Currency Investing Throughout Recent Centuries*

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Abstract

The literature on currency investing generally bases its analysis on the most recent period since 1983 and uses short-term bills as the investment vehicle. I analyze the risk and return characteristics of currency investing over an extended period using data that reaches back as far as 1788, and I extend the analysis to long-term bonds. Excess returns on currencies have been predictable throughout history across various periods and robust to using long-term bonds. The risk premia estimates indicate nominal exchange rates are not stationary and are informative about the time-variations in the pricing kernel in a reduced-form pricing model.

1 Introduction

A rapidly growing literature in finance is uncovering various ways in which currency investments produce high positive excess returns. The most often studied strategy is the currency carry trade, which goes long currencies with high interest rates and goes short currencies with low interest rates. Lustig, Roussanov, and Verdelhan (2014) introduce a version of the carry trade called the 'dollar carry trade', which focuses on the carry trade of a single currency and shows it also produces high positive premia. A series of papers by Menkhoff, Sarno, Schmeling, and Schrimpf (2012a, 2017) and Asness, Moskowitz, and Pedersen (2013) document momentum and reversal effects in currency markets. Ang and Chen (2017) use the slope of the yield curve (term spread), while Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) use the volatility of exchange rates to document additional variables that predict excess returns in currency investments.

In addition, extensive literature in international finance has debated the stationarity of nominal exchange rates. As early as Hansen and Hodrick (1980) and Fama (1984), empirical analysis of currency returns has indicated that nominal exchange rates are not stationary.[1] . Non-stationarity implies that international financial markets have a long-run component that is ever-evolving and not in equilibrium. These empirical studies have focused on using the forward exchange rates, or equivalently short-term interest rates (short rates). Recent work by Lustig, Stathopoulos, and Verdelhan (2019) argues that using long-term interest rates (long bonds) presents a puzzling result: short rates suggest that nominal exchange rates are stationary, but long bonds do not. However, any investigation of long-run stationarity would benefit from a longer historical perspective.

Common across these studies is that they use a relatively limited history of data.

[1] In contrast, the stationarity of real exchange rates is generally well established.

Almost every study begins after 1973, following the end of the Bretton Woods system when major currencies began to float freely. While underlying economics might differ under fixed versus floating currency exchange regimes, there is no ex-ante reason to exclude observations based on exchange regimes. In fact, capturing multiple regimes, business cycles, and rare events is critical for understanding the nature of economic equilibrium. Yet, the most common starting point for these studies is 1983, when data on forward exchange rates, which embeds short-term interest rates, became available from commonly accessed data providers. A notable exception is Accominotti, Cen, Chambers, and Marsh (2019), who extend forward exchange rate data back to 1919 but only study the carry trade. Using forward exchange rate data has the advantage that it accounts for transaction costs from the perspective of a hypothetical arbitrageur. However, an arbitrageur's perspective is not the correct perspective for understanding the underlying economic sources of risk premia in currency investments. In fact, as an alternative, abstracting away from implementability concerns and using historical interest rates rather than forward exchange rates allows for a broader study of the historical performance of currency investing.

I develop a comprehensive historical view of returns on currency investing that spans over two centuries and reach back as far as 1788. In order to conduct this study, I abstract away fully from various implementability concerns. Admittedly, this is purely a historical thought experiment since I ignore constraints that a historical arbitrageur would have faced. I frame the results in the context of a reduced-form model, but even such framework requires an assumption that financial markets are complete. In addition to transaction costs, there also would have been binding constraints that would have prevented free movement of capital across countries.

Furthermore, a wide enough cross-section of historical short rates is only available from around 1854. Rather than an experiment where capital is stored at the short rate, an alternative experiment is one where capital is invested in a different asset, such as long bonds. This alternative allows for an additional robustness test and allows for even longer historical data. Unfortunately, returns on long bonds must be inferred from changes in recorded yields and may reflect additional risk premia for exposures to sovereign default risk or other economic sources of premia. Furthermore, most studies in the literature take the perspective of an investor in a home currency. However, no single currency was dominant across all of history that could serve as a natural home, so my experimental design needs to be truly base-currency neutral.

