03	0.02	0.07	0.11	0.09	0.05	0.10	0.08
t/o (%)	26.7	42.7	53.0	44.1	27.7			
fp (%)	2.70	1.99	2.10	2.32	3.58			
gap (%)	-1.30	-0.28	0.32	0.92	2.02			

Developed Countries

	output-gap-sorted portfolios					**GAP**	**Linear**	**Rank**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**($\mathbf{P_5}$-$\mathbf{P_1}$)**	**weights**	**weights**
mean (%)	-0.24	3.24	1.64	1.82	3.31	**3.55*** **	**1.45*** **	**2.22** **
fx (%)	*-1.13*	*2.33*	*0.30*	*1.15*	*2.36*	*3.49*	*1.34*	*2.12*
ir (%)	*0.89*	*0.91*	*1.34*	*0.66*	*0.95*	*0.06*	*0.11*	*0.10*
Sharpe	-0.02	0.37	0.15	0.19	0.35	**0.46**	**0.46**	**0.37**
std (%)	10.21	8.84	10.93	9.49	9.4	7.7	3.1	6.0
mdd (%)	45.4	29.4	29.8	34.4	23.2	37.7	8.5	17.3
skew	-0.03	0.02	-0.52	-0.10	-0.09	-0.14	0.08	0.03
kurt	4.40	3.85	5.78	3.70	3.53	5.63	4.26	4.62
ac(1)	0.04	0.02	0.08	0.06	0.04	0.03	0.00	-0.02
t/o (%)	22.7	40.3	53.3	40.0	22.8			
fp (%)	0.74	1.03	1.27	0.90	0.93			
gap (%)	-1.11	-0.27	0.31	0.74	1.69			

PANEL B: Main Currencies Entering each Portfolio (and percentage of sample in the portfolio)

	All Countries				*Developed Countries*			
	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest
$\mathbf{P_1}$	NZD (30%)	NOK (29%)	JPY (27%)	AUD (21%)	NOK (33%)	NZD (30%)	JPY (29%)	AUD (20%)
$\mathbf{P_2}$	GBP (37%)	CHF (28%)	AUD (25%)	MXN (22%)	GBP (39%)	AUD (28%)	CHF (23%)	DEM (23%)
$\mathbf{P_3}$	GBP (28%)	MXN (20%)	AUD (19%)	SEK (18%)	GBP (25%)	ITL (16%)	AUD (15%)	FRF (14%)
$\mathbf{P_4}$	DEM (29%)	JPY (26%)	SEK (26%)	CAD (24%)	SEK (28%)	JPY (26%)	CAD (24%)	GBP (22%)
$\mathbf{P_5}$	NOK (25%)	PLN (23%)	CZK (21%)	NZD (17%)	NOK (28%)	DEM (24%)	SEK (23%)	JPY (22%)

The table presents descriptive statistics for currency portfolios sorted by country-level output gaps (Panel A) and the main currencies entering each portfolio (Panel B). The output trend is estimated using a two-year ahead forecasted trend. In Panel A, currency portfolios are split between those containing *all* countries and a smaller sub-sample of *developed* countries. Portfolios are rebalanced monthly with strong (weak) economy currencies entering P_5 (P_1). We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components. The superscripts *, **, *** represent significance of the GAP portfolios at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition we report the Sharpe ratio (*Sharpe*), standard deviation (*std*), maximum drawdown (*mdd*), skewness (*skew*), kurtosis (*kurt*), and first-order autocorrelation coefficient (*ac(1)*). We also report the average turnover (*t/o*), forward premium (*fp*) and output gap (*gap*) for each portfolio. *GAP* is a portfolio long P_5 and short P_1. Linear and rank weights are portfolios with positions in every currency, in which the weights are calculated based on relative output gaps (see Section 4 for further details). In Panel B we report the main currencies entering the five output-gap-sorted portfolios. The percentage of months in the sample in which a currency enters a portfolio is reported in parentheses. The sample runs from October 1983 to January 2016. The data is described in Section 3.

