Business Cycles and Currency Returns*

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Abstract

We find a strong link between currency returns and the relative strength of the business cycle. Buying currencies of strong economies and selling currencies of weak economies generates high returns in both the cross section and time series of countries. These returns stem primarily from spot exchange rate predictability, are uncorrelated with common currency strategies, and cannot be understood using traditional risk factors. We also show that a business cycle factor implied by our results is priced in a broad currency cross section. These results contrast with a vast literature that detects no linkages between currency fluctuations and macroeconomic variables.

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1 Introduction

It is a common perception that fluctuations in exchange rates cannot be satisfactorily explained, never mind predicted, by macroeconomic fundamentals either in- or out-of-sample. This is especially evident at short and intermediate horizons from one month to a year that are relevant to most investors (Meese and Rogoff, 1983; Engel, Mark, and West, 2007; Rossi, 2013). This macroeconomic 'disconnect' is puzzling since exchange rate fluctuations should be driven by an underlying macroeconomic process. In the same way that the return on a company's stock is theoretically linked to the company's fundamentals, the return on a country's currency should be a function of its underpinning economic fundamentals. Yet we have a limited understanding of whether or how currency returns are related to macroeconomic conditions across countries.

In this paper, we focus on the broadest measure of aggregate macroeconomic conditions constituting a key building block in theoretical models of exchange rates – the business cycle – and provide new evidence suggesting that business cycles are a key driver and powerful predictor of currency excess returns and spot exchange rate fluctuations. The business cycle is a crucial component of present value models of exchange rate determination using Taylor rule reaction functions, in which the currencies of economies where current output is above potential are expected to appreciate (Engel and West, 2005). Moreover, in the macro-finance literature the existence of a relationship between business cycles and currency returns is a necessary condition for risk-based models to have empirical validity (Cochrane, 2017).[1]

Our empirical approach moves away from traditional forecasting of *bilateral* exchange rate movements using time-series regression analysis, which has been the common focus in most of the earlier literature.[2] By contrast, we focus on *relative* business cycles using a portfolio approach that has proven successful in recent studies shedding new light on exchange rate determination

[1]The business cycle is a common feature of macro-finance models of asset pricing with endogenous risk premia, which argue in various ways that the spillovers of business cycles from one country to another make some currencies safer or riskier than others (see, e.g., Martin, 2013; Hassan, 2013; Tran, 2013; Ready, Roussanov, and Ward, 2017; Richmond, 2016). The earlier work of Lustig and Verdelhan (2007) considers a link between consumption growth and currency excess returns, while Koijen, Lustig, and Van Nieuwerurgh (2017) show that the business cycle is a priced state variable in the cross-section and time-series of stock and bond markets. Our contribution in this paper is entirely empirical and we do not attempt to test directly a specific theoretical model; rather our objective is to examine the existence of an empirical link between business cycles and currency returns.

[2]See, e.g., Mark (1995), Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008), Rossi (2013).

(Lustig and Verdelhan, 2007; Lustig, Roussanov, and Verdelhan, 2011; Menkhoff et al., 2012b, 2017; Lettau, Maggiori, and Weber, 2014; Verdelhan, 2017; Lustig and Richmond, 2017). This approach allows us to gather information in both the cross section and time series of countries' business cycles to view predictability through the lens of an international investor trying to exploit a potential link between business cycles and exchange rates. Such an investor cares principally about currency excess returns and evaluates predictability in a multi-currency portfolio setting on the basis of economic metrics. In our empirical analysis we address the following set of questions: Do business cycles predict currency returns in a portfolio setting? If so, why is the finding different to the previously documented findings in the time-series literature, and could an investor earn positive returns from an investment strategy capitalizing on this predictability? And finally, can the returns be understood as compensation for risk?

We split our empirical analysis into two parts. In the first part we explore predictability using the full sample of data to measure business cycles. We do so in light of the earlier evidence in the literature finding macro fundamentals cannot predict exchange rates even when the econometrician has perfect foresight of macroeconomic outcomes (Meese and Rogoff, 1983; Cheung, Chinn, and Garcia Pascual, 2005). In the second part, we move entirely out of sample to avoid revised or forward looking data, taking the perspective of a currency investor to consider the investment performance, diversification benefits, and risk characteristics associated with currency return predictability.

Throughout the paper we use the output gap as our measure of business cycle conditions. The output gap is a common macroeconomic measure of the aggregate state of the economy, defined as the percentage deviation in output from its long-run trend. Since it is not directly observable, we measure the output gap using several commonly adopted methods in the literature, including the filters proposed by Hodrick and Prescott (HP, 1980) and Baxter and King (1999), the quadratic time trend used by Clarida, Gali, and Gertler (1998), and the linear projection method recently introduced by Hamilton (2017).[3] Using monthly data from 1983 to 2016 for

[3]Hamilton (2017) 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. Although the focus is to improve on the HP filter out-of-sample, Hamilton's analysis and criticisms are relevant for all other filters commonly used in this literature. Therefore, we use the Hamilton procedure in our out-of-sample analysis, implementing the procedure recursively conditioning only on data available at the time of sorting. While the output gap is a common

a cross-section of 27 countries, we find that sorting currencies into portfolios on the basis of output gaps generates a monotonic increase in excess returns as we move from the portfolios of the weakest economies' currencies – i.e. those with current output most below potential – to the portfolios of the strongest economies' currencies – i.e. those with current output most above potential. Furthermore, we find that a 1/N time-series portfolio strategy that takes long positions in countries with output gaps above the United States and short positions in countries with output gaps below the United States also generates impressive predictability. In both cases, the predictive power for currency excess returns is driven almost entirely by the spot exchange rate component rather than interest rate differentials. This result stands in contrast to a large literature in empirical exchange rate modelling, which for decades has struggled to find evidence of a connection between macro variables and exchange rates.

Importantly, our approach does not regurgitate existing findings in the literature. Sorting currencies by output gaps is not equivalent, for example, to the currency carry trade that requires sorting currencies by their nominal interest rates. We highlight the intuition for this point in Figure 1 using two common carry trade currencies – the Australian dollar and Japanese yen. The interest rate differential is highly persistent and has been consistently positive between the two countries in recent decades. A carry trade investor would have thus always been long the Australian dollar and short the Japanese yen. In contrast the output gap differential varies substantially over time, and an output-gap investor would have taken both long and short positions in the Australian dollar and Japanese yen as their relative business cycles fluctuated.

These findings suggest a strong predictive link from business cycles to currency returns, and raise questions as to why our results differ from those in the long-standing international macro-finance literature. The answers lie in both the time series and cross section. Our portfolio results from the time series indicate that high output gap currencies *usually* appreciate – the output gap provides a better-than-chance prediction of future exchange rate movements and the size of

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, although this result was challenged by Rogoff and Stavrakeva (2008), who argue against the robustness of the predictability across different subsample periods.

the return increases with the output gap. But the high volatility of exchange rates relative to macro fundamentals makes it difficult to outperform a random walk on statistical grounds due to low test power. The second reason relates to a cross-sectional 'level' factor (the average output gap relative to the United States), which leads to coefficient instability. In periods when the economy of the United States is relatively weak, all currencies tend to appreciate against the U.S. dollar – even those with output gaps *below* the United States. In contrast, currencies of weak economies depreciate substantially against the U.S. dollar when the United States is relatively strong compared to all other countries. The time-series literature typically fails to account for these state-dependent coefficients, while the cross section is immune to them.[4]

The in-sample analysis uses the entire sample to calculate output gaps. While this is useful for studying the existence of a relationship between relative economic conditions and exchange rates using the longest sample of data at our disposal, the use of forward-looking information raises questions as to whether the relationship is economically valuable. Moving out-of-sample and using real-time output data from 1999 to 2016, we indeed find that the results are qualitatively identical. The data we use mimics the information set available to investors during this period and thus sorting is conditional only on information available at the time. The out-of-sample Sharpe ratios for the high-minus-low cross-sectional strategy, which we denote as GAP_{CS}, reaches 0.72 (without transaction costs) and 0.50 (net of costs). In the time series, the strategy which goes long (short) currencies issued by countries with output gaps above (below) the United States, denoted as GAP_{TS}, generates a Sharpe ratio of 0.65 (0.50 after costs). The two strategies exhibit a correlation of around 35% and thus the investment performance increases further once these strategies are combined.[5] In essence, the results imply that currency excess returns are higher for stronger economies, i.e. those in a more favorable state of the business cycle, and are robust to various ways of constructing the portfolio strategy. For example, the results hold when assigning linear or rank weights (and thus trading all currencies simultaneously), which reassures us that

[4]The above argument also constitutes a potential explanation for the well-documented instability of the coefficients associated with macro variables in time series models of the exchange rate (see e.g., Sarno and Valente, 2009; Rossi, 2013; Fratzscher et al., 2015).

[5]Moskowitz, Ooi, and Pedersen (2012) provide evidence of time-series strategy performance, while Baz et al. (2015) consider combinations of time-series and cross-sectional strategies across asset classes using carry, value and momentum signals.

they are not driven by a few outlier currencies but apply generally to the broader cross section.

The out-of-sample performance, as with the in-sample results, stems mainly from the predictability of spot exchange rates rather than from interest rate differentials. That is, currencies of strong economies tend to appreciate and those of weak economies tend to depreciate over the subsequent month. This feature makes the returns from exploiting business cycle information different from the returns delivered by most canonical currency investment strategies, and most notably distinct from carry (which generates a negative exchange rate return). Indeed, we find the time-series correlations between both GAP_{CS} and GAP_{TS} strategies and the currency carry trade are essentially zero, and the correlations with other canonical currency investment strategies – such as "dollar carry" (Lustig, Roussanov, and Verdelhan, 2014), momentum (Menkhoff et al., 2012b), and value (Menkhoff et al., 2017) – are also low and close to zero.[6] 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. This apparent lack of correlation also implies that the output gap strategy offers useful diversification gains to an investor who adds it to a conventional menu of currency portfolios, and we quantify these gains in the empirical analysis.

We then ask whether the returns of output-gap-sorted portfolios reflect compensation for risk. We address this question by testing the pricing power of conventional risk factors using standard linear asset pricing models, and find no evidence that factors proposed in the literature are priced in the cross section of currency returns sorted on output gaps. Finally, we discuss our empirical findings in the context of the existing theoretical literature and consider the possibility that business cycles proxy for a priced state variable as implied by many macro-finance models of currency premia. To do so, we consider the pricing power of a business cycle factor, taken to equal the returns on the GAP_{CS} strategy, and test whether it is priced in the cross section of currencies. We find that the pricing power of the factor is strong and not confined to portfolios sorted on output gaps, extending to other popular currency cross sections, including portfolios

[6]Lustig, Roussanov, and Verdelhan (2014) propose a "dollar carry trade" strategy which trades a basket of currencies against the U.S. dollar on the basis of the average forward discount relative to the United States. Their strategy is different from the standard carry trade, and the returns compensate U.S. investors for taking on aggregate risk by shorting the dollar in bad times, when the U.S. price of risk is high. Our strategy is distinct conceptually – in that it directly sorts on relative business cycles across countries rather than on interest rate (forward discount) information – and empirically we document that the returns of the dollar carry trade are only mildly correlated with the returns to our strategy.

sorted on carry (interest rate differentials), momentum and value. We thus provide the first tentative evidence in support of a large theoretical macro-finance literature linking business cycles to currency premia.

The remainder of the paper is as follows. Section 2 describes the data and defines the currency portfolios studied in the empirical analysis. Section 3 reports in-sample results on the predictive information content of business cycles for currency excess returns, whereas Section 4 presents out-of-sample results on the performance and diversification gains from incorporating information on relative business cycles. Section 5 reports the results for asset pricing tests designed to explore whether the returns to output-gap-sorted portfolios can be understood as compensation for risk, and whether a business cycle risk factor implied by our results is priced in the cross section of currencies. Section 6 concludes. An Internet Appendix reports additional results and some technical details on the construction of output gap measures.

2 Data and Currency Portfolios

This section describes the main data employed in the empirical analysis as well as the construction of output gaps both in- and out-of-sample.

2.1 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.[7]

[7] Full details of the Datastream mnemonics we use and sample period available for each currency pair is provided in Table A1 of the Internet Appendix. The sample includes both major and liquid emerging market currencies, and the choice of countries reflects data availability for the (real-time) industrial production data from the OECD, which are described below.

2.2 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

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

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

$$RX_{t+1} = \frac{Spot_{t+1} - Spot_t}{Spot_t} - \frac{Fwd_t - Spot_t}{Spot_t}. \tag{2}$$

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.

2.3 The Output Gap and Data on Economic Activity

The output gap is defined as the logarithm of the difference between actual (y_t) and 'potential' ($\bar{y}_t$) output, $gap_t = y_t - \bar{y}_t$. 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 decompose a country's output into the trend and cyclical 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 short-term deviations and serves as our empirical proxy for the output gap.