I begin by constructing an extended historical dataset of foreign exchange rates, short-term interest rates, and long-term interest rates and design an empirical experiment that overcomes these technical difficulties. Rather than creating a dataset from the perspective of a US investor allocating all funds into foreign investments, I include investments in the US as the trivial zero excess return investment.[2] By including the option to invest in the home currency, this study is made base-currency neutral. Moreover, I can infer returns on long bonds by estimating the capital gains of holding longer-term bonds from changes in bond yields with minor assumptions. In total, I have data covering upwards of 21 currencies across 230 years. Armed with this dataset, I construct currency investment portfolios based on various strategies and run panel regression analyses to examine their statistical significance.

To interpret the empirically observed returns on currency investing in the context of pricing models, I consider the reduced-form model setting used by Alvarez and Jermann (2005) and Lustig, Stathopoulos, and Verdelhan (2019). Under complete financial markets, excess returns on foreign short rate currency investments and long bond currency investments can be interpreted as differential risk reflected in the pricing kernels across countries. The framework shows that whereas the short rate carry trade is driven by differences in total variability of the pricing kernel,

[2] Ang and Chen (2017), Koijen, Moskowitz, Pedersen, and Vrugt (2018), and Bekaert and Panayotov (2020) also includes the US dollar as an investment vehicle in their studies.

long bond carry trade is driven by only the permanent shocks to the pricing kernel. In this framework, the investments in hedged long bonds can also interpreted as reflecting cross-country differences in the variability of total shocks left unexplained by the permanent shocks. Currency hedged foreign long bond investment involves investing in foreign long bond and shorting foreign short rate, without conducting any currency exchanges. This is equivalent to excess return on the long bond in local currency terms.

The longer historical perspective and the empirical designed used in this paper provides useful insights. First, the carry trade is robust throughout history across various periods and robust to using long bonds instead of short rates. Recent study by Lustig, Stathopoulos, and Verdelhan (2019) also investigate investing in long bonds but form portfolios based on short term rates and on the slope of the yield curve. They find such long bond portfolios do not produce a return premium and interpret the results as a puzzling downward term structure of currency carry trade risk premia.[3] In contrast to their findings, I find that investments in long bond do produce positive excess returns when portfolios are formed using long term interest rates rather than using short term rates or on the term spread. This result is consistent with Koijen, Moskowitz, Pedersen, and Vrugt (2018) who find that carry trade is robust to using long bond. In addition, I find that the long bond carry trade is also robust throughout the extended sample. Both the short rate carry trade and the long bond carry trade fits within the framework of the reduced-form model without producing restrictions on pricing equations that would be difficult to explain.

Both the long bond carry trade and the short rate carry trade exhibit characteristics that vary across different regimes. The carry trade returns are lower during

[3] Based on this puzzle, recent theoretical models such as Zviadadze (2017) and Greenwood, Hanson, Stein, and Sunderam (2023) incorporate features where investing in short rates deliver a carry risk premium but not so with investing in long bonds.

fixed exchange rate regimes, such as under the Gold Standard or under the Bretton Woods Agreement. However, foreign exchange rate volatility was significantly lower, an therefore amounts to high risk-adjusted returns during these periods. The one point in history when the carry trades failed to produce high returns is during the economic recovery periods following the World Wars. But otherwise, the carry trade would have produced high returns going all the way back to 1788. The dollar carry trade, which focuses on investments in the US dollar according to the US interest rate relative to the global average rate, would have also exhibited qualitatively similar patterns. This trade would have also produced robust positive returns throughout history, except for during the economic recovery following the World Wars and one additional period around the US Civil War period. Panel regressions confirm these results.

This historical perspective also offers additional insights into other currency strategies. The currency momentum effect does not seems to be robust to using a sample that goes back far in history. Based on data starting in 1788, currency momentum trade would have produced positive returns only during the latter half of the sample, but not throughout the entire sample. Panel regressions also fail to detect a robust currency momentum effect. For currency reversals, the effect only seems to exist within the sample studied by earlier papers. Outside the most recent period after the break-down of the Bretton Woods Agreement, there is no evidence of currency reversal trade producing positive abnormal return premium. These results suggest that data-snooping bias could be an issue, unless there exists some time-varying underlying mechanism at work that drives these effects. An examination that extends the study by Ang and Chen (2017) of currency predictability using the slope of the yield curve suggests constructing currency hedged bond portfolios. This strategy produces Sharpe ratios that are double that of the carry trade and is robust across all periods.[4]