Table A.8:

Output-Gap-Sorted Portfolios: Descriptive Statistics and Main Currencies Entering each Portfolio (Eurozone Investor)

PANEL A: Descriptive Statistics

	All Countries								*Developed Countries*							
	output-gap-sorted portfolios					**GAP**	**Linear**	**Rank**	*output-gap-sorted portfolios*					**GAP**	**Linear**	**Rank**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**($\mathbf{P_5}$-$\mathbf{P_1}$)**	**weights**	**weights**	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**($\mathbf{P_5}$-$\mathbf{P_1}$)**	**weights**	**weights**
mean (%)	-0.13	1.32	2.43	4.28	5.79	**5.92*****	**2.80*****	**5.05*****	-0.60	1.24	1.97	2.41	4.92	**5.52*****	**2.29*****	**4.23*****
fx (%)	*-2.30*	*-0.59*	*0.48*	*2.04*	*2.01*	*4.32*	*2.14*	*3.94*	*-1.17*	*0.43*	*0.98*	*1.41*	*3.75*	*4.92*	*2.01*	*3.79*
ir (%)	*2.17*	*1.91*	*1.95*	*2.24*	*3.78*	*1.61*	*0.66*	*1.10*	*0.57*	*0.81*	*0.99*	*1.00*	*1.17*	*0.60*	*0.28*	*0.44*
Sharpe	-0.01	0.15	0.23	0.46	0.65	**0.75**	**0.90**	**0.90**	-0.06	0.13	0.19	0.25	0.54	**0.68**	**0.70**	**0.68**
std (%)	10.00	8.98	10.43	9.29	8.97	7.89	3.12	5.59	10.25	9.63	10.44	9.57	9.1	8.1	3.3	6.2
mdd (%)	40.4	34.2	23.9	23.6	24.4	9.0	4.8	7.4	44.2	34.2	30.4	29.0	24.4	9.0	5.5	8.6
skew	-0.04	-0.52	-0.44	-0.20	-0.24	-0.12	0.01	0.12	-0.01	-0.11	-0.18	-0.08	-0.04	0.25	0.27	0.46
kurt	4.33	4.53	5.29	4.18	3.99	4.31	4.29	4.63	4.60	4.32	4.19	4.91	3.22	5.39	4.69	5.22
ac(1)	0.02	0.11	0.09	0.02	0.09	0.01	0.09	0.11	0.05	0.07	0.06	-0.01	0.12	0.08	0.11	0.13
t/o (%)	44.1	57.4	66.0	60.3	44.2				40.3	57.9	71.4	59.0	41.9			
fp (%)	2.31	2.01	1.91	2.23	4.25				0.50	0.99	1.03	1.17	1.10			
gap (%)	-3.01	-0.90	0.12	1.12	2.94				-2.57	-0.84	0.11	0.98	2.51			

PANEL B: Main Currencies Entering each Portfolio (and percentage of sample in the portfolio)

	All Countries				*Developed Countries*			
	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest
$\mathbf{P_1}$	CHF (27%)	NZD (27%)	NOK (24%)	JPY (21%)	CHF (27%)	NZD (27%)	NOK (27%)	JPY (22%)
$\mathbf{P_2}$	GBP (33%)	AUD (26%)	USD (25%)	CAD (23%)	GBP (34%)	USD (25%)	AUD (24%)	CAD (24%)
$\mathbf{P_3}$	GBP (26%)	CAD (22%)	USD (21%)	CZK (19%)	GBP (20%)	USD (18%)	AUD (15%)	CHF (14%)
$\mathbf{P_4}$	USD (26%)	GBP (25%)	CAD (24%)	SEK (23%)	GBP (29%)	CAD (27%)	USD (26%)	AUD (22%)
$\mathbf{P_5}$	NOK (27%)	NZD (25%)	JPY (25%)	CHF (19%)	NOK (30%)	NZD (29%)	JPY (27%)	SEK (22%)

The table presents descriptive statistics for currency portfolios sorted by country-level output gaps (Panel A) and the main currencies entering each portfolio (Panel B). The output trend is estimated using a Hodrick-Prescott filter. In Panel A, currency portfolios are split between those containing *all* countries and a smaller sub-sample of *developed* countries. Portfolios are rebalanced monthly with strong (weak) economy currencies entering P_5 (P_1). We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components. The superscripts *, **, *** represent significance of the GAP portfolios at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition we report the Sharpe ratio (*Sharpe*), standard deviation (*std*), maximum drawdown (*mdd*), skewness (*skew*), kurtosis (*kurt*), and first-order autocorrelation coefficient (*ac(1)*). We also report the average turnover (*t/o*), forward premium (*fp*) and output gap (*gap*) for each portfolio. *GAP* is a portfolio long P_5 and short P_1. Linear and rank weights are portfolios with positions in every currency, in which the weights are calculated based on relative output gaps (see Section 4 for further details). In Panel B we report the main currencies entering the five output-gap-sorted portfolios. The percentage of months in the sample in which a currency enters a portfolio is reported in parentheses. The sample runs from October 1983 to January 2016. The data is described in Section 3.