To measure economic activity we use data on (log) industrial production obtained from the OECD's *Original Release Data and Revisions Database*. The database provides monthly 'vintages' of data, allowing researchers to know exactly what information was available to market participants on particular macroeconomic variables at the end of each given month, and is thus free of revisions and forward looking information. For example, in December 1999, the available U.S. industrial production data ran from January 1960 until October 1999. In the out-of-sample analysis, we thus assume that an investor constructing a currency strategy at the end of December 1999 would have no knowledge of either the November or December 1999 values and could thus only condition their investment decision on data ending in October 1999. This assumption inherently biases the out-of-sample results downwards, given the availability of other relevant information at the time. Nonetheless, our out-of-sample results can provide a lower bound for assessing the usefulness of relative business cycle information across countries.

2.3.1 In-sample

For the in-sample 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 we end the sample in January 2016 to coincide with the last industrial production data point available for most countries in the sample in April 2016. We estimate output gaps using various statistical techniques to extract a cyclical component from macroeconomic data: (i) the linear projection method of Hamilton (2017), (ii) the Hodrick-Prescott (HP) (1980, 1997) filtered output gap, (iii) the Baxter-King (1999) filter, and the quadratic trend specification used by Clarida, Gali, and Gertler (1998). We provide further details of the parameters and functional forms of these statistical techniques in the Internet Appendix.

2.3.2 Out-of-sample

For the out-of-sample analysis, we use the full set of monthly industrial production vintages from December 1999 until January 2016.[8] Each monthly vintage records the industrial production data available to an investor in that particular month. In the out-of-sample analysis, we construct output gap estimates using each monthly vintage in turn, applying the linear projection method of

[8]The data becomes available from February 1999 onwards, but the early months have unusually short samples and missing observations. We therefore choose to begin the analysis with the most complete dataset, which begins with the December 1999 vintage.

Hamilton (2017), and therefore the resulting estimate at time t is conditioned only on information available at t.

The linear projection methodology requires the estimation of the following time-series regression:

$$y_{i,t} = \alpha_i + \sum_{s=0}^{11} \beta_{i,s} y_{i,t-24-s} + \varepsilon_{i,t} \tag{3}$$

where $y_{i,t}$ is the (log) value of industrial production for country i available at time t. We regress time-t values on their corresponding value from two-years (24-months) earlier, and include eleven additional lags following the suggestion of Hamilton (2017).[9] We measure the cyclical component as $c_t = y_t - \hat{y}_t$, where $\hat{y}_t$ is the fitted value from the regression in (3). Our measure is therefore purely backward-looking, making no use of either revised data or forward-looking information.

2.4 Output Gap Portfolios

2.4.1 Cross Section

At the end of each month t, we sort currencies into five portfolios on the basis of their output gap. 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 compute the excess return for each portfolio as an equally weighted average of individual currency excess returns within the portfolio. In our out-of-sample analysis, we refer to the difference between Portfolio 5 (P_5) and Portfolio 1 (P_1) as the GAP_{CS} strategy, which is a tradeable investment strategy that exploits the relative cross-sectional spread in business cycle conditions around the world. 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).

2.5 Time Series

At the end of each month t, we form a 1/N (equally weighted) strategy that takes long positions in the currencies of countries with output gaps above the United States and short positions in

[9] If industrial production is only available at quarterly intervals we use 4 lags beginning 8-quarters earlier.

the currencies of countries with output gaps below the United States. The strategy thus invests in all currencies available at each point in time, under the expectation that countries with higher (lower) output gaps than the United States should subsequently offer higher (lower) currency excess returns. In the out-of-sample analysis, we refer to this portfolio strategy as GAP_{TS}.

3 Business Cycles and Currency Returns: In-Sample

In this section, we explore the business cycles' predictive power for currency excess returns in-sample, i.e., using the full sample of industrial production data. This approach follows a vast literature studying whether macro fundamentals can predict exchange rates when the econometrician has perfect foresight of macroeconomic outcomes (Meese and Rogoff, 1983; Mark, 1995; Rossi, 2013). Our benchmark is a 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 cross-sectional 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 this cross-sectional strategy, we also implement a time-series strategy that takes an equal weight in all currencies, with the direction of the trade depending on whether the output gap of a country is higher (long position) or lower (short position) than the U.S. output gap.

This analysis uses the longest possible data sample for output gaps applied to revised data and allows us to address the general question of whether there is a meaningful link between economic conditions across countries and currency returns, both in the cross section and the time series. We examine the out-of-sample investment performance in the following section.

3.1 The Link Between Business Cycles and Currency Returns

In Table 1, we present the average excess returns on the five output-gap-sorted portfolios, which monotonically increase from P_1 to P_5 for two of the four output gap measures employed; the two exceptions are the Baxter-King filter and the linear projection, which display a slight non-monotonicity from portfolio P_2 to P_3. The spread in returns between P_1 to P_5 is sizeable, from 4.56% to 6.66% per annum, and is statistically different from zero at the 1% level for each measure of the output gap employed. Interestingly, the time-series portfolio also delivers a statistically significant spread in returns, which ranges from 2.14% to 3.83% per annum.

Further scrutiny of the results in Table 1 reveal that the predictability is mainly driven by predicting spot exchange rates (in the row denoted fx), whereas the interest rate differential contributes very little (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.[10] 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 non-monotonically; however, the spread is rather low, consistent with the fact that the returns from sorting on output gaps are not driven by interest rate differentials.

The results in Table 1 are qualitatively identical for all four measures of the output gap considered, indicating that they lead to similar portfolio sorts each month (i.e., similar ranking of countries by the state of the business cycle). In Table 2, we report evidence on the correlation across the portfolio sorts obtained by the different output gap measures. Panel A of Table 2 reports both linear correlation coefficients (below the diagonal) and Spearman rank correlations (above the diagonal) for each pair of output gap measures. To calculate these measures we first collect the cross-sectional correlations (either linear or rank) at each month t. We then calculate the mean of these correlations by averaging across the full sample (the values do not, therefore, reflect a *single* time-series correlation). While the correlations are not perfect they are sizeable, and in a range between 0.41 to 0.65. In Panel B of Table 2 we also report the results from a principal component analysis applied to the output gap estimates for the four different measures. To do so, each month we collect the four cross-sectional vectors of output gaps and extract the proportion of variance explained by the four associated principal components. The average percentage of cross-sectional

[10]For comparison, we present the equivalent descriptive statistics for forward-premia-sorted (carry) portfolios in Table A2 of the Internet Appendix.

variation explained by the first principal component is a hefty 86%, indicating that the output gap measures have a very strong common component.

In Table 3, we present the results from a principal component decomposition of the returns of the five portfolios sorted on output gaps, across each of the four measures of output gap considered. The results indicate a strong factor structure in currency portfolio returns sorted by output gaps. The first principal component accounts for most of the variation in portfolio returns, but the loadings appear to be almost identical across the five portfolios, suggesting that this component is essentially a 'level' factor. The second principal component appears instead to be a 'slope' factor and the loadings of the five portfolios on this component display a tendency to increase (monotonically for two of the output gap measures) from negative values for P_1 to positive values for P_5. Therefore, it is the second principal component that is key to explaining the cross-sectional difference in excess returns. These features of the factor structure resemble the features displayed by carry portfolios sorted on interest rate differentials, where the 'slope' factor is key to understanding carry trade excess returns. However, we also find that the second principal component for portfolios sorted on output gaps is orthogonal to the analogous '*Slope*' factor documented by Lustig, Roussanov, and Verdelhan (2011), confirming that sorting currencies on output gaps is very different from sorting currencies on interest rates.[11]

3.2 Why Can We Detect Exchange Rate Predictability?

The results in this section suggest a strong predictive link between the relative state of the business cycle and future currency excess returns, which is mainly driven by spot exchange rate predictability. Currencies of strong economies tend to appreciate, while currencies of weak economies tend to depreciate over the subsequent month. While this result is supportive of much theory of ex-

[11] In addition, we find that sorting on output gaps is very different from sorting on Taylor rule fundamentals. Specifically, we consider a standard Taylor rule with coefficients of 1.5 and 0.5 on inflation and the output gap respectively. We then use the implied interest rates to sort currencies. The results, presented in Table A3 in the Internet Appendix for the case of the HP-filtered output gap applied to the full sample period, suggest that this strategy provides impressive in-sample performance with Sharpe ratios of 0.9 and 0.65 in the cross section and time series, respectively. However, the resulting currency excess returns are highly correlated with carry excess returns (correlations of 0.84 and 0.51), suggesting that essentially sorting on Taylor rule fundamentals mimics a standard carry trade. More importantly, the returns from the output-gap-sorted strategy display modest correlations of 0.25 and 0.36 with the excess returns from sorting on Taylor rule fundamentals, indicating that the two sorts are different.

change rate determination that predicts the existence of a relationship between exchange rates and business cycles, it stands in sharp contrast with a large empirical literature – based generally on time series analysis – that has struggled to find evidence in favor of such a relationship. This sharp difference in results is due to our method of analysis, based on a portfolio setting. The portfolio results from the time series indicate that high output gap currencies *usually* appreciate – the output gap provides a better-than-chance prediction of future exchange rate movements and the size of the return increases with the output gap.

To further investigate this finding, we also calculate whether a market timing strategy that goes long (short) currencies with output gaps above the United States provides *statistically* significant evidence in favor of return predictability. To do so, we implement the z-score test of Henriksson and Merton (1981) across all observations in our sample. This statistic evaluates the directional accuracy of predictions and, specifically, tests the null hypothesis of no directional predictive ability against the alternative that there is some directional predictive ability. Thus, we calculate $p = r/n$, for which r is the number of correct forecasts and n is the total number of forecasts. If the output gap can predict the direction of exchange rate movements, we should reject the null hypothesis ($p = 0.5$) in favour of the alternative ($p > 0.5$). We evaluate this hypothesis by calculating the test statistic

$$Z = \frac{E[p] - 0.5}{\sqrt{Var[p]}} \sim \mathcal{N}(0, 1) \tag{4}$$

where $E[p] = r/n$ and $Var[p] = p(1-p)/n$. We report results in Table 4. Across the four methods for constructing output gaps, we find each offers predictability in the direction of both currency excess returns as well as exchange rate returns. The value of $E[p]$ ranges from 0.53 to 0.55, while the test statistics are large and highly statistically significant at the 1% level in all cases. These findings are consistent with the positive returns generated using a time-series portfolio strategy. When we run the same test on the 26 bilateral pairs we find, however, that for only 7 to 9 pairs do we observe predictability of currency excess returns that is statistically significant at the 5% level, and only between 6 and 9 offer spot exchange rate predictability. In contrast, between 15 and 24 (16 and 23) of currency pairs generate an $E[p]$ greater than 0.5 for excess returns (exchange rate returns), indicating the difficulty in overcoming statistical hurdles without sufficient statistical power. Therefore it is perhaps of little surprise, given the high volatility of exchange rates relative to macro fundamentals, that it is difficult to outperform a random walk on purely statistical grounds when using bilateral currency returns in a time series setting.

We provide further evidence of the time-series effect in Figure 2. In the top-left hand plot, we show the relationship between the distribution of output gaps (across all observations) and the subsequent average currency excess return. Following a monotonically increasing pattern, currencies with the highest output gaps (relative to the United States) tend to subsequently offer the highest currency excess returns. Focusing only on the time series, however, fails to consider whether there is also a "level" effect – Baz et al. (2015) show that cross-sectional strategies are, under certain conditions, equal to time-series strategies hedged for the level effect. In this case, the level represents the average conditional variable, i.e., the average output gap of each country against the United States.

In the top-middle and top-right plots in Figure 2, we consider the level effect by presenting the same information for periods in which the average output gap is above that in the United States ('strong foreign growth') and for periods in which the average output gap is below that in the United States ('weak foreign growth'). It can be seen that during relatively weak periods in the United States all foreign currencies tend to appreciate against the U.S. dollar – even those with *weaker* economies (i.e., with lower output gaps).

These results are consistent with parameter instability in time series studies. Similarly, negative output gap currencies depreciate substantially against the U.S. dollar when the United States is relatively strong compared to other countries. The time-series literature cannot account for these state-dependent coefficients, while the cross-sectional approach is immune to this issue and exploits the fact that the currencies of *relatively* strong economies tend to appreciate against the currencies of relatively weaker economies – ignoring any base (level) effect.

The time series and cross sectional relationships are highlighted further in the bottom three plots in Figure 2. They show the relationship between output gap differentials and average currency excess returns within three portfolios: weak economies (Portfolio 1), average growth economies (Portfolio 3), and strong economies (Portfolio 5). Within each portfolio, we see the monotonic time-series effect – stronger economies tend to offer higher subsequent returns. The cross-sectional effect can be seen by viewing the average relative output gap across portfolios. In Portfolio 5, even negative output gaps relative to the United States tend to be associated with positive returns, but in Portfolio 1 these same negative output gaps are associated with strongly negative returns, which a time series approach would not uncover.