This study follows a recent development in the literature that examines currency investments across a broad cross-section of currencies, rather than time-series analysis of select pairs of two currencies. Currency portfolios are formed according to various signals, such as interest rates and past currency appreciations. Lustig and Verdelhan (2007) and Lustig, Roussanov, and Verdelhan (2011) examine currency portfolio returns starting in 1955 and 1983, respectively, and find that two principal factors, a carry trade factor and a 'dollar factor', can summarize much of currency investment returns. There is an extensive literature that tries to explain the source of risk premia to the carry trade, such as Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011), but the vast majority continues to focus on the floating exchange rate period after the 1970s. The paper closest to mine is Baltussen, Swinkels, and van Vliet (2021) who also investigate return premiums with a historical perspective that span two centuries. They provide a broad analysis of various strategies across multiple asset classes that includes currencies, but also covers equities, bonds, and commodities. In contrast, I focus on detailed analysis of currency investing and understanding the sources of return premiums. Among papers that focus on currency investing, two papers closest to mine are Doskov and Swinkels (2015) and Accominotti, Cen, Chambers, and Marsh (2019), who examine the carry trade beginning in 1900 and 1919, respectively. Doskov and Swinkels (2015) use the annual-frequency database by Dimson, Stauton, and Marsh (2013) to extend their sample, whereas Accominotti, Cen, Chambers, and Marsh (2019) use daily-frequency data from forward market in London. Whereas these two papers focus on the short rate carry trade I examine other types of currency investment portfolios and spans an additional century of

[4] A similar strategy is also investigated by Koijen, Moskowitz, Pedersen and Vrugt (2018) who use the yield difference between 10-year bonds and 2-year bonds to capture "roll-down" along the yield curve find similarly high return premium over a shorter sample.

data.

The findings of my study to is related also related to an extensive literature in international finance that documents violations of uncovered interest rate parity (UIP). Hassan and Mano (2019) offer a comprehensive decomposition relating the two sets of findings. The earliest works that examine violations of UIP, such as Hansen and Hodrick (1980) and Fama (1984), have focused on the period after 1973, following the break down of the Bretton Woods Agreement and the end of the fixed exchange rate regime. Hansen and Hodrick (1980) also examined the violation of UIP in an earlier post World War I period from January 1922 to July 1926, but they also limited their study to a period of floating exchange rate regime. While there are economic reasons to focus on periods with floating exchange rate regimes, currency investments could still be a viable strategy under fixed exchange rate regimes, and the same pricing mechanism ought to still hold in either regime. Lothian and Taylor (1996) and Lothian and Wu (2011), do examine violations of purchasing power parity (PPP) and UIP, respectively, for a period spanning two centuries beginning in 1791 and ending in 1990. However, they only examine two currency pairs (GBP vs. USD and GBP vs. FRF). Relative to these studies, this paper examines the returns on currency investing over an extended period, spanning a variety of regimes, across a broader cross-section of currencies, and based on a variety of currency investment strategies.

More broadly, there is also a line of literature in other areas of financial economics that investigates the robustness of other predictability results using an extended historical data. Schwert (1990) examines the predictability of the US stock market using macroeconomic variables going back to 1889. More recently, Golez and Koudijs (2018) investigate the robustness of aggregate stock market predictability using the dividend-to-price ratio as far back as 1629. In the literature of cross-sectional predictability, Davis, Fama, and French (2000) examine the robustness of the predictive ability of book-to-market using data going back to 1929. Similarly, recent work by Linnainmaa and Roberts (2018) reexamines the cross-sectional predictability using accounting variables using data starting from 1918. Jordà, Knoll, Kuvshinov, Schularick, and Taylor (2019) examine historical returns of all major asset classes from 16 economies going back to 1870. This paper follows this rich tradition in the literature of conducting out-of-sample tests of empirical findings by going further back in history.

2 Interpreting Bond and Currency Risk Premia

First, I review a framework for interpreting and linking risk premia across short-term bonds, long-term bonds, and currency returns. The reduced-form approach along the lines of Backus, Foresi, and Telmer (2001), Alvarez and Jermann (2005), Lustig, Stathopoulus, and Verdelhan (2019), and many others can tractably incorporate multiple factors. Time-variations in pricing kernels give rise to time-varying risk premia on various long-lived assets, such as that of long-term bonds. An enormous body of research has found that priced risk factors include interest rate factors like the level and the slope of the yield curve in addition to macro variables like inflation and output (see, for example, a summary of affine term structure models in Piazzesi, 2010). I summarize and briefly interpret the relevant key results from the literature below.