Table A.9:

Output-Gap-Sorted Portfolios: Descriptive Statistics and Main Currencies Entering each Portfolio (British Investor)

PANEL A: Descriptive Statistics

	All Countries								*Developed Countries*							
	output-gap-sorted portfolios					**GAP**	**Linear**	**Rank**	*output-gap-sorted portfolios*					**GAP**	**Linear**	**Rank**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**($\mathbf{P_5}$-$\mathbf{P_1}$)**	**weights**	**weights**	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**($\mathbf{P_5}$-$\mathbf{P_1}$)**	**weights**	**weights**
mean (%)	-0.18	0.80	2.35	4.47	6.24	**6.42*** **	**2.97*** **	**5.31*** **	-0.55	1.07	1.53	2.89	4.76	**5.31*** **	**2.26*** **	**4.14*** **
fx (%)	*-2.25*	*-1.22*	*0.58*	*2.03*	*2.41*	*4.66*	*2.20*	*4.04*	*-1.11*	*0.26*	*0.70*	*1.83*	*3.44*	*4.56*	*1.95*	*3.62*
ir (%)	*2.07*	*2.02*	*1.77*	*2.44*	*3.83*	*1.76*	*0.77*	*1.27*	*0.56*	*0.82*	*0.83*	*1.06*	*1.31*	*0.75*	*0.31*	*0.52*
Sharpe	-0.02	0.09	0.23	0.48	0.70	**0.80**	**0.95**	**0.94**	-0.05	0.11	0.15	0.30	0.53	**0.66**	**0.71**	**0.68**
std (%)	10.20	9.14	10.14	9.38	8.95	8.06	3.12	5.66	10.26	9.70	10.46	9.62	9.0	8.0	3.2	6.1
mdd (%)	40.8	33.7	26.5	21.1	21.9	9.0	3.8	6.6	43.0	33.7	33.1	26.4	21.9	9.0	5.6	8.8
skew	-0.06	-0.49	-0.24	-0.28	-0.25	-0.03	0.15	0.30	-0.01	-0.13	-0.14	-0.08	0.00	0.21	0.31	0.53
kurt	4.52	4.69	4.68	4.33	4.02	4.30	4.05	4.49	4.63	4.28	4.14	4.83	3.26	5.43	4.56	5.22
ac(1)	0.03	0.08	0.09	0.03	0.11	0.01	0.10	0.12	0.05	0.07	0.07	0.01	0.11	0.07	0.11	0.13
t/o (%)	44.9	58.4	67.5	59.1	43.4				40.5	58.1	71.4	57.4	40.3			
fp (%)	2.21	2.06	1.75	2.43	4.22				0.50	1.00	0.85	1.21	1.19			
gap (%)	-3.08	-0.96	0.11	1.18	3.01				-2.57	-0.84	0.11	0.99	2.51			

PANEL B: Main Currencies Entering each Portfolio (and percentage of sample in the portfolio)

	All Countries				*Developed Countries*			
	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest
$\mathbf{P_1}$	CHF (26%)	NZD (26%)	NOK (24%)	JPY (20%)	CHF (27%)	NZD (27%)	NOK (27%)	JPY (23%)
$\mathbf{P_2}$	USD (31%)	DEM (26%)	AUD (26%)	CAD (24%)	USD (32%)	DEM (25%)	CAD (24%)	AUD (23%)
$\mathbf{P_3}$	USD (31%)	CAD (22%)	DEM (22%)	AUD (18%)	USD (22%)	DEM (18%)	AUD (17%)	CAD (15%)
$\mathbf{P_4}$	DEM (27%)	CAD (25%)	SEK (23%)	USD (23%)	USD (28%)	CAD (26%)	DEM (25%)	AUD (22%)
$\mathbf{P_5}$	NOK (26%)	NZD (25%)	JPY (23%)	CHF (20%)	NOK (30%)	NZD (29%)	JPY (27%)	SEK (22%)