4 Business Cycles and Currency Returns: Out-of-Sample

The results in the previous section are obtained in sample in the sense that the output gap is constructed using revised industrial production data across the full sample for each country, which is clearly unavailable in real time. In this section we analyze the investment performance of currency strategies that sort on output gaps by moving the analysis out of sample. To do so, we employ the linear projection procedure of Hamilton (2017) to construct the output gap recursively as we move through the sample. This procedure is applied to vintage data, which form the information set for industrial production data an investor could have used if implementing the strategy in real time, accounting for both delays in data releases and revisions. These vintage data are available from December 1999. In addition, for the cross-sectional strategy GAP_{CS}, we also construct portfolios based on linear weights and rank weights as implemented by Asness, Moskowitz, and Pedersen (2013), which allows us to trade all currencies available rather than just the corner portfolios. These portfolio construction schemes serve as useful checks that the performance is not generated purely by some outlier currencies. Furthermore, we analyze the impact of transaction costs.

In addition to analyzing the performance of currency strategies sorting on output gaps, we also compare the out-of-sample returns arising from these strategies to a number of other portfolio strategies. This is useful to assess whether sorting on output gaps simply recovers returns that can be obtained in other or simpler ways, or whether they constitute a novel source of exchange rate predictability which can offer diversification gains to investors. Therefore, before presenting the out-of-sample evidence, we describe other currency portfolio strategies which we use for comparison.

4.1 Alternative Currency Portfolios, Factors and Strategies

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.

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.

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 the 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 (FX) rate appreciation over the same period versus the U.S. dollar. To provide a more stable measure of the FX 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 FX 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.

Other Factors and Portfolios. In addition to the portfolios described above, we also compare the properties of the output-gap portfolios against other popular strategies and factors in the literature. These include: (i) the **Dollar** factor, proposed by Lustig, Roussanov, and Verdelhan (2011), which is essentially a market factor in currency space, equal to the average return of a large basket of foreign currencies against the U.S. dollar; (ii) the **Dollar Carry** strategy as proposed by Lustig, Roussanov, and Verdelhan (2014), which conditions the Dollar factor on the average forward premia of currencies against the U.S. and thus goes long (short) the U.S. dollar whenever interest rates are relatively high (low) in the United States; (iii) the **Global Imbalance** factor of Della Corte, Riddiough, and Sarno (2016), which is a factor that compensates investors for financing risky economies with large stocks of liabilities that issue the majority of those in foreign currency; (iv) the **Trend-Following** risk factors proposed by Fung and Hsieh (2001), which reflect the option-like returns typically generated by hedge funds (we use the FX and interest-rate trend-following returns); (v) the Pástor and Stambaugh (2003) measure of **Aggregate Market Liquidity**, and (vi) the **Market Risk Premium** collected from Kenneth French's website.[12]

[12]The hedge fund risk factors returns are available on David A. Hsieh's website at `http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls`. We collect liquidity data from Lubos Pastor's website at `http://faculty.chicagobooth.edu/lubos.pastor/research/` and market data from Kenneth French's website at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. We thank each author for making their data publicly available.

4.2 The Out-of-Sample Investment Performance

In Panel A of Table 5 we report the gross returns from implementing the GAP_{CS} strategy out of sample using high-minus-low portfolios, linear weights and rank portfolios. We also report the returns from implementing the time-series variant of this strategy, GAP_{TS}, and combinations of the GAP_{TS} strategy with the cross-sectional strategies. We observe that all but one investment strategy presented generate statistically significant returns at the 1% level. The Sharpe ratio of GAP_{CS} is 0.72 when using a high-minus-low strategy and when using rank weights, while it is slightly higher at 0.74 when using linear weights. GAP_{TS} generates a Sharpe ratio of 0.65 out of sample, and the Sharpe ratio always increases when the cross-sectional strategies are combined with the GAP_{TS} strategy, reaching 0.82. This is due to the fact that the correlation between GAP_{CS} and GAP_{TS} is positive but far from perfect.[13]

In Panel B of Table 5 we report results in the same format as Panel A for returns net of transaction costs, i.e. accounting for bid-ask spreads.[14] The Sharpe ratio for GAP_{CS} goes down from 0.72 to 0.50 when adjusting for bid-ask spreads, and the Sharpe ratio for GAP_{TS} reduces from 0.65 to 0.50, while the combination of GAP_{CS} and GAP_{TS} generates a Sharpe ratio of about 0.60. In short, transaction costs do not wipe out the performance of strategies that sort on output gaps out of sample, and the Sharpe ratios remain attractive even after accounting for transaction costs, so that qualitatively the out-of-sample results are identical with and without accounting for costs.[15]

The results in Table 5 also confirm that the predictive power stems mainly from spot rate

[13]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 output-gap-strategy out-of-sample from the separate perspectives of Eurozone, British, Japanese, and Swiss investors. The results, reported in Table A5 in the Internet Appendix, indicate no qualitative changes to our results based on a U.S. perspective.

[14]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.

[15]In Table A4 we again consider portfolios obtained on the basis of interest rates implied by Taylor rules, exactly as for Table A3 but using real-time data for the out-of-sample period. While the results confirm the attractive investment performance of the Taylor rule strategy, they also confirm the in-sample result shown in Table A3, that this strategy is very highly correlated with the carry trade while being only modestly correlated with our strategy sorting on output gaps.

predictability rather than interest rate differentials: approximately 90% of the total return is delivered from the FX component across all portfolios considered. Therefore the basic features of exchange rate predictability recorded in sample appear to hold out of sample.

4.3 Relationship with Other Strategies

Table 6 reports a battery of correlation coefficients between the returns from the strategies sorting on output gap, and the various combinations examined in Table 5, with the returns from a variety of currency strategies and equity-based strategies. The results are reported for returns obtained out of sample for all strategies. The main point arising from this table is that the returns of each variant of the GAP_{CS} strategy, the GAP_{TS} strategy and their combinations are generally uncorrelated, or only mildly correlated, with any of the strategies and factors considered. For example, for the GAP_{CS} strategy the correlations range from zero (for the U.S. equity market) to 0.24 (for the Dollar factor), and they are of similar magnitude for each variant of our strategy. This result suggests the strategies sorting on output gap contain novel economic information and seem unlikely to be a mechanical relabelling of an existing currency strategy or factor.

4.4 Diversification Gains

Taken together, the previous results suggest that the GAP_{CS} 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 the GAP_{CS} strategy 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_{CS} strategy for a currency investor, we combine it with various canonical currency strategies and assess its value added in terms of performance. In Panel A of Table 7 we first show the out-of-sample returns from carry, dollar carry, momentum, and value strategies during our sample period. We can see that the value strategy performs worse during this sample, with a Sharpe ratio of basically zero, and carry performs best with a

Sharpe ratio of 0.58. We also consider a strategy that combines the above four canonical strategies with equal weights (EW). This generates a higher Sharpe ratio of 0.74 relative to each individual strategy by exploiting (albeit simplistically with equal weights) the imperfect correlation of returns across the individual strategies. In essence, the results in Panel A of Table 7 provide us with a benchmark on performance of standard currency strategies, and we ask whether combining them with the GAP_{CS} strategy improves performance and to what extent. We report results in Panel B of Table 7, both when we combine each individual strategy with GAP_{CS} and when we add GAP_{CS} to the equally-weighted strategy alongside carry, dollar carry, momentum, and value. The results indicate that adding the GAP_{CS} strategy to this menu of strategies delivers substantially higher Sharpe ratios. For example, the Sharpe ratio of the carry trade improves from 0.58 to 0.85, and the equally-weighted strategy which includes all four benchmark strategies and GAP_{CS} delivers a Sharpe ratio of 0.87, in contrast to 0.74 that is obtained when GAP_{CS} is excluded.

Overall, we view these findings as a confirmation of the value the GAP_{CS} strategy adds when included in a currency portfolio, driven by its desirable return and correlation properties with existing currency-based strategies.

5 Asset Pricing and Implications

In this section, we begin by investigating if a range of alternative pricing models can explain the returns generated by output-gap sorted portfolios. The purpose of this analysis is to evaluate whether the relationship between currency returns and business cycles can be understood from a risk-return perspective. We go on to consider the role business cycles may also play as a novel source of risk, motivated by the broad macro-finance literature and the inherent link between the stochastic discount factor (SDF) and aggregate macroeconomic conditions, before discussing the implications and challenges for future theoretical work.

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:

$$E_t[M_{t+1} RX^j_{t+1}] = 0 \tag{5}$$

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

$$M_{t+1} = 1 - b' \left(f_{t+1} - \mu \right) \tag{6}$$

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

$$E[RX^j] = \lambda' \beta^j \tag{7}$$

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}.

5.1 Pricing Output-Gap Portfolios

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 then consider various second factors, including: the slope factor (CAR) proposed by Lustig, Roussanov, and Verdelhan (2011); the global imbalance factor (IMB) of Della Corte, Riddiough, and Sarno (2016); the volatility factor (VOL) of Menkhoff et al. (2012a), in its factor-mimicking version[16]; and a GAP factor constructed simply as the excess return from the GAP_{CS} strategy. The GAP

[16] Specifically, we construct a tradeable version of the VOL factor as the fitted values in a regression of global FX volatility risk on currency returns following the procedure implemented by Menkhoff et al. (2012a).

factor essentially measures the excess returns generated by sorting currencies on the output gap information (i.e., the return to the GAP_{CS} strategy), and is increasing in the spread of output gaps across the world: it is therefore a measure of the return arising from divergence in business cycles, so that the more business cycles diverge across countries the more the currencies of fast-growing countries appreciate. Our test assets are the five output-gap sorted currency portfolios obtained using out-of-sample conditioning information as described in Section 4. The portfolio returns therefore begin in January 2000 and end in January 2016. We later expand the test assets to consider larger cross sections, given that asset pricing tests tend to have low power in small cross sections of assets.

Cross-Sectional Regressions. Table 8 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, the Root Mean Squared Error (RMSE), 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^2_1 distributed random variables (see, Jagannathan and Wang, 1996; Ren and Shimotsu, 2009). The p-values of the HJ distance measure are reported in brackets.

In Panel A of Table 8 we report results for two-factor SDF models that include DOL and, in turn, the carry factor CAR, the volatility risk factor VOL, the global imbalance risk factor IMB, and the GAP_{CS} factor. The results suggest none of the pricing factors are statistically significant at conventional significance levels (both in terms of factor loading and price of risk) with the exception of the GAP_{CS} factor. The models involving CAR, VOL and IMB also show fairly low explanatory power in terms of the cross-sectional R^2 (never greater than 42%), which is surprising considering the relative ease in achieving *high* R^2 statistics when test assets are characterized by a strong factor structure (Lewellen, Nagel, and Shanken, 2010). In contrast, the SDF involving DOL and GAP_{CS} generates a high R^2 of 72% and a substantially lower RMSE relative to other SDF specifications, indicating that the pricing errors are much lower. The p-values from the HJ distance measure are always above 5% with the exception of the SDF involving CAR. However, this is likely due to the low power of the HJ statistic in our small cross section of five test assets and, in the absence of statistical significance of factor loadings and risk prices for all risk factors other than GAP_{CS}, this result cannot be viewed as supportive of these pricing models.

The results also confirm that DOL offers no pricing power (beyond acting as a constant in the model), as evidenced by not contributing significantly to explaining variation in the SDF. This finding is consistent with the findings of Lustig, Roussanov, and Verdelhan (2011) when pricing interest-rate-sorted portfolios. Overall, the results in Table 8 suggest that the only factor that can price the currency excess returns obtained from sorting on output gaps is GAP_{CS} and that conventional risk factors from the currency literature are not priced. This finding highlights the novelty of the returns and the need for alternative risk factors to account for this cross section.

5.2 A Business Cycle Factor?

Next, we consider further the possibility that the returns from portfolios sorted on output gaps are compensation for risk linked to the relative state of business cycle conditions. The theoretical link between aggregate macroeconomic conditions and asset prices is fundamental to the study of asset pricing, and most classes of risk-based models require the SDF to be a function of the business cycle (see Cochrane, 2017, for a comprehensive review and reconciliation of the link between business cycles and the *second* priced factor across asset pricing models).[17] Specifically, we carry out asset pricing tests from two SDF specifications: a two-factor model including DOL and CAR, which is the most common benchmark in the literature since its introduction by Lustig,

[17] In complementary work, Maurer, To, and Tran (2016) use the currency market as a setting to empirically estimate country-specific SDFs and a document a linear relationship with domestic output gaps.

Roussanov, and Verdelhan (2011), and a three-factor model which also includes the GAP_{CS} factor. This allows to gauge the incremental pricing power of a business cycle factor beyond the carry factor benchmark.

Test Portfolios. We consider three sets of test portfolios, increasing in the number of portfolios. We first consider the five output-gap-sorted portfolios (as in Table 8), which constitute a small set of test assets for the purpose of asset pricing tests. However, 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. We conduct the asset pricing tests both without the pricing factors in the test assets (Panel A of Table 9) and including them (Panel B of Table 9). Lewellen, Nagel, and Shanken (2010) advocate adding risk factors as test assets to ensure the factors price themselves (i.e., $\lambda \approx E[R_{factor}]$).