2.1 Pricing Kernel and Currency Risk Premium

Under complete markets with no-arbitrage conditions, there exists a stochastic discount factor or the growth rate of the pricing kernel, $M_{t+1} \equiv \Lambda_{t+1}/\Lambda_t$, which prices any payoff at time $t+1$, P_{t+1}, such that the price at time t, P_t, satisfies

$$P_t = \mathrm{E}_t[M_{t+1}P_{t+1}] = \mathrm{E}_t\left[\frac{\Lambda_{t+1}}{\Lambda_t}P_{t+1}\right]. \tag{1}$$

Equivalently, for any gross return R_{t+1}[5] ,

$$\mathrm{E}_t[M_{t+1}R_{t+1}] = 1. \tag{2}$$

The price of a n-period zero coupon bond, P_t^n, is

$$P_t^n = \mathrm{E}_t[M_{t+1}P_{t+1}^{n-1}] = \mathrm{E}_t\left[\prod_{k=1}^{n} M_{t+k}\right] = \mathrm{E}_t\left[\frac{\Lambda_{t+n}}{\Lambda_t}\right]. \tag{3}$$

Denote the one-period gross return of a n-period as $R_{t+1}^n = P_{t+1}^{n-1}/P_t^n$. The log-return of a one-period risk-free rate, denoted $r_{f,t}$, is

$$r_{f,t} \equiv \log(R_{t+1}^1) = -\log \mathrm{E}_t[M_{t+1}]. \tag{4}$$

The pricing kernel embodies risk premia, which potentially vary over time. In structural approaches, the pricing kernel is determined by the preferences of a representative agent and production technologies to explain foreign exchange rate risk premia, like the habit consumption approach of Verdelhan (2010) and the long-run risk model used by Croce and Colacito (2011).

Whereas many papers have assumed that shocks to the pricing kernels are normally distributed, Backus, Chernov, and Zin (2014) provide a convenient method of evaluating the variability of pricing kernels in terms of entropy. They define conditional entropy, $L_t(M_{t+1})$, of the stochastic discount factor as

$$L_t(M_{t+1}) = \log \mathrm{E}_t(M_{t+1}) - \mathrm{E}_t \log(M_{t+1}). \tag{5}$$

[5] The use of 'gross returns' to denote the pay-offs of a one-unit investment follows convention established in Cochrane (2000).

In the special case where M_{t+1} is conditionally log-normally distributed, $L_t(M_{t+1}) = \frac{1}{2}\text{var}(M_{t+1})$. With departure from normality, entropy accounts for all higher-order cumulants such as skewness and excess kurtosis.[6]

Under complete financial markets, there exists an analogous pricing kernel in foreign country i denoted with superscripts. The foreign pricing kernel prices all bonds in the foreign country through analogous relation to equation (3),

$$P_t^{i,(n)} = \mathrm{E}_t[M_{t+1}^i P_{t+1}^{i,(n-1)}] = \mathrm{E}_t\left[\prod_{k=1}^{n} M_{t+k}^i\right] = \mathrm{E}_t\left[\frac{\Lambda_{t+n}^i}{\Lambda_t^i}\right], \tag{6}$$

where $P_t^{i,(n)}$ is the time t price of the foreign n-period zero coupon bond denominated in foreign currency.

Denote the spot exchange rate S_t^i at time t as the domestic price of one unit of foreign currency i. For an investor in country i starting with one unit of foreign currency, converting to domestic currency at rate S_t^i, receiving any domestic gross return R_{t+1}, and then converting back to foreign currency at the end of the period at $1/S_{t+1}^i$ satisfies $\mathrm{E}_t[M_{t+1}^i S_t^i / S_{t+1}^i R_{t+1}] = 1$. Therefore, under complete financial markets, $M_{t+1} = M_{t+1}^i S_t^i / S_{t+1}^i$ and the exchange rate change is the ratio of the pricing kernels in the foreign and domestic country:

$$\frac{S_{t+1}^i}{S_t^i} = \frac{M_{t+1}^i}{M_{t+1}}. \tag{7}$$

By denoting the natural logarithms of variables with lowercases, the rate of foreign currency appreciation is

$$\Delta s_{t+1}^i = s_{t+1}^i - s_t^i = m_{t+1}^i - m_{t+1}. \tag{8}$$

This is derived by many authors including Bansal (1997) and Backus, Foresi and Telmer (2001).