The table presents descriptive statistics for currency portfolios sorted by country-level output gaps (Panel A) and the main currencies entering each portfolio (Panel B). The output trend is estimated using a Hodrick-Prescott filter. In Panel A, currency portfolios are split between those containing *all* countries and a smaller sub-sample of *developed* countries. Portfolios are rebalanced monthly with strong (weak) economy currencies entering P_5 (P_1). We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components. The superscripts *, **, *** represent significance of the GAP portfolios at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition we report the Sharpe ratio (*Sharpe*), standard deviation (*std*), maximum drawdown (*mdd*), skewness (*skew*), kurtosis (*kurt*), and first-order autocorrelation coefficient (*ac(1)*). We also report the average turnover (*t/o*), forward premium (*fp*) and output gap (*gap*) for each portfolio. *GAP* is a portfolio long P_5 and short P_1. Linear and rank weights are portfolios with positions in every currency, in which the weights are calculated based on relative output gaps (see Section 4 for further details). In Panel B we report the main currencies entering the five output-gap-sorted portfolios. The percentage of months in the sample in which a currency enters a portfolio is reported in parentheses. The sample runs from October 1983 to January 2016. The data is described in Section 3.

Table A.10:

Output-Gap-Sorted Portfolios: Descriptive Statistics and Main Currencies Entering each Portfolio (Japanese Investor)

PANEL A: Descriptive Statistics

All Countries

	output-gap-sorted portfolios P_1	P_2	P_3	P_4	P_5	**GAP (P_5-P_1)**	**Linear weights**	**Rank weights**
mean (%)	-0.03	1.10	2.24	4.48	5.91	**5.94*** **	**2.88*** **	**5.07*** **
fx (%)	*-2.09*	*-1.01*	*0.44*	*2.16*	*2.07*	*4.17*	*2.12*	*3.86*
ir (%)	*2.06*	*2.11*	*1.80*	*2.32*	*3.83*	*1.77*	*0.75*	*1.21*
Sharpe	0.00	0.12	0.23	0.47	0.66	**0.74**	**0.92**	**0.90**
std (%)	10.14	9.20	9.62	9.53	8.98	8.07	3.13	5.65
mdd (%)	38.6	34.1	23.9	26.3	20.2	9.3	4.2	7.2
skew	-0.04	-0.53	-0.14	-0.22	-0.23	-0.05	0.16	0.29
kurt	4.59	4.64	4.47	4.17	3.98	4.24	4.14	4.71
ac(1)	0.03	0.09	0.04	0.03	0.11	0.02	0.08	0.11
t/o (%)	45.3	58.2	68.0	60.6	43.9			
fp (%)	2.20	2.13	1.78	2.35	4.21			
gap (%)	-3.07	-0.96	0.10	1.17	3.01			

Developed Countries

	output-gap-sorted portfolios P_1	P_2	P_3	P_4	P_5	**GAP (P_5-P_1)**	**Linear weights**	**Rank weights**
mean (%)	-0.42	1.36	1.45	2.87	4.42	**4.84*** **	**2.17*** **	**3.90*** **
fx (%)	*-0.95*	*0.43*	*0.58*	*1.92*	*3.12*	*4.07*	*1.87*	*3.43*
ir (%)	*0.53*	*0.93*	*0.87*	*0.95*	*1.30*	*0.77*	*0.30*	*0.47*
Sharpe	-0.04	0.14	0.15	0.29	0.49	**0.60**	**0.68**	**0.65**
std (%)	10.21	9.74	9.98	9.77	9.0	8.0	3.2	6.0
mdd (%)	41.2	34.1	31.4	27.4	20.2	9.3	5.7	9.1
skew	0.01	-0.18	-0.05	-0.03	0.01	0.19	0.32	0.53
kurt	4.70	4.23	3.89	4.65	3.24	5.38	4.65	5.41
ac(1)	0.05	0.07	0.02	0.01	0.12	0.08	0.10	0.12
t/o (%)	40.8	57.9	71.9	59.2	41.3			
fp (%)	0.46	1.12	0.91	1.12	1.15			
gap (%)	-2.55	-0.84	0.09	0.98	2.51			

PANEL B: Main Currencies Entering each Portfolio (and percentage of sample in the portfolio)