Cross-Sectional Regressions. Starting from Panel A of Table 9, 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.[18] We know from Table 8 that this SDF specification cannot price the returns from output gap-sorted portfolios. We find that this SDF, which is known to be powerful at pricing carry portfolios, also does not explain satisfactorily the other cross sections considered. Specifically, the factor loading on CAR is statistically insignificant from zero, and the R^2 is low. The HJ distance test does not indicate a rejection of the model in two cases but, with an insignificant factor loading and low R^2, the HJ

[18]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 was confirmed in Table 8 and occurs with our results in Table 9 as well.

distance result cannot be considered as supportive of the SDF.

When augmenting the SDF specification with the GAP_{CS} factor, we find that both the loading and the price of risk for the GAP_{CS} factor enter with positive and statistically significant coefficients. Moreover, the factor loading on CAR continues to be statistically insignificant. The R^2 for the three-factor model including the DOL, CAR and GAP_{CS} factors is substantially higher (in the range between 68% and 73%) and the RMSE is substantially lower than the two-factor specification that excludes GAP_{CS}.

In Panel B of Table 9 we carry out the same tests while augmenting the test assets to include CAR in the two-factor SDF, and both CAR and GAP_{CS} in the three-factor SDF. The results are qualitatively identical to those in Panel A. Specifically, while we observe statistically significant risk prices for CAR, this is due to the inclusion of CAR as a test asset. The factor loading on CAR remains imprecisely estimated, although it is significant at the ten percent level in the case of five test assets. More importantly, the results from the three-factor model indicate that the addition of the GAP_{CS} factor leads to statistically significant factor loadings and risk prices on GAP_{CS}, much higher R^2 and much lower RMSE than the two-factor specifications.[19]

5.3 Theoretical Implications

The asset pricing results suggest that standard risk factors used in the literature cannot explain the returns from currency portfolios that sort on output gaps. However, the business cycle risk factor we have employed does so, and also appears to be priced in other cross sections of currency returns which are notoriously difficult to price (e.g. momentum). This result is supportive of the broad macro-finance literature that predicts a tight link between business cycle risk and asset returns, including long-run risk models, rare disaster models, and habit models (Cochrane, 2017). On the other hand, this literature typically predicts a close relationship between business cycles and interest rates, and aims at explaining returns to the carry trade (Colacito and Croce, 2013; Farhi and Gabaix, 2016; Ready, Roussanov, and Ward, 2017; Richmond, 2016).

The lack of correlation between the returns to the carry trade strategy (and also momentum

[19] In the Internet Appendix Tables A6 and A7, we present the equivalent results for the IMB and VOL risk factors. In Table A8, we present the asset pricing results for the same set of test portfolios but for which the SDF is a two-factor linear combination of DOL and GAP_{CS} factors.

and value) and the returns from the GAP_{CS} strategy pose a challenge to these existing theories. Accounting for this lack of correlation requires richer macro-finance models which can generate persistent differentials in interest rates across countries (to explain carry trades) while at the same time allowing for currency excess returns to offer compensation for divergence in business cycles.[20] Most likely, achieving this task requires moving beyond models with a single shock, which generate a tight connection between carry and business cycles. Moreover, most international macro-finance models are endowment economies, where the output gap plays no role (e.g., Verdelhan, 2010), whereas most international models with production economies and a meaningful account of the output gap (like a new Keynesian model) either do not have risk premia or cannot account very well for the failure of uncovered interest rate parity (Obstfeld and Rogoff, 1995; Cavallo and Ghironi, 2002; Clarida, Gali, and Gertler, 2002). In essence, understanding deeply the facts established in our paper requires an international macro-finance theory of exchange rate determination with endogenous risk premia and, most likely, two sources of shocks. This constitutes a serious and important challenge for theory in this area.

6 Conclusions

The results in this paper are supportive of a strong link between relative business cycles and currency returns. The relationship is evident in-sample and out-of-sample, in both the time series and cross section, and is driven almost entirely by the foreign exchange rate return rather than nominal interest rate differentials. Any theoretical explanation for the relationship between currency excess returns and business cycles must therefore be different from a carry trade based explanation.

The results stand in contrast to the well-known difficulty of predicting foreign exchange returns using macroeconomic variables. Our approach is different and uses relative information and portfolio-based economic evaluation. We show the results improve for two reasons. First, in the time series, while there is statistical predictability of foreign exchange *direction*, it is only evident once all observations are pooled – bilateral predictability still appears elusive. Critically,

[20] Colacito et al. (2017) provide promising theoretical developments in accounting for highly persistent interest rate differentials that may provide a foundation for incorporating additional important empirical facts.

the economic evaluation via portfolios reduces volatility, increases the power of the test and thus magnifies the pooled statistical predictability. Second, in the cross section, our relative sorting procedure is immune from level effects, which determine the relationship between business cycles and currency returns over time and across states. But these level effects matter: when the United States is relatively weak, all currencies tend to appreciate, even those with comparatively weaker economies than the United States. These effects are not captured using standard time-series predictive regressions.

The return predictability we document is useful for global investors seeking novel sources of portfolio diversification. The output-gap based portfolio has zero correlation with the carry trade and close to zero correlations with all other currency trading strategies we consider. Furthermore, output gap portfolios do not appear to offer compensation for risks documented in the literature to date. The macro-finance theoretical literature has, however, the central feature that business cycles are inherently related to stochastic discount factors and thus risk loadings. And indeed, we find that a factor created using our approach is not only priced in the cross section of output-gap-sorted portfolios, but also in other cross sections including currency carry, value and momentum portfolios. We thus provide the first tentative evidence supportive of this link in the broad international asset pricing literature.

The evidence in this paper points towards several directions for future theoretical work. First, we highlight the need to break the link between the aggregate state of the macro-economy and carry-based theories – carry-based theories need to incorporate very persistent interest-rate differentials that mean-revert over much longer periods than do relative business cycles. Second, to account for both carry and output-gap returns requires multiple-shock models and thus multiple sources of return premia, possibly across bonds and currency markets. Finally, the results indicate the need for a meaningful output gap to be modelled in international finance theory and thus for deviations from aggregate trend growth to play a role in asset price determination.

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Table 1: Descriptive Statistics of In-Sample Output-Gap-Sorted Portfolios

The table presents descriptive statistics for five currency portfolios sorted by output gaps. The output gap at time t is estimated as (log) industrial production at t minus the (log) trend in industrial production at t. The trend is estimated in four ways using a (i) Hodrick-Prescott filter; (ii) Baxter-King filter, (iii) linear projection and (iv) quadratic time trend. Portfolios are rebalanced monthly with strong (weak) economy currencies entering P_5 (P_1). We report summary statistics for the annualized excess mean return and its decomposition between the exchange rate (*fx*) and interest rate (*ir*) components. We also report the Sharpe ratio (*Sharpe*), standard deviation (*std*), skewness (*skew*), kurtosis (*kurt*), maximum drawdown (*mdd*), average turnover (*t/o*), average forward premium (*fp*) and average output gap (*gap*) for each portfolio. The *Cross Section* portfolio is long P_5 and short P_1. The *Time Series* portfolio takes a 1/N position in currencies, going long (short) currencies issued by countries with an output gap above (below) the United States' output gap. The superscripts *, **, *** represent significance of the *Cross Section* and *Time Series* portfolios at the 10%, 5% and 1% level using Newey and West (1987) standard errors. The sample is from October 1983 to January 2016.

Hodrick-Prescott Filter	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**Cross Section**	**Time Series**
mean (%)	-0.25	0.96	2.77	4.00	6.41	6.66***	2.45***
fx (%)	*-2.34*	*-1.03*	*0.88*	*1.58*	*2.72*	*5.06*	*2.03*
ir (%)	*2.09*	*1.99*	*1.89*	*2.41*	*3.69*	*1.60*	*0.41*
Sharpe	-0.02	0.11	0.27	0.43	0.71	0.82	0.54
std	10.18	9.09	10.12	9.32	9.05	8.14	4.57
skew	-0.06	-0.47	-0.28	-0.27	-0.28	0.01	-0.92
kurt	4.49	4.72	4.75	4.39	3.97	4.32	10.89
mdd (%)	42.5	34.2	23.9	23.6	24.4	9.0	8.6
t/o (%)	44.8	58.2	67.2	60.6	44.8		
fp (t, %)	2.23	2.03	1.80	2.45	4.15		
gap (t, %)	-3.08	-0.96	0.11	1.17	3.01		

Baxter-King Filter	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**Cross Section**	**Time Series**
mean (%)	-0.44	2.45	2.39	3.72	5.97	6.41***	3.83***
fx (%)	*-2.34*	*0.65*	*0.49*	*1.23*	*1.92*	*4.26*	*3.38*
ir (%)	*1.90*	*1.80*	*1.90*	*2.49*	*4.06*	*2.15*	*0.44*
Sharpe	-0.04	0.26	0.26	0.39	0.68	0.77	0.74
std	10.15	9.50	9.33	9.51	8.82	8.31	5.21
skew	-0.08	0.06	-0.21	-0.29	-0.61	0.07	-0.39
kurt	3.94	3.83	4.32	4.22	5.00	4.25	5.70
mdd (%)	49.0	28.8	26.1	24.6	21.8	23.0	9.2
t/o (%)	10.0	21.8	29.8	23.1	11.6		
fp (t, %)	1.91	1.87	1.75	2.38	4.81		
gap (t, %)	-2.75	-0.84	0.18	1.30	3.01		

Linear Projection	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**Cross Section**	**Time Series**
mean (%)	0.46	2.85	2.23	3.18	5.41	4.95***	3.72***
fx (%)	*-2.25*	*0.93*	*0.27*	*1.13*	*1.95*	*4.20*	*3.36*
ir (%)	*2.71*	*1.92*	*1.96*	*2.05*	*3.46*	*0.74*	*0.37*
Sharpe	0.05	0.32	0.23	0.33	0.56	0.66	0.72
std	9.80	8.91	9.59	9.65	9.63	7.47	5.18
skew	-0.24	-0.24	-0.50	-0.07	-0.54	-0.34	-1.23
kurt	4.66	5.21	4.79	3.58	5.44	5.13	10.94
mdd (%)	40.4	28.4	31.8	29.4	19.1	35.3	11.6
t/o (%)	26.0	43.8	52.7	44.5	26.4		
fp (t, %)	2.68	2.01	1.90	2.17	3.97		
gap (t, %)	-1.33	-0.30	0.31	0.90	1.98		

Quadratic Time Trend	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**Cross Section**	**Time Series**
mean (%)	0.27	1.99	3.08	4.21	4.83	4.56***	2.14**
fx (%)	*-1.04*	*-0.16*	*0.02*	*1.54*	*1.75*	*2.80*	*1.95*
ir (%)	*1.31*	*2.15*	*3.06*	*2.67*	*3.08*	*1.76*	*0.19*
Sharpe	0.03	0.21	0.32	0.49	0.51	0.60	0.41
std	10.05	9.58	9.76	8.66	9.53	7.56	5.27
skew	-0.23	-0.21	-0.07	-0.51	-0.15	-0.68	-1.24
kurt	4.23	4.58	4.29	4.50	5.02	6.29	10.93
mdd (%)	38.9	28.5	31.1	24.8	21.5	18.3	16.5
t/o (%)	20.0	32.9	44.3	33.8	19.7		
fp (t, %)	1.17	2.04	3.15	2.87	3.35		
gap (t, %)	-8.41	-3.35	-0.22	2.59	7.78		

Table 2: The Correlation and Factor Structure of Output Gap Measures

The table presents the average cross-sectional correlation and factor structure in output gaps. The output gap at time t is estimated as (log) industrial production at t minus the (log) trend in industrial production at t. The trend is estimated in four ways using a (i) Hodrick-Prescott filter; (ii) Baxter-King filter, (iii) linear projection and (iv) quadratic time trend. In Panel A, the entries below the diagonal are linear Pearson correlations, which are calculated by taking the time-series average of monthly cross-sectional correlations for all available currencies. The entries above the diagonal are Spearman rank correlations, also calculated by taking the time-series average of monthly cross-sectional correlations for all available currencies. In Panel B, we present the average percentage of the cross-sectional variation accounted for by each principal component (PC). To calculate this, we estimate the variation explained by each PC each month and then take a time-series average across all months in the sample. The sample is from October 1983 to January 2016.