[6] Backus, Chernov, and Zin (2014) shows that $L_t(M_{t+1}) = k_{2t}/2! + k_{3t}/3! + k_{4t}/4! + \cdots$ where k_{it} is the ith conditional cumulants of $\log M_{t+1}$.

The literature has extensively considered excess returns on purchasing foreign currency i, investing the proceeds in a foreign short rate for one period to earn the foreign interest rate, $r^i_{f,t}$, and then converting the funds back into domestic currency. I can apply equations (4) and (5) to above to derive the foreign exchange risk premium of the ith currency as the difference in the spread of the conditional entropies of the domestic and foreign pricing kernels:

Currency Risk Premium (Short-Rate):

$$\mathrm{E}_t[\Delta s^i_{t+1} + r^i_{f,t} - r_{f,t}] = L_t(M_{t+1}) - L_t(M^i_{t+1}). \tag{9}$$

Uncovered interest rate parity (UIP) proposes that the right-hand side of equation (9) is zero, and if the foreign interest rate is greater than the domestic interest rate, $r^i_{f,t} > r_{f,t}$, then the foreign currency is expected to depreciate, $\mathrm{E}_t[\Delta s^i_{t+1}] < 0$. However, this relation generally does not hold empirically.

Investing in foreign currency earns a risk premium when there is a large difference between the conditional entropy of the domestic pricing kernel, $L_t(M_{t+1})$, and the entropy of the foreign pricing kernel, $L^i_t(M_{t+1})$. When the domestic pricing kernel is more variable than its foreign counterpart, a domestic investor putting money outside the country has to be compensated at a higher rate, which generates currency risk premium. Moreover, equation (9) shows that any factor that differentially affects domestic or foreign pricing kernels can potentially generate currency risk premium and predict foreign exchange excess returns.

2.2 Pricing Kernel Decomposition and Bond Risk Premium

In the empirical analysis of this article, I focus on shocks that influence either the short end of the yield curve, the long-term bond yields, or the slope of the yield curve. Following Alvarez and Jermann (2005) and Lustig, Stathopoulus, and Verdelhan (2019), it is useful to decompose the pricing kernel Λ_t into two components and consider a hypothetical infinite maturity zero-coupon bond. Alvarez and Jermann (2005) proves that, under some regularity conditions, the pricing kernel Λ_t can be uniquely decomposed into a transitory component Λ_t^T and a permanent component Λ_t^P,

$$\Lambda_t = \Lambda_t^T \Lambda_t^P, \tag{10}$$

where the latter is a martingale with $\mathrm{E}_t \Lambda_{t+1}^P = \Lambda_t^P$. Moreover, they show that there exists a value β such that $\Lambda_t^P = \lim_{n\to\infty} \frac{E_t[\Lambda_{t+n}]}{\beta^n}$ and $\Lambda_t^T = \lim_{n\to\infty} \frac{\beta^n}{P_t^{(n)}}$. which is the limit of the pricing relation in equation (3) as $n \to \infty$. The stochastic discount factors can analogously be defined as the growth rates of transitory and permanent components of the pricing kernel as $M_{t+1}^T = \Lambda_{t+1}^T / \Lambda_t^T$ and $M_{t+1}^P = \Lambda_{t+1}^P / \Lambda_t^P$, respectively.

Since the permanent component is a martingale, $\mathrm{E}_t(M_{t+1}^P) = 1$. Therefore, the conditional entropy of the permanent component is simply

$$L_t(M_{t+1}^P) = -\mathrm{E}_t \log(M_{t+1}^P). \tag{11}$$

This allows the entropy of the pricing kernel to be decomposed into

$$L_t(M_{t+1}) = -r_{f,t} - \mathrm{E}_t \log(M_{t+1}^P) - \mathrm{E}_t \log(M_{t+1}^T) = L_t(M_{t+1}^P) - \mathrm{E}_t \log(M_{t+1}^T) - r_{f,t}. \tag{12}$$