	All Countries Highest	2^{nd} highest	3^{rd} highest	4^{th} highest	*Developed Countries* Highest	2^{nd} highest	3^{rd} highest	4^{th} highest
$\mathbf{P_1}$	CHF (26%)	NZD (26%)	NOK (24%)	USD (20%)	CHF (28%)	NZD (27%)	NOK (27%)	USD (23%)
$\mathbf{P_2}$	GBP (30%)	DEM (27%)	AUD (25%)	CAD (23%)	GBP (32%)	DEM (26%)	CAD (24%)	AUD (23%)
$\mathbf{P_3}$	GBP (31%)	CAD (22%)	DEM (21%)	AUD (19%)	GBP (22%)	AUD (17%)	DEM (17%)	CAD (15%)
$\mathbf{P_4}$	DEM (27%)	CAD (25%)	SEK (25%)	GBP (23%)	GBP (29%)	CAD (27%)	DEM (24%)	SEK (21%)
$\mathbf{P_5}$	NZD (26%)	NOK (26%)	USD (23%)	CHF (20%)	NZD (31%)	NOK (30%)	USD (27%)	SEK (22%)

The table presents descriptive statistics for currency portfolios sorted by country-level output gaps (Panel A) and the main currencies entering each portfolio (Panel B). The output trend is estimated using a Hodrick-Prescott filter. In Panel A, currency portfolios are split between those containing *all* countries and a smaller sub-sample of *developed* countries. Portfolios are rebalanced monthly with strong (weak) economy currencies entering P_5 (P_1). We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components. The superscripts *, **, *** represent significance of the GAP portfolios at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition we report the Sharpe ratio (*Sharpe*), standard deviation (*std*), maximum drawdown (*mdd*), skewness (*skew*), kurtosis (*kurt*), and first-order autocorrelation coefficient (*ac(1)*). We also report the average turnover (*t/o*), forward premium (*fp*) and output gap (*gap*) for each portfolio. *GAP* is a portfolio long P_5 and short P_1. Linear and rank weights are portfolios with positions in every currency, in which the weights are calculated based on relative output gaps (see Section 4 for further details). In Panel B we report the main currencies entering the five output-gap-sorted portfolios. The percentage of months in the sample in which a currency enters a portfolio is reported in parentheses. The sample runs from October 1983 to January 2016. The data is described in Section 3.

Table A.11:

Output-Gap-Sorted Portfolios: Descriptive Statistics and Main Currencies Entering each Portfolio (Swiss Investor)

PANEL A: Descriptive Statistics

	All Countries								*Developed Countries*							
	output-gap-sorted portfolios					**GAP**	**Linear**	**Rank**	*output-gap-sorted portfolios*					**GAP**	**Linear**	**Rank**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	$\mathbf{(P_5\text{-}P_1)}$	**weights**	**weights**	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	$\mathbf{(P_5\text{-}P_1)}$	**weights**	**weights**
mean (%)	-0.07	1.18	1.53	4.69	6.63	**6.70*** **	**3.06*** **	**5.49*** **	-0.07	0.50	1.20	3.27	4.92	**4.99*** **	**2.36*** **	**4.31*** **
fx (%)	*-2.20*	*-0.75*	*-0.40*	*2.36*	*2.85*	*5.05*	*2.34*	*4.31*	*-0.68*	*-0.27*	*0.27*	*2.24*	*3.72*	*4.40*	*2.08*	*3.87*
ir (%)	*2.13*	*1.94*	*1.92*	*2.33*	*3.78*	*1.65*	*0.72*	*1.18*	*0.61*	*0.77*	*0.92*	*1.03*	*1.20*	*0.59*	*0.28*	*0.43*
Sharpe	-0.01	0.13	0.15	0.51	0.71	**0.82**	**0.97**	**0.96**	-0.01	0.05	0.12	0.36	0.53	**0.62**	**0.73**	**0.70**
std (%)	10.27	9.09	9.87	9.17	9.28	8.13	3.16	5.69	10.27	9.57	10.36	9.16	9.3	8.1	3.2	6.1
mdd (%)	37.2	34.2	24.4	23.6	24.4	8.2	4.6	6.9	39.9	34.2	37.7	23.6	24.4	10.9	5.8	8.8
skew	-0.04	-0.48	-0.34	-0.21	-0.24	0.00	0.03	0.11	0.08	-0.19	-0.14	-0.01	0.02	0.20	0.23	0.45
kurt	4.41	4.38	5.56	3.86	4.15	4.50	4.39	4.71	4.08	5.14	4.08	3.89	3.09	4.81	5.09	5.80
ac(1)	0.03	0.10	0.07	0.03	0.11	0.04	0.10	0.12	0.05	0.07	0.08	0.03	0.11	0.08	0.13	0.13
t/o (%)	44.8	59.5	66.8	60.0	44.4				39.4	57.9	73.4	58.2	40.9			
fp (%)	2.27	1.97	1.88	2.33	4.24				0.55	0.96	0.93	1.20	1.13			
gap (%)	-3.06	-0.91	0.10	1.13	2.99				-2.54	-0.77	0.08	0.93	2.49			