Panel A: Output-Gap Correlations

	HP	**BK**	**LP**	**QT**
Hodrick-Prescott Filter (HP)		0.63	0.51	0.41
Baxter-King Filter (BK)	0.65		0.55	0.53
Linear Projection (LP)	0.54	0.56		0.47
Quadratic Time-trend (QT)	0.45	0.58	0.48	

Panel B: Output-Gap Factor Structure

	$\mathbf{PC_1}$	$\mathbf{PC_2}$	$\mathbf{PC_3}$	$\mathbf{PC_4}$
var explained	86%	10%	3%	1%

Table 3: Principal Components of Output-Gap-Sorted Portfolios

The table presents results from a principal component decomposition of the returns to five currency portfolios sorted by output gaps. The output gap at time t is estimated as (log) industrial production at t minus the (log) trend in industrial production at t. The trend is estimated in four ways using a (i) Hodrick-Prescott filter; (ii) Baxter-King filter, (iii) linear projection and (iv) quadratic time trend. Portfolios are rebalanced monthly with strong (weak) economy currencies entering P_5 (P_1). We report the loading of each portfolio on all five principal components (PCs) and the percentage of total return variation explained by each PC. The sample is from October 1983 to January 2016.

Hodrick-Prescott Filter

	$\mathbf{PC_1}$	$\mathbf{PC_2}$	$\mathbf{PC_3}$	$\mathbf{PC_4}$	$\mathbf{PC_5}$
P_1	0.47	-0.71	0.46	-0.08	-0.23
P_2	0.43	-0.19	-0.33	0.00	0.82
P_3	0.49	0.18	-0.25	0.75	-0.32
P_4	0.44	0.19	-0.47	-0.64	-0.38
P_5	0.40	0.63	0.63	-0.11	0.19
var explained	78%	8%	5%	5%	4%

Baxter-King Filter

	$\mathbf{PC_1}$	$\mathbf{PC_2}$	$\mathbf{PC_3}$	$\mathbf{PC_4}$	$\mathbf{PC_5}$
P_1	0.48	-0.51	0.69	0.11	-0.16
P_2	0.46	-0.18	-0.24	-0.26	0.79
P_3	0.45	-0.18	-0.52	-0.39	-0.59
P_4	0.46	0.25	-0.27	0.81	-0.02
P_5	0.38	0.78	0.36	-0.34	-0.05
var explained	79%	7%	6%	4%	4%

Linear Projection

	$\mathbf{PC_1}$	$\mathbf{PC_2}$	$\mathbf{PC_3}$	$\mathbf{PC_4}$	$\mathbf{PC_5}$
P_1	0.45	-0.85	0.00	0.04	-0.26
P_2	0.42	-0.03	-0.39	-0.15	0.80
P_3	0.45	0.40	-0.57	-0.19	-0.53
P_4	0.46	0.27	0.25	0.81	0.04
P_5	0.45	0.21	0.68	-0.53	0.00
var explained	78%	7%	6%	5%	4%

Quadratic Time Trend

	$\mathbf{PC_1}$	$\mathbf{PC_2}$	$\mathbf{PC_3}$	$\mathbf{PC_4}$	$\mathbf{PC_5}$
P_1	0.48	-0.08	0.70	-0.34	-0.40
P_2	0.47	-0.10	0.24	0.21	0.82
P_3	0.45	-0.52	-0.60	-0.40	-0.04
P_4	0.40	-0.10	-0.13	0.80	-0.41
P_5	0.43	0.84	-0.29	-0.17	-0.02
var explained	78%	7%	6%	5%	4%

Table 4: Can Output Gaps Predict the Direction of Currency Premia and Foreign Exchange Rate Returns?
The table presents evidence on the directional predictability of currency premia and foreign exchange rate returns following Henriksson and Merton (1981). At the end of each month we forecast the return over the following month to be positive if the output gap is larger than in the United States. The output gap at time t is estimated as (log) industrial production at t minus the (log) trend in industrial production at t. The trend is estimated in four ways using a (i) Hodrick-Prescott filter; (ii) Baxter-King filter, (iii) linear projection and (iv) quadratic time trend. We calculate $E[p]$ using the full-sample of data, where $p = r/n$, r is the number of correct predictions and n is the total number of predictions. The test statistics (*test stat*) is given by $Z = \frac{E[p]-0.5}{\sqrt{Var[p]}} \sim \mathcal{N}(0,1)$, where $Var[p] = p(1-p)/n$. A value > 1.64 indicates the null hypothesis (no directional predictability) can be rejected at the 5% significance level. We also report the bilateral success rate. This reflects the number of bilateral currency pairs for which $p > 0.5$. We also report the bilateral significance, which indicates the number of bilateral currency pairs for which the null hypothesis (no directional predictability) can be rejected at the 5% significance level. The sample is from October 1983 to January 2016.

	Hodrick Prescott	Baxter King	Linear Projection	Quadratic Time Trend
	currency excess returns			
E[p]	0.54***	0.55***	0.54***	0.53***
test stat	6.10	7.45	6.64	5.08
bilateral success	24/26	19/26	24/26	15/26
bilateral significance	7/26	7/26	9/26	7/26
	foreign exchange returns			
E[p]	0.53***	0.54***	0.54***	0.53***
test stat	5.05	6.48	6.02	4.97
bilateral success	23/26	19/26	23/26	16/26
bilateral significance	6/26	8/26	9/26	6/26

Table 5: The Out-of-Sample Investment Performance of Currency Trading Strategies
The table presents investment performance for output gap currency trading strategies. The output gap is estimated using monthly 'vintages' of real-time industrial production data from the OECD's *Real-Time Data and Revisions Database*. To estimate the output-gap we follow the linear projection procedure in Hamilton (2017) by running the regression, $y_{i,t} = \alpha_i + \sum_{s=0}^{11} \beta_{i,s} y_{i,t-24-s} + \varepsilon_{i,t}$ each month, in which y is (log) industrial production. The output gap is constructed as the difference between the most recently available data point at time t (y_t) and the fitted value from the regression. GAP_{CS} is a *high-minus-low* portfolio formed as $P_5 - P_1$, after sorting currencies into five portfolios. LIN and RNK take a position in all currencies with the weight determined by either the magnitude or relative size of the output gap. GAP_{TS} is a 1/N time-series strategy long (short) currencies issued by countries with an output gap above (below) the United States' output gap. The three COM portfolios take 50−50 weights in GAP_{TS} and the GAP_{CS}, LIN and RNK strategies. We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components, we also report the Sharpe ratio (*Sharpe*), skewness (*skew*), kurtosis (*kurt*) and maximum drawdown (*mdd*). The superscripts *, **, *** represent significance of the strategies' mean excess returns at the 10%, 5% and 1% significance levels using Newey and West (1987) corrected standard errors. The sample runs from December 1999 to January 2016.

Panel A: Investment Performance *Excluding* Bid-Ask Spreads

	GAP_{CS}	LIN	RNK	GAP_{TS}	COM_{GAP}	COM_{LIN}	COM_{RNK}
mean (%)	4.92***	2.16***	3.88***	2.76**	3.82***	2.45***	3.30***
fx (%)	4.21	1.74	3.38	2.83	3.50	2.26	3.08
ir (%)	0.71	0.42	0.49	-0.07	0.33	0.19	0.22
Sharpe	0.72	0.74	0.72	0.65	0.82	0.82	0.82
skew	0.31	0.34	0.25	-0.70	-0.01	-0.46	-0.23
kurt	2.83	3.23	3.24	5.17	3.02	3.49	3.25
mdd (%)	6.88	2.91	5.40	4.27	4.66	2.97	4.03

Panel B: Investment Performance *Including* Bid-Ask Spreads

	GAP_{CS}	LIN	RNK	GAP_{TS}	COM_{GAP}	COM_{LIN}	COM_{RNK}
mean (%)	3.46**	1.45**	2.50**	2.14*	2.79**	1.78**	2.31**
fx (%)	3.10	1.19	2.34	2.37	2.71	1.76	2.33
ir (%)	0.36	0.25	0.15	-0.22	0.08	0.03	-0.02
Sharpe	0.50	0.50	0.46	0.50	0.60	0.60	0.57
skew	0.31	0.33	0.24	-0.70	-0.01	-0.46	-0.24
kurt	2.81	3.20	3.22	5.19	3.01	3.50	3.26
mdd (%)	6.86	2.91	5.39	4.27	4.66	2.97	4.03

Table 6: Correlations Between Trading Strategies

The table presents linear correlation coefficients between trading strategies. In the upper panel we report correlations between output gap currency trading strategies. The output gap is estimated using monthly 'vintages' of real-time industrial production data from the OECD's *Real-Time Data and Revisions Database*. To estimate the output-gap we follow the linear projection procedure in Hamilton (2017) by running the regression, $y_{i,t} = \alpha_i + \sum_{s=0}^{11} \beta_{i,s} y_{i,t-24-s} + \varepsilon_{i,t}$ each month, in which y is (log) industrial production. The output gap is constructed as the difference between the most recently available data point at time t (y_t) and the fitted value from the regression. GAP_{CS} is a *high-minus-low* portfolio formed as $P_5 - P_1$, after sorting currencies into five portfolios. LIN and RNK take a position in all currencies with the weight determined by either the magnitude or relative size of the output gap. GAP_{TS} is a 1/N time-series strategy long (short) currencies issued by countries with an output gap above (below) the United States' output gap. The three COM portfolios take 50−50 weights in the GAP_{TS} and the GAP_{CS}, LIN and RNK strategies. In the lower panel we present correlations between the output gap currency trading strategies and various currency and equity-based strategies. We include full details of these strategies in Section 4. The sample runs from December 1999 to January 2016.

Output Gap Currency Trading Strategies

	GAP_{CS}	LIN	RNK	GAP_{TS}	COM_{GAP}	COM_{LIN}	COM_{RNK}
High-Minus-Low GAP_{CS}							
Linear Weights (LIN)	0.86						
Rank Weights (RNK)	0.88	0.93					
GAP_{TS}	0.36	0.34	0.38				
GAP Model Combo (COM_{GAP})	0.90	0.79	0.83	0.73			
LIN Model Combo (COM_{LIN})	0.68	0.74	0.73	0.89	0.91		
RNK Model Combo (COM_{RNK})	0.78	0.81	0.87	0.79	0.94	0.96	

Alternative Trading Strategies in Currency and Equity Markets

	GAP_{CS}	LIN	RNK	GAP_{TS}	COM_{GAP}	COM_{LIN}	COM_{RNK}
HML_{fx}	0.06	0.07	0.02	0.02	0.06	0.05	0.03
Dollar	0.24	0.21	0.22	0.23	0.28	0.27	0.27
Dollar Carry	0.23	0.21	0.22	0.23	0.28	0.27	0.27
Value	0.15	0.03	0.13	0.04	0.13	0.05	0.11
Momentum	0.07	0.15	0.08	-0.06	0.02	0.03	0.02
Global Imbalance	0.13	0.12	0.10	0.23	0.20	0.22	0.18
Foreign Exchange Trend Strategy	0.08	0.08	0.08	0.07	0.09	0.09	0.09
Interest Rate Trend Strategy	0.07	0.12	0.13	-0.22	-0.05	-0.10	-0.03
Illiquidity	0.08	0.12	0.04	0.21	0.15	0.21	0.14
U.S. Equity	0.00	-0.04	-0.01	0.10	0.05	0.06	0.05

Table 7: Diversification Benefits

The table presents the investment performance of common currency trading strategies and the impact on performance from adding the GAP_{CS} strategy. The output gap is estimated using monthly 'vintages' of real-time industrial production data from the OECD's *Real-Time Data and Revisions Database*. To estimate the output gap we follow the linear projection procedure in Hamilton (2017) by running the regression, $y_{i,t} = \alpha_i + \sum_{s=0}^{11} \beta_{i,s} y_{i,t-24-s} + \varepsilon_{i,t}$ each month, in which y is (log) industrial production. The output gap is constructed as the difference between the most recently available data point at time t (y_t) and the fitted value from the regression. GAP_{CS} is a *high-minus-low* portfolio formed as $P_5 - P_1$, after sorting currencies into five portfolios. In Panel A, we report the investment performance of popular currency investment strategies, in which CAR is the currency carry trade; $DCAR$ is the "dollar carry" trade; MOM is a momentum trade; VAL is a value trade and EW is a 1/N portfolio that takes an equal position in each individual currency strategy. We include full details of these strategies in Section 4. In Panel B, we add the GAP_{CS} strategy to each individual strategy and to the broader equally-weighted (EW) portfolio. We report summary statistics for the annualized excess mean return, the Sharpe ratio (*Sharpe*), standard deviation (*std*), skewness (*skew*), kurtosis (*kurt*), maximum drawdown, percentage increase in Sharpe ratio (%Δ Sharpe) and weight in the GAP_{CS} portfolio (w_{GAP}). The superscripts *, **, *** represent significance of the strategies' mean excess returns at the 10%, 5% and 1% confidence levels using Newey and West (1987) corrected standard errors. The sample runs from December 1999 to January 2016.

Panel A: Excluding Output Gap Strategy

	CAR	DCAR	MOM	VAL	EW
mean (%)	6.34**	2.60	1.41	0.05	2.60***
Sharpe	0.58	0.31	0.16	0.01	0.74
std	10.91	8.51	9.01	8.65	3.53
skew	-0.72	-0.49	0.28	0.47	-0.24
kurt	5.23	4.78	3.31	4.42	4.13
mdd (%)	0.16	0.17	0.23	0.39	0.07

Panel B: Including Output Gap Strategy

	GAP_{CS}+ CAR	GAP_{CS}+ DCAR	GAP_{CS}+ MOM	GAP_{CS}+ VAL	EW
mean (%)	5.61***	3.74***	3.15**	2.47*	3.06***
Sharpe	0.85	0.62	0.54	0.42	0.87
std	6.64	6.07	5.87	5.93	3.53
skew	-0.11	-0.30	0.34	0.54	0.12
kurt	4.38	3.91	3.57	5.10	4.20
mdd (%)	0.07	0.09	0.08	0.19	0.06
%Δ *Sharpe*	45.6	102	243	7625	17.7
w_{GAP} *(%)*	50.0	50.0	50.0	50.0	20.0

Table 8: Asset Pricing Output Gap Portfolios

The table presents cross-sectional asset pricing results. We construct various two-factor linear SDF's that include the DOL factor plus a second pricing factor, including carry (CAR), global imbalance (IMB), volatility (VOL), and GAP_{CS}. In each model, we price five output-gap sorted currency portfolios. 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% significance levels using Newey and West (1987) corrected standard errors. We also report goodness-of-fit statistics for each model including the R^2 statistic, Root Mean Squared Pricing Error (RMSE) 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. We provide full details of the pricing factors in Section 5. The sample runs from December 1999 to January 2016.

	SDF Loadings (b)		**Risk Prices (λ)**		**Model Fit**		
	DOL	FAC	DOL	FAC	R^2	RMSE	HJ_{dist}
DOL + CAR	0.22	0.19	0.02	0.03	0.11	1.69	0.22
							[0.03]
DOL + IMB	-1.39	7.52	0.04*	0.26	0.42	1.59	0.19
							[0.61]
DOL + VOL	-3.22	-40.52	0.03	-0.03	0.40	1.51	0.21
							[0.47]
DOL + GAP_{CS}	0.08	0.83***	0.02	0.05***	0.72	0.95	0.13
							[0.35]

Table 9: Asset Pricing with a Business Cycle Risk Factor

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-side) and DOL, CAR and GAP_{CS} (3 pricing factors, right-side). In Panel B, we include the CAR and GAP_{CS} pricing factors as test assets. 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% significance 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 sample runs from December 1999 to January 2016.

Panel A: Excluding Pricing Factors as Test Portfolios

	2 Pricing Factors ($DOL + CAR$)							**3 Pricing Factors** ($DOL + CAR + \text{GAP}_{\text{CS}}$)								
	Loadings (b)		**Risk Prices** (λ)		**Model Fit**			**Loadings** (b)			**Risk Prices** (λ)			**Model Fit**		
	DOL	CAR	DOL	CAR	R^2	RMSE	HJ_{dist}	DOL	CAR	GAP_{CS}	DOL	CAR	GAP_{CS}	R^2	RMSE	HJ_{dist}
5 TPs (gap)	0.22	0.19	0.02	0.03	0.11	1.69	0.22 [0.03]	0.07	0.14	0.82***	0.02	0.03	0.05***	0.73	0.94	0.13 [0.20]
10 TPs (val, mom)	0.19	0.08	0.02	0.01	-0.05	1.32	0.22 [0.81]	-0.31	0.43	2.57**	0.02	0.07	0.14**	0.73	0.67	0.16 [0.96]
20 TPs (gap, car, val, mom)	0.18	0.36	0.02	0.05*	0.34	1.36	0.33 [0.99]	-0.02	0.35	1.05***	0.02	0.06**	0.06***	0.68	0.94	0.30 [0.99]

Panel B: Including Pricing Factors as Test Portfolios

	2 Pricing Factors ($DOL + CAR$)							**3 Pricing Factors** ($DOL + CAR + \text{GAP}_{\text{CS}}$)								
	Loadings (b)		**Risk Prices** (λ)		**Model Fit**			**Loadings** (b)			**Risk Prices** (λ)			**Model Fit**		
	DOL	CAR	DOL	CAR	R^2	RMSE	HJ_{dist}	DOL	CAR	GAP_{CS}	DOL	CAR	GAP_{CS}	R^2	RMSE	HJ_{dist}
5 TPs (gap)	0.20	0.45*	0.02	0.07**	0.56	1.56	0.22 [0.15]	0.05	0.42*	0.82***	0.02	0.07**	0.05***	0.87	0.82	0.31 [0.89]
10 TPs (val, mom)	0.16	0.41	0.02	0.06**	0.45	1.37	0.23 [0.80]	-0.02	0.40	0.97***	0.02	0.06**	0.06***	0.75	0.96	0.19 [0.91]
20 TPs (gap, car, val, mom)	0.17	0.41	0.02	0.06**	0.51	1.34	0.69 [0.91]	0.00	0.40	0.91***	0.02	0.06**	0.05***	0.78	0.92	0.69 [0.98]

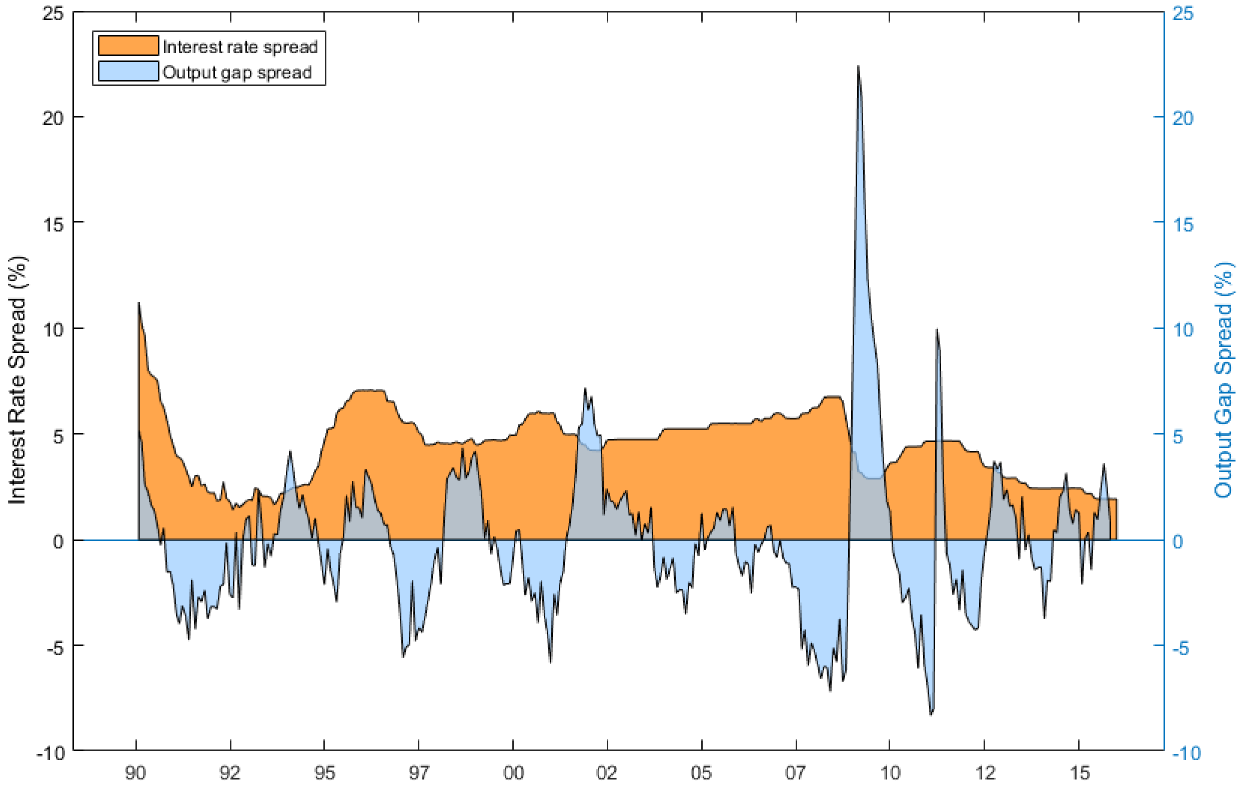
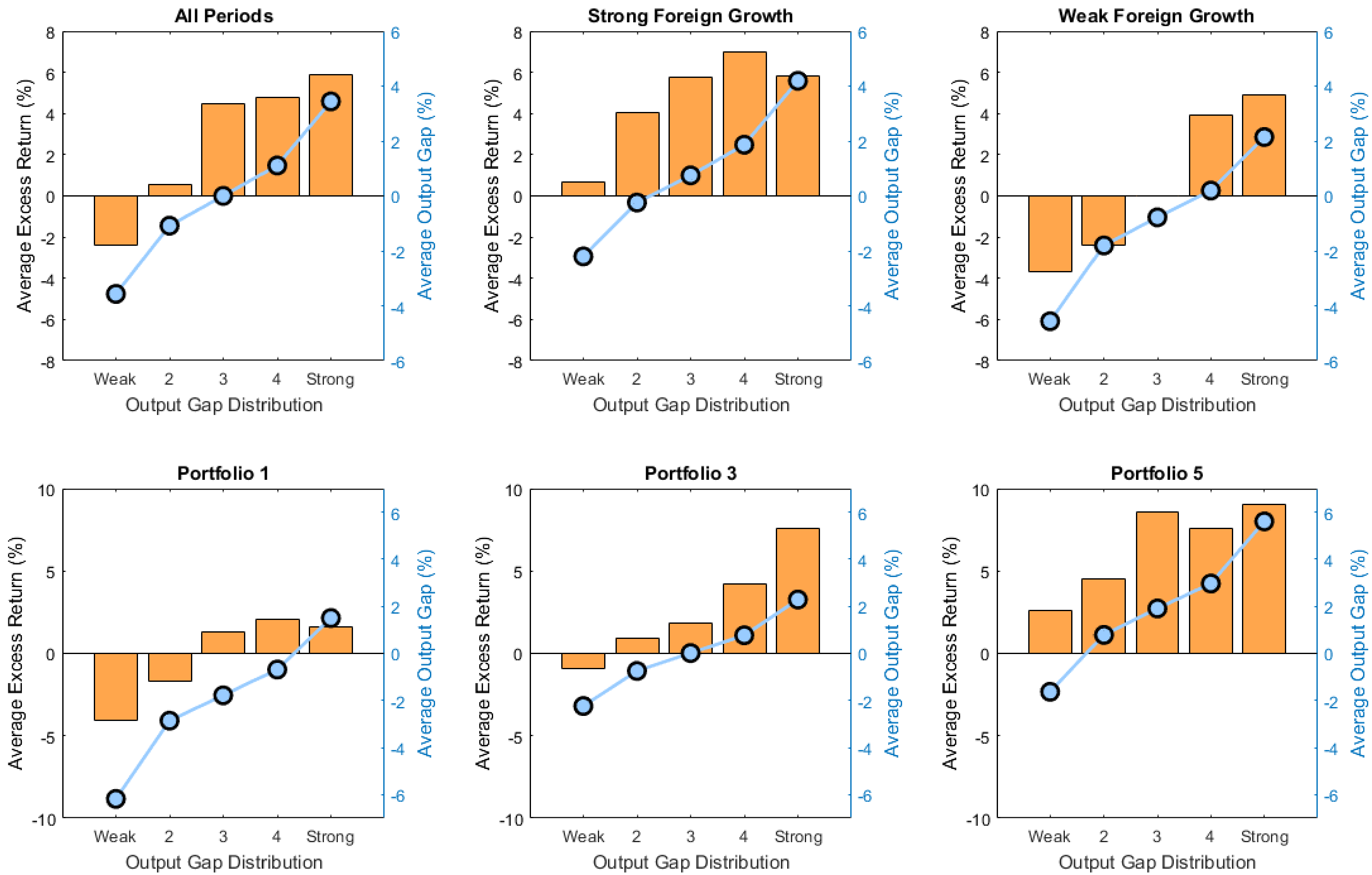


Figure 1: Australian and Japanese Interest Rate and Output Gap Spreads
The figure plots the interest-rate- and output-gap-spread between Australia and Japan. The interest-rates reflect one-month euro-deposit rates, while the output gaps are calculated using the Hodrick-Prescott filter. When a series is above the origin, it indicates the Australian value is higher (i.e., either a higher interest rate or output gap).

Figure 2: Excess Currency Returns and the Distribution of Output Gaps

The figure plots the average excess currency return at time t, conditional on the output gap observed at time t-1. For each plot, we sort observed output gaps and subsequent currency excess returns across a set of observations from the lowest (weakest) output gap to the highest (strongest) output gap. We split the data into five quintiles and report the average excess currency return (orange bar) and average output gap (blue line). The 'All Periods' figure includes every observation in the sample. The 'Strong' ('Weak') Foreign Growth sample includes all observations in which the average output gap of all countries is above (below) that in the United States. In the lower-half of the figure, we plot the figures in which the observations are restricted to particular portfolio allocations. For example, the observations in Portfolio 1 reflect the lowest output gaps at any given point that would have been allocated to Portfolio 1, when sorting currencies into five equally weighted portfolios as in Table 1.