PANEL B: Main Currencies Entering each Portfolio (and percentage of sample in the portfolio)

	All Countries				*Developed Countries*			
	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest
$\mathbf{P_1}$	USD (27%)	NZD (26%)	NOK (24%)	JPY (20%)	USD (29%)	NZD (28%)	NOK (28%)	JPY (23%)
$\mathbf{P_2}$	GBP (31%)	CAD (28%)	AUD (26%)	DEM (26%)	GBP (32%)	CAD (30%)	DEM (25%)	AUD (24%)
$\mathbf{P_3}$	CAD (29%)	GBP (27%)	DEM (23%)	MXN (20%)	CAD (23%)	GBP (19%)	DEM (17%)	USD (15%)
$\mathbf{P_4}$	DEM (27%)	CAD (27%)	GBP (26%)	SEK (23%)	GBP (30%)	CAD (26%)	DEM (26%)	AUD (22%)
$\mathbf{P_5}$	NOK (26%)	NZD (25%)	JPY (24%)	USD (19%)	NOK (31%)	NZD (29%)	JPY (28%)	SEK (22%)

The table presents descriptive statistics for currency portfolios sorted by country-level output gaps (Panel A) and the main currencies entering each portfolio (Panel B). The output trend is estimated using a Hodrick-Prescott filter. In Panel A, currency portfolios are split between those containing *all* countries and a smaller sub-sample of *developed* countries. Portfolios are rebalanced monthly with strong (weak) economy currencies entering P_5 (P_1). We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components. The superscripts *, **, *** represent significance of the GAP portfolios at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition we report the Sharpe ratio (*Sharpe*), standard deviation (*std*), maximum drawdown (*mdd*), skewness (*skew*), kurtosis (*kurt*), and first-order autocorrelation coefficient (*ac(1)*). We also report the average turnover (*t/o*), forward premium (*fp*) and output gap (*gap*) for each portfolio. *GAP* is a portfolio long P_5 and short P_1. Linear and rank weights are portfolios with positions in every currency, in which the weights are calculated based on relative output gaps (see Section 4 for further details). In Panel B we report the main currencies entering the five output-gap-sorted portfolios. The percentage of months in the sample in which a currency enters a portfolio is reported in parentheses. The sample runs from October 1983 to January 2016. The data is described in Section 3.

Table A.12:

Output-Gap-Sorted Portfolios: Descriptive Statistics and Main Currencies Entering each Portfolio (net transaction costs)

PANEL A: Descriptive Statistics

	All Countries							
	output-gap-sorted portfolios					**GAP**	**Linear**	**Rank**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**($\mathbf{P_5}$-$\mathbf{P_1}$)**	**weights**	**weights**
mean (%)	-0.25	-1.04	0.24	2.10	3.31	**5.59*** **	**5.04*** **	**2.20*** **
fx (%)	*-2.34*	*-3.00*	*-1.63*	*0.34*	*1.02*	*2.06*	*3.75*	*1.62*
ir (%)	*2.09*	*1.95*	*1.87*	*1.76*	*2.28*	*3.53*	*1.29*	*0.57*
Sharpe	-0.02	-0.10	0.03	0.21	0.36	**0.62**	**0.62**	**0.69**
std (%)	10.18	10.17	9.10	10.10	9.31	9.03	8.15	3.19
mdd (%)	42.5	50.6	35.3	24.8	24.4	25.1	10.5	5.6
skew	-0.06	-0.07	-0.49	-0.30	-0.27	-0.29	-0.01	0.09
kurt	4.49	4.45	4.76	4.75	4.40	3.96	4.32	4.24
ac(1)	0.03	0.03	0.08	0.08	0.00	0.10	0.01	0.07
t/o (%)	44.8	44.8	58.2	67.2	60.6	44.81		
fp (%)	2.23	2.23	2.03	1.80	2.45	4.15		
gap (%)	-3.08	-3.08	-0.96	0.11	1.17	3.01		