INTERNET APPENDIX

Business Cycles and Currency Returns

NOT FOR PUBLICATION

Estimating the Output Gap In-Sample

Hodrick-Prescott Filter

The Hodrick-Prescott filter minimizes the following expression to produce a new time series of trend output, $y^{tr}_{i,t}$

$$\sum_{t=1}^{T}(y_{i,t} - y^{tr}_{i,t})^2 + \lambda \sum_{t=2}^{T-1}[(y^{gr}_{i,t+1} - y^{gr}_{i,t}) - (y^{tr}_{i,t} - y^{tr}_{i,t-1})]^2 \tag{8}$$

where $y_{i,t}$ is the logarithm of industrial production at time t for country i, λ is a weighing factor to control the smoothness of the trend line. The lower the value of λ, the more the resulting trend will resemble the raw data series. We follow the suggestion of Hodrick and Prescott (1980) and Prescott and Kydland (1990) and set $\lambda = 1600$ to smooth quarterly data and $\lambda = 14400$ to smooth monthly data. The output gap (cyclical component) is then constructed as the difference between $y_{i,t}$ and the trend series extracted from the filter $c_{i,t} = y_{i,t} - y^{tr}_{i,t}$.

Baxter-King Filter

The Baxter-King filter is removes both low and high frequency components from a time series. Specifically it involves the estimation of the moving average model

$$\hat{y}_{i,t} = \sum_{n=-K}^{K} B_n x_{t-n}$$

The values B_n can be estimated using an inverse Fourier transform such that they minimize the mean squared error between y_t and $\hat{y}_t$ (see Priestley, 1981). We follow the suggestion of Baxter and King (1999) and set K=12 for quarterly data and K=36 for monthly data. We also set standard upper and lower limits for the cutoff frequency of 6 and 32 quarters for quarterly data and 8 and 96 months for monthly data.

Linear Projection

We follow the linear projection method proposed by Hamilton (2017) and project (log) industrial production at time t on 12-lags of industrial production beginning 24-months earlier[1]

$$y_{i,t} = \alpha_i + \sum_{s=0}^{11} \beta_{i,s} y_{i,t-24-s} + \varepsilon_{i,t}$$

The output gap (cyclical component) is then constructed as the difference between $y_{i,t}$ and the fitted value from the above regression $c_{i,t} = y_{i,t} - \hat{y}_{i,t}$.

[1]For quarterly industrial production time series we project onto four lags beginning eight-quarters earlier.

Quadratic Time Trend

The quadratic time trend projects the logarithm of industrial production on a time trend t and quadratic time trend t^2

$$y_{i,t} = \alpha_i + \beta_{i,1}t + \beta_{i,2}t^2 + \varepsilon_{i,t}$$

The output gap (cyclical component) is then constructed as the difference between $y_{i,t}$ and the fitted value from the above regression $c_{i,t} = y_{i,t} - \hat{y}_{i,t}$.

Table A1: Foreign Exchange Rate Data

			DataStream Codes				
Country	**Code**	**Currency**	**Spot**	**1M Forward**	**Source**	**Start Date**	**End Date**
Austria	ATS	schilling	AUSTSC$	USATS1F	Reuters	31/12/1996	31/12/1998
Australia	AUD	dollar	BBAUDSP	BBAUD1F	Barclays	31/12/1984	31/01/2016
Belgium	BEF	franc	BELGLU$	USBEF1F	Reuters	31/12/1996	31/12/1998
Brazil	BRL	real	BRACRU$	USBRL1F	Reuters	31/03/2004	31/01/2016
Canada	CAD	dollar	BBCADSP	BBCAD1F	Barclays	31/12/1984	31/01/2016
Switzerland	CHF	franc	BBCHFSP	BBCHF1F	Barclays	31/10/1983	31/01/2016
Chile	CLP	peso	CHILPE$	USCLP1F	Reuters	31/03/2004	31/01/2016
Czech Republic	CZK	koruna	TDCZKSP	TDCZK1M	Reuters	31/12/1996	31/01/2016
Germany*	DEM	deutschemark	BBDEMSP	BBDEM1F	Barclays	31/10/1983	31/01/2016
Spain	ESP	peseta	SPANPE$	USESP1F	Reuters	31/12/1996	31/12/1998
Finland	FIM	markka	FINMAR$	USFIM1F	Reuters	31/12/1996	31/12/1998
France	FRF	franc	BBFRFSP	BBFRF1F	Barclays	31/10/1983	31/12/1998
UK	GBP	pound	BBGBPSP	BBGBP1F	Barclays	31/10/1983	31/01/2016
Ireland	IEP	punt	BBIEPSP	BBIEP1F	Barclays	31/10/1993	31/12/1998
Iceland	ISK	krona	ICEKRO$	USISK1F	Reuters	31/03/2004	31/01/2016
Italy	ITL	lira	BBITLSP	BBITL1F	Barclays	31/03/1984	31/12/1998
Japan	JPY	yen	BBJPYSP	BBJPY1F	Barclays	31/10/1983	31/01/2016
South Korea	KRW	won	KORSWO$	USKRW1F	Reuters	28/02/2002	31/01/2016
Mexico	MXN	peso	MEXPES$	USMXN1F	Reuters	31/12/1996	31/01/2016
Netherlands	NLG	guilder	BBNLGSP	BBNLG1F	Barclays	31/10/1983	31/12/1998
Norway	NOK	krone	BBNOKSP	BBNOK1F	Barclays	31/12/1984	31/01/2016
New Zealand	NZD	dollar	BBNZDSP	BBNZD1F	Barclays	31/12/1984	31/01/2016
Poland	PLN	zloty	TDPLNSP	TDPLN1M	Reuters	31/08/1996	31/01/2016
Portugal	PTE	escudo	PORTES$	USPTE1F	Reuters	31/12/1996	31/12/1998
Sweden	SEK	krona	BBSEKSP	BBSEK1F	Barclays	31/12/1984	31/01/2016
Turkey** (first lira)	TRY	lira	TURKLI$	USTRY1F	Reuters	31/12/1996	31/10/2000
Turkey (second lira)	TRY	lira	TURKLI$	USTRY1F	Reuters	31/03/2004	31/01/2016

* We replace the German deutschemark with the euro after 1998.
** We remove the period of hyperinflation in Turkey due to large deviations from CIP.

Table A2: Descriptive Statistics of Carry-Trade Portfolios

The table presents descriptive statistics for five currency portfolios sorted by forward premia. Portfolios are rebalanced monthly with high (low) interest rate currencies entering P_5 (P_1). We report summary statistics for the annualized excess mean return and its decomposition between the exchange rate (*fx*) and interest rate (*ir*) components. We also report the Sharpe ratio (*Sharpe*), standard deviation (*std*), skewness (*skew*), kurtosis (*kurt*), maximum drawdown (*mdd*), average turnover (*t/o*), average forward premium (*fp*) and average output gap (*gap*) for each portfolio. The *Cross Section* portfolio is long P_5 and short P_1. The *Time Series* portfolio takes a 1/N position in currencies, going long (short) currencies issued by countries with an interest rate above (below) the United States' interest rate. The superscripts *, **, *** represent significance of the *Cross Section* and *Time Series* portfolios at the 10%, 5% and 1% level using Newey and West (1987) standard errors. The sample is from October 1983 to January 2016.

	Taylor Rule					**Cross**	**Time**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**Section**	**Series**
mean (%)	-0.63	1.02	3.88	2.83	7.17	7.80***	4.43***
fx (%)	*1.58*	*1.35*	*2.54*	*-0.40*	*-3.05*	*-4.63*	*0.85*
ir (%)	*-2.20*	*-0.33*	*1.34*	*3.22*	*10.22*	*12.43*	*3.59*
Sharpe	-0.06	0.11	0.42	0.29	0.68	0.72	0.79
std	9.80	9.30	9.23	9.72	10.49	10.87	5.60
skew	0.26	-0.09	-0.29	-0.48	-0.63	-0.93	-1.14
kurt	3.80	3.73	5.12	4.85	5.56	5.30	9.32
mdd (%)	54.0	32.6	23.2	27.8	19.9	19.8	8.2
t/o (%)	18.5	25.6	29.6	24.1	13.5		
fp (t, %)	-2.15	-0.32	1.25	3.25	10.94		
gap (t, %)	-0.04	0.02	0.08	-0.05	0.30		

Table A3: Descriptive Statistics of Taylor-Rule Portfolios

The table presents descriptive statistics for five currency portfolios sorted by their Taylor-rule implied interest rate. The Taylor rule at time t is calibrated to equal $1.5\pi_t + 0.5y_t$, where π is inflation and y is the in-sample output gap calculated using a Hodrick-Prescott filter. Portfolios are rebalanced monthly with high (low) implied interest rate currencies entering P_5 (P_1). We report summary statistics for the annualized excess mean return and its decomposition between the exchange rate (*fx*) and interest rate (*ir*) components. We also report the Sharpe ratio (*Sharpe*), standard deviation (*std*), skewness (*skew*), kurtosis (*kurt*), maximum drawdown (*mdd*), average turnover (*t/o*), average forward premium (*fp*) and average output gap (*gap*) for each portfolio. The *Cross Section* portfolio is long P_5 and short P_1. The *Time Series* portfolio takes a 1/N position in currencies, going long (short) currencies issued by countries with a Taylor-rule implied interest rate above (below) the United States' Taylor-rule implied interest rate. The superscripts *, **, *** represent significance of the *Cross Section* and *Time Series* portfolios at the 10%, 5% and 1% level using Newey and West (1987) standard errors. We also report the correlation of the *Cross Section* and *Time Series* portfolios with the equivalent portfolios when sorted on output gaps as in Table 1 (ρ_{GAP}) and interest rates as in Table A1 (ρ_{CAR}). The sample is from October 1983 to January 2016.

	Taylor Rule					**Cross**	**Time**
	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$	**Section**	**Series**
mean (%)	-1.52	1.19	4.25	2.68	7.45	8.97***	2.75***
fx (%)	*-0.56*	*1.07*	*2.74*	*0.16*	*-1.67*	*-1.11*	*0.32*
ir (%)	*-0.96*	*0.12*	*1.51*	*2.52*	*9.12*	*10.08*	*2.43*
Sharpe	-0.16	0.12	0.45	0.28	0.75	0.90	0.65
std	9.59	9.79	9.36	9.45	9.92	9.92	4.25
skew	0.16	-0.10	-0.33	-0.42	-0.55	-0.42	-1.04
kurt	4.05	3.88	4.79	4.35	4.57	4.85	9.99
mdd (%)	61.3	34.7	25.2	28.8	20.6	13.8	11.2
t/o (%)	24.94	40.92	43.48	33.17	12.94		
fp (t, %)	-0.85	0.19	1.37	2.50	9.87		
gap (t, %)	-1.59	-0.18	0.36	0.50	1.11		
ρ_{GAP}						0.25	0.36
ρ_{CAR}						0.84	0.51

Table A4: The Out-of-Sample Investment Performance of Taylor-Rule Trading Strategies

The table presents investment performance for Taylor-rule based trading strategies. The Taylor rule at time t is calibrated to equal $1.5\pi_t + 0.5y_t$, where π is inflation and y is the out-of-sample output gap calculated using monthly 'vintages' of real-time industrial production data from the OECD's *Real-Time Data and Revisions Database.* To estimate the output-gap we follow the linear projection procedure in Hamilton (2017) by running the regression, $y_{i,t} = \alpha_i + \sum_{s=0}^{11} \beta_{i,s} y_{i,t-24-s} + \varepsilon_{i,t}$ each month, in which y is (log) industrial production. The output gap is constructed as the difference between the most recently available data point at time t (y_t) and the fitted value from the regression. CS is a *high-minus-low* portfolio formed as $P_5 - P_1$, after sorting currencies into five portfolios. LIN and RNK take a position in all currencies with the weight determined by either the magnitude or relative size of the implied interest rate. TS is a 1/N time-series strategy long (short) currencies issued by countries with an implied rate above (below) the United States' implied rate. The three COM portfolios take 50−50 weights in TS and the CS, LIN and RNK strategies. We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components, we also report the Sharpe ratio (*Sharpe*), skewness (*skew*), kurtosis (*kurt*) and maximum drawdown (*mdd*). The superscripts *, **, *** represent significance of the strategy mean excess returns at the 10%, 5% and 1% significance levels using Newey and West (1987) corrected standard errors. We also report the correlation of the portfolios with the equivalent portfolios when sorted on output gaps as in Table 5 (ρ_{GAP}) and interest rates (ρ_{CAR}). The sample runs from December 1999 to January 2016.