	Developed Countries							
	output-gap-sorted portfolios					**GAP**	**Linear**	**Rank**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**($\mathbf{P_5}$-$\mathbf{P_1}$)**	**weights**	**weights**
mean (%)	-1.25	0.64	1.37	1.85	4.25	**4.20*** **	**1.64*** **	**2.95*** **
fx (%)	*-1.70*	*-0.07*	*0.49*	*0.95*	*3.22*	*3.86*	*1.49*	*2.76*
ir (%)	*0.45*	*0.70*	*0.88*	*0.90*	*1.04*	*0.34*	*0.14*	*0.19*
Sharpe	-0.12	0.07	0.13	0.19	0.47	**0.52**	**0.50**	**0.48**
std (%)	10.24	9.62	10.43	9.57	9.1	8.1	3.3	6.2
mdd (%)	52.1	35.3	35.5	33.6	25.1	10.5	6.9	11.3
skew	-0.02	-0.11	-0.19	-0.08	-0.05	0.23	0.26	0.45
kurt	4.57	4.33	4.20	4.91	3.21	5.41	4.70	5.24
ac(1)	0.05	0.07	0.06	-0.02	0.11	0.07	0.10	0.12
t/o (%)	40.3	57.9	71.4	59.0	41.9			
fp (%)	0.50	0.99	1.03	1.17	1.10			
gap (%)	-2.57	-0.84	0.11	0.98	2.51			

PANEL B: Main Currencies Entering each Portfolio (and percentage of sample in the portfolio)

	All Countries				*Developed Countries*			
	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest	Highest	2^{nd} highest	3^{rd} highest	4^{th} highest
$\mathbf{P_1}$	CHF (26%)	NZD (26%)	NOK (24%)	SEK (20%)	CHF (27%)	NZD (27%)	NOK (27%)	JPY (22%)
$\mathbf{P_2}$	GBP (31%)	DEM (27%)	AUD (26%)	CAD (23%)	GBP (34%)	DEM (25%)	AUD (24%)	CAD (24%)
$\mathbf{P_3}$	GBP (29%)	CAD (22%)	DEM (22%)	MXN (18%)	GBP (20%)	DEM (18%)	AUD (15%)	CHF (14%)
$\mathbf{P_4}$	DEM (28%)	CAD (26%)	GBP (24%)	SEK (23%)	GBP (29%)	CAD (27%)	DEM (26%)	AUD (22%)
$\mathbf{P_5}$	NOK (26%)	NZD (25%)	JPY (24%)	CHF (19%)	NOK (30%)	NZD (29%)	JPY (27%)	SEK (22%)

The table presents descriptive statistics for currency portfolios sorted by country-level output gaps (Panel A) and the main currencies entering each portfolio (Panel B). The output trend is estimated using a Hodrick-Prescott filter. In Panel A, currency portfolios are split between those containing *all* countries and a smaller sub-sample of *developed* countries. Portfolios are rebalanced monthly with strong (weak) economy currencies entering P_5 (P_1). We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components. The superscripts *, **, *** represent significance of the GAP portfolios at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition we report the Sharpe ratio (*Sharpe*), standard deviation (*std*), maximum drawdown (*mdd*), skewness (*skew*), kurtosis (*kurt*), and first-order autocorrelation coefficient (*ac(1)*). We also report the average turnover (*t/o*), forward premium (*fp*) and output gap (*gap*) for each portfolio. *GAP* is a portfolio long P_5 and short P_1. Linear and rank weights are portfolios with positions in every currency, in which the weights are calculated based on relative output gaps (see Section 4 for further details). In Panel B we report the main currencies entering the five output-gap-sorted portfolios. The percentage of months in the sample in which a currency enters a portfolio is reported in parentheses. The sample runs from October 1983 to January 2016. The data is described in Section 3.

Table A.13:
Output-Gap Portfolios Sorted on Real-Time Data (net transaction costs)