Panel A: Investment Performance *Excluding* Bid-Ask Spreads

	CS	LIN	RNK	TS	COM_{CS}	COM_{LIN}	COM_{RNK}
mean (%)	6.05**	3.24***	4.68**	3.40**	4.73***	3.33***	4.04***
fx (%)	-2.34	-1.23	-1.49	1.48	-0.41	0.15	0.02
ir (%)	8.39	4.47	6.17	1.92	5.13	3.18	4.02
Sharpe	0.63	0.73	0.64	0.79	0.77	0.87	0.78
skew	-0.25	-0.70	-0.25	-0.19	-0.22	-0.52	-0.34
kurt	3.35	6.06	3.34	5.70	3.27	4.51	3.61
mdd (%)	9.57	4.47	7.34	4.31	6.17	3.84	5.21
ρ_{GAP}	0.24	0.18	0.17	0.21	0.26	0.23	0.23
ρ_{CAR}	0.79	0.87	0.83	0.44	0.77	0.69	0.74

Panel B: Investment Performance *Including* Bid-Ask Spreads

	CS	LIN	RNK	TS	COM_{CS}	COM_{LIN}	COM_{RNK}
mean (%)	4.75*	2.52**	3.37*	2.78***	3.77**	2.65***	3.08**
fx (%)	-3.34	-1.78	-2.49	1.02	-1.14	-0.36	-0.71
ir (%)	8.09	4.30	5.85	1.77	4.91	3.01	3.79
Sharpe	0.50	0.57	0.46	0.65	0.61	0.69	0.59
skew	-0.26	-0.73	-0.27	-0.21	-0.23	-0.54	-0.35
kurt	3.37	6.15	3.36	5.74	3.28	4.55	3.64
mdd (%)	9.55	4.45	7.32	4.30	6.16	3.83	5.20
ρ_{GAP}	0.24	0.18	0.17	0.21	0.26	0.23	0.23
ρ_{CAR}	0.79	0.87	0.83	0.44	0.77	0.69	0.74

Table A5: The Out-of-Sample Investment Performance of Currency Trading Strategies with Alternative Base Currencies

The table presents investment performance for output gap currency trading strategies from the perspective of German, Japanese, British and Swiss investors. The output gap is estimated using monthly 'vintages' of real-time industrial production data from the OECD's *Real-Time Data and Revisions Database*. To estimate the output-gap we follow the linear projection procedure in Hamilton (2017) by running the regression, $y_{i,t} = \alpha_i + \sum_{s=0}^{11} \beta_{i,s} y_{i,t-24-s} + \varepsilon_{i,t}$ each month, in which y is (log) industrial production. The output gap is constructed as the difference between the most recently available data point at time t (y_t) and the fitted value from the regression. GAP_{CS} is a *high-minus-low* portfolio formed as $P_5 - P_1$, after sorting currencies into five portfolios. LIN and RNK take a position in all currencies with the weight determined by either the magnitude or relative size of the output gap. GAP_{TS} is a 1/N time-series strategy long (short) currencies issued by countries with an output gap above (below) the United States' output gap. The three COM portfolios take $50-50$ weights in GAP_{TS} and the GAP_{CS}, LIN and RNK strategies. We report summary statistics for the annualized mean, which is then further split between the exchange rate (*fx*) and interest rate (*ir*) components, we also report the Sharpe ratio (*Sharpe*), skewness (*skew*), kurtosis (*kurt*) and maximum drawdown (*mdd*). The superscripts *, **, *** represent significance of the strategies' mean excess returns at the 10%, 5% and 1% significance levels using Newey and West (1987) corrected standard errors. The sample runs from December 1999 to January 2016.

Panel A: German Investor

	GAP_{CS}	LIN	RNK	GAP_{TS}	COM_{GAP}	COM_{LIN}	COM_{RNK}
mean (%)	5.61***	2.24***	3.88***	1.76**	3.73***	2.05***	2.87***
fx (%)	4.84	1.72	3.26	2.25	3.57	2.01	2.78
ir (%)	0.77	0.52	0.62	-0.49	0.16	0.03	0.09
Sharpe	0.79	0.76	0.72	0.50	0.80	0.74	0.73

Panel B: Japanese Investor

	GAP_{CS}	LIN	RNK	GAP_{TS}	COM_{GAP}	COM_{LIN}	COM_{RNK}
mean (%)	4.49***	1.93***	3.40***	4.19**	4.41***	3.13***	3.86***
fx (%)	4.08	1.61	3.07	3.68	3.92	2.68	3.41
ir (%)	0.41	0.32	0.33	0.51	0.49	0.44	0.45
Sharpe	0.66	0.68	0.67	0.61	0.82	0.77	0.80

Panel C: British Investor

	GAP_{CS}	LIN	RNK	GAP_{TS}	COM_{GAP}	COM_{LIN}	COM_{RNK}
mean (%)	4.98***	2.27***	4.12***	1.51**	3.26***	1.91***	2.83***
fx (%)	4.51	1.87	3.70	1.24	2.87	1.55	2.47
ir (%)	0.47	0.41	0.41	0.27	0.39	0.36	0.36
Sharpe	0.72	0.77	0.77	0.40	0.69	0.66	0.71

Panel D: Swiss Investor

	GAP_{CS}	LIN	RNK	GAP_{TS}	COM_{GAP}	COM_{LIN}	COM_{RNK}
mean (%)	6.35***	2.32***	4.25***	0.66	3.55***	1.54**	2.50***
fx (%)	5.43	1.76	3.59	1.21	3.35	1.51	2.42
ir (%)	0.92	0.56	0.66	-0.55	0.21	0.03	0.08
Sharpe	0.91	0.81	0.81	0.14	0.73	0.48	0.59

Table A6: Asset Pricing with a Business Cycle Risk Factor

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 IMB (2 pricing factors, left-side) and DOL, IMB and GAP_{CS} (3 pricing factors, right-side). In Panel B, we include the IMB and GAP_{CS} pricing factors as test assets. 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% significance 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 sample runs from December 1999 to January 2016.

Panel A: Excluding Pricing Factors as Test Portfolios

	2 Pricing Factors ($DOL + IMB$)							**3 Pricing Factors** ($DOL + IMB + \mathrm{GAP_{CS}}$)								
	Loadings (b)		**Risk Prices** (λ)		**Model Fit**			**Loadings** (b)			**Risk Prices** (λ)			**Model Fit**		
	DOL	IMB	DOL	IMB	R^2	RMSE	HJ_{dist}	DOL	IMB	$\mathrm{GAP_{CS}}$	DOL	IMB	$\mathrm{GAP_{CS}}$	R^2	RMSE	HJ_{dist}
5 TPs (gap)	-1.39	7.52	0.04*	0.26	0.42	1.59	0.19 [0.19]	-0.80	4.51	0.73	0.04*	0.16	0.06***	0.74	1.07	0.15 [0.43]
10 TPs (val, mom)	-0.13	2.04	0.03	0.08*	0.20	1.20	0.20 [0.92]	-0.27	1.26	1.85*	0.03	0.05	0.11*	0.65	0.80	0.14 [0.98]
20 TPs (gap, car, val, mom)	-0.20	2.43*	0.03	0.09**	0.49	1.35	0.41 [0.98]	-0.28	2.03	0.93**	0.03	0.08**	0.06***	0.70	1.04	0.37 [0.99]

Panel B: Including Pricing Factors as Test Portfolios

	2 Pricing Factors ($DOL + IMB$)							**3 Pricing Factors** ($DOL + IMB + \mathrm{GAP_{CS}}$)								
	Loadings (b)		**Risk Prices** (λ)		**Model Fit**			**Loadings** (b)			**Risk Prices** (λ)			**Model Fit**		
	DOL	IMB	DOL	IMB	R^2	RMSE	HJ_{dist}	DOL	IMB	$\mathrm{GAP_{CS}}$	DOL	IMB	$\mathrm{GAP_{CS}}$	R^2	RMSE	HJ_{dist}
5 TPs (gap)	0.13	1.28***	0.04*	0.05***	0.25	1.70	0.25 [0.15]	-0.02	1.19**	0.85***	0.04*	0.05***	0.06***	0.73	0.99	0.36 [0.89]
10 TPs (val, mom)	0.05	1.36***	0.03	0.05***	0.23	1.18	0.20 [0.96]	-0.10	1.24**	0.96***	0.03	0.05***	0.06***	0.62	0.85	0.16 [0.99]
20 TPs (gap, car, val, mom)	-0.01	1.65**	0.04	0.06***	0.43	1.41	0.41 [0.99]	-0.13	1.47**	0.91***	0.04	0.06***	0.06***	0.68	1.05	0.47 [0.99]

Table A7: Asset Pricing with a Business Cycle Risk Factor
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-side) and DOL, VOL and GAP_{CS} (3 pricing factors, right-side). In Panel B, we include the VOL and GAP_{CS} pricing factors as test assets. 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% significance 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 sample runs from December 1999 to January 2016.

Panel A: Excluding Pricing Factors as Test Portfolios

	2 Pricing Factors ($DOL+VOL$)							**3 Pricing Factors** ($DOL+VOL+\text{GAP}_{\text{CS}}$)								
	Loadings (b)		**Risk Prices** (λ)		**Model Fit**			**Loadings** (b)			**Risk Prices** (λ)			**Model Fit**		
	DOL	VOL	DOL	VOL	R^2	RMSE	HJ_{dist}	DOL	VOL	GAP_{CS}	DOL	VOL	GAP_{CS}	R^2	RMSE	HJ_{dist}
5 TPs (gap)	-3.22	-40.52	0.03	-0.03	0.40	1.51	0.21 [0.47]	4.58	52.69	1.61	0.03	0.04	0.05***	0.77	0.94	0.13 [0.62]
10 TPs (val, mom)	-0.02	-3.37	0.02	0.00	-0.07	1.29	0.21 [0.85]	-0.89	-7.93	2.40**	0.02	-0.01*	0.14**	0.72	0.67	0.17 [0.95]
20 TPs (gap, car, val, mom)	-0.56	-9.64	0.03	-0.01**	0.34	1.42	0.37 [0.99]	-0.65	-8.38	1.04***	0.02	-0.01**	0.07***	0.64	1.05	0.34 [0.99]

Panel B: Including Pricing Factors as Test Portfolios

	2 Pricing Factors ($DOL+VOL$)							**3 Pricing Factors** ($DOL+VOL+\text{GAP}_{\text{CS}}$)								
	Loadings (b)		**Risk Prices** (λ)		**Model Fit**			**Loadings** (b)			**Risk Prices** (λ)			**Model Fit**		
	DOL	VOL	DOL	VOL	R^2	RMSE	HJ_{dist}	DOL	VOL	GAP_{CS}	DOL	VOL	GAP_{CS}	R^2	RMSE	HJ_{dist}
5 TPs (gap)	-1.58*	-21.68**	0.03	-0.02***	0.58	1.49	0.38 [0.03]	-0.23	-4.35	0.83**	0.03	-0.01	0.05***	0.83	0.99	0.36 [0.84]
10 TPs (val, mom)	-0.09	-4.10	0.02	-0.01	0.37	1.25	0.30 [0.57]	-0.35	-5.03	0.95***	0.02	-0.01	0.06***	0.74	0.89	0.25 [0.73]
20 TPs (gap, car, val, mom)	-0.57	-9.70	0.03	-0.01**	0.45	1.39	0.38 [0.99]	-0.63	-8.45	0.88**	0.02	-0.01**	0.06***	0.72	1.02	0.43 [0.99]

Table A8: Asset Pricing with a Business Cycle Risk Factor

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_{CS}. In Panel B, we include the GAP_{CS} pricing factors as a test asset. 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% significance 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 sample runs from December 1999 to January 2016.

Panel A: Excluding Pricing Factor as Test Portfolio

	2 Pricing Factors ($DOL + \mathrm{GAP_{CS}}$)						
	Loadings (b)		**Risk Prices** (λ)		**Model Fit**		
	DOL	$\mathrm{GAP_{CS}}$	DOL	$\mathrm{GAP_{CS}}$	R^2	RMSE	HJ_{dist}
5 TPs (gap)	0.08	0.83***	0.02	0.05***	0.72	0.95	0.13 [0.35]
10 TPs (val, mom)	-0.15	1.96**	0.02	0.11*	0.50	0.91	0.17 [0.95]
20 TPs (gap, car, val, mom)	0.02	1.06***	0.02	0.06***	0.38	1.31	0.33 [0.99]

Panel B: Including Pricing Factor as Test Portfolio

	2 Pricing Factors ($DOL + \mathrm{GAP_{CS}}$)						
	Loadings (b)		**Risk Prices** (λ)		**Model Fit**		
	DOL	$\mathrm{GAP_{CS}}$	DOL	$\mathrm{GAP_{CS}}$	R^2	RMSE	HJ_{dist}
5 TPs (gap)	0.08	0.84***	0.02	0.05***	0.80	0.86	0.31 [0.87]
10 TPs (val, mom)	0.03	0.94***	0.02	0.05***	0.57	1.00	0.19 [0.89]
20 TPs (gap, car, val, mom)	0.04	0.93***	0.02	0.05***	0.46	1.29	0.42 [0.99]