PANEL A: Forecasted Trend and Industrial Production Momentum

	output-gap-sorted portfolios					**GAP**	*output-gap-sorted portfolios*					**GAP**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	$(\mathbf{P_5}$-$\mathbf{P_1})$	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	$(\mathbf{P_5}$-$\mathbf{P_1})$
mean (%)	1.06	0.67	-0.61	4.30	5.01	**2.73***	0.43	1.68	1.42	1.73	3.95	**2.37***
fx (%)	*-1.17*	*-1.21*	*-1.95*	*2.31*	*2.21*	*2.60*	*-1.48*	*-0.35*	*-0.46*	*-0.51*	*1.78*	*2.43*
ir (%)	*2.23*	*1.88*	*1.34*	*2.00*	*2.80*	*0.13*	*1.91*	*2.03*	*1.88*	*2.24*	*2.17*	*-0.06*
Sharpe	0.11	0.07	-0.07	0.43	0.49	**0.40**	0.05	0.20	0.15	0.17	0.38	**0.30**
std (%)	9.33	9.37	9.05	10.07	10.13	6.89	9.30	8.54	9.60	10.05	10.44	7.82
mdd (%)	24.3	26.2	31.7	15.7	16.7	14.9	23.6	16.8	23.9	22.5	17.8	15.7
skew	-0.17	-0.88	-0.59	-0.46	-0.27	0.17	-0.28	-0.11	-0.60	-0.28	-0.46	0.14
kurt	4.27	6.63	5.06	4.87	3.28	2.80	4.01	4.20	5.17	4.10	4.37	5.36
ac(1)	-0.02	0.08	0.06	0.09	0.07	0.03	0.00	-0.02	0.08	0.06	0.06	-0.14
t/o (%)	20.9	40.6	44.2	43.6	22.3		34.8	54.1	54.3	55.9	35.0	
fp (%)	2.41	2.00	1.60	2.16	2.89		2.12	2.07	2.03	2.37	2.42	
gap (%)	-1.72	-0.58	0.12	0.83	2.24		-4.06	-0.59	1.66	3.93	8.29	

PANEL B: Amplitude Adjusted Composite Leading Indicator

	output-gap-sorted portfolios					**GAP**	*output-gap-sorted portfolios*					**GAP**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	$(\mathbf{P_5}$-$\mathbf{P_1})$	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	$(\mathbf{P_5}$-$\mathbf{P_1})$
mean (%)	-2.67	-0.90	1.22	-2.49	3.82	**5.15****	-2.13	0.07	-1.83	-0.73	3.43	**4.27****
fx (%)	*-5.76*	*-2.33*	*-0.53*	*-3.74*	*1.83*	*6.56*	*-4.89*	*-1.47*	*-3.53*	*-2.00*	*1.25*	*5.14*
ir (%)	*3.09*	*1.43*	*1.74*	*1.25*	*1.99*	*-1.42*	*2.76*	*1.54*	*1.70*	*1.27*	*2.18*	*-0.87*
Sharpe	-0.23	-0.10	0.12	-0.23	0.37	**0.68**	-0.18	0.01	-0.17	-0.07	0.34	**0.53**
std (%)	11.52	9.45	10.50	10.95	10.34	7.53	11.80	9.90	10.78	10.53	10.04	7.99
mdd (%)	37.8	31.5	22.4	34.4	27.9	12.5	33.5	24.5	33.2	29.0	20.8	11.7
skew	-0.44	-0.21	-0.37	-0.82	-0.66	-0.22	-0.09	0.18	-0.93	-0.82	-0.89	-0.47
kurt	3.87	3.79	4.73	4.70	6.38	4.87	3.94	4.01	6.18	4.53	5.87	3.52
ac(1)	-0.05	0.02	0.01	0.02	0.23	-0.05	-0.11	-0.04	0.11	0.07	0.17	0.04
t/o (%)	23.9	40.5	36.0	36.5	26.4		23.9	41.1	36.1	36.1	25.5	
fp (%)	3.25	1.60	1.85	1.44	2.20		2.91	1.71	1.80	1.49	2.40	
gap (%)	-2.82	-1.14	0.04	1.32	3.04		-2.93	-1.06	0.20	1.59	3.49	

The table presents descriptive statistics for currency portfolios sorted by country-level output gaps (Panel A). The output trend is estimated using either a forecasting equation (left-hand-side) or as a random walk (right-hand-side). In Panel B, we present descriptive statistics for currency portfolios sorted by real-time country-level composite leading indicators. The leading indicator is measured as the latest datapoint (left-hand-side) or with a six-month lag (right-hand-side). Portfolios are rebalanced monthly with strong (weak) economy currencies entering P_5 (P_1). We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components. The superscripts *, **, *** represent significance of the GAP portfolios at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. In addition we report the Sharpe ratio (*Sharpe*), standard deviation (*std*), maximum drawdown (*mdd*), skewness (*skew*), kurtosis (*kurt*), and first-order autocorrelation coefficient (*ac(1)*). We also report the average turnover (*t/o*), forward premium (*fp*) and output gap (*gap*) for each portfolio. *GAP* is a portfolio long P_5 and short P_1. The data is described in Section 3.