Consider an infinite maturity zero-coupon bond with gross return and price denoted by $R_{t+1}^\infty = \lim_{n\to\infty} R_{t+1}^{(n)}$ and $P_t^\infty = \lim_{n\to\infty} P_t^{(n)}$. Alvarez and Jermann (2005) shows in its Appendix that

$$R_{t+1}^\infty = \frac{P_{t+1}^\infty}{P_t^\infty} = \lim_{n\to\infty} \frac{\mathrm{E}_{t+1}\left[\frac{\Lambda_{t+n+1}}{\Lambda_{t+1}}\right]}{\mathrm{E}_t\left[\frac{\Lambda_{t+n}}{\Lambda_t}\right]} = \frac{\Lambda_t}{\Lambda_{t+1}} \frac{\Lambda_{t+1}^P}{\Lambda_t^P} = \frac{\Lambda_t^T}{\Lambda_{t+1}^T} = 1/M_{t+1}^T. \tag{13}$$

Therefore, the returns on infinite maturity zero-coupon bonds reflect only shocks in the transitory component of the pricing kernel.

Since one-period zero-coupon bond reflects expected value of the total pricing kernel, we can separate information about the two components of the pricing kernel by considering return on infinite maturity bond relative to that of a one-period bond. Consider the log excess return of the infinite maturity zero-coupon bond,

$$\mathrm{E}_t[r_{t+1}^{\infty} - r_{f,t}] = \mathrm{E}_t[\log R_{t+1}^{\infty}] - r_{f,t} = -\log \mathrm{E}_t(M_{t+1}^{T}) - r_{f,t}. \tag{14}$$

This difference doesn't equate the entropy of the transitory component because transitory shocks may be correlated with permanent shocks. It is useful to define $L_t(M_{t+1}^T) \equiv L_t(M_{t+1}) - L_t(M_{t+1}^P)$ as the difference between the entropy of the entire pricing kernel and that of the permanent component. This can be thought of as overall entropy left unexplained by the entropy of the permanent component. Combining with equation (12) yields:

Term Risk Premium:

$$\mathrm{E}_t[r_{t+1}^{\infty} - r_{f,t}] = L_t(M_{t+1}) - L_t(M_{t+1}^P) = L_t(M_{t+1}^T). \tag{15}$$

Hence excess returns of infinite maturity bonds are informative about the transitory component of overall entropy. Alvarez and Jermann (2005) uses this relationship to construct bounds on the variability of the pricing kernels. Notably, if there are only permanent shocks, then $\mathrm{E}_t[r_{t+1}^{\infty} - r_t] = 0$ and the expectation hypothesis holds. If some shocks are not permanent, risk premium on long-term bonds is generated.

Lustig, Stathopoulus, and Verdelhan (2019) extends this decomposition by considering one-period return on a foreign country i infinite horizon zero-coupon bond relative to one-period return on a domestic infinite horizon zero-coupon bond. From equations (7) and (13), the gross return on such portfolio can be written as:

$$\frac{R_{t+1}^{i,\infty}}{R_{t+1}^{\infty}} \frac{S_{t+1}^i}{S_t^i} = \frac{M_{t+1}^T}{M_{t+1}^{i,T}} \frac{M_{t+1}^i}{M_{t+1}} = \frac{M_{t+1}^{i,P}}{M_{t+1}^P}. \tag{16}$$

Therefore, the return on a foreign infinite period bond relative to domestic infinite period bond reflects the change in the ratios of the permanent components of the pricing kernel in the foreign and domestic countries. The expected differences in log-returns of infinite period bonds can be simplified by applying equations (9) and (15) to:

Currency Risk Premium (Long-Bond):

$$\begin{aligned}
\mathrm{E}_t[r^{i,\infty}_{t+1} + \Delta s^i_{t+1} - r^{\infty}_{t+1}] &= \mathrm{E}_t\left[\left(r^{i,\infty}_{t+1} - r^i_{f,t}\right) + \left(\Delta s^i_{t+1} + r^i_{f,t} - r_{f,t}\right) - \left(r^{\infty}_{t+1} - r_{f,t}\right)\right] \\
&= L_t(M^P_{t+1}) - L_t(M^{i,P}_{t+1}). \qquad (17)
\end{aligned}$$

Hence, the differences in returns on foreign infinite period bonds provide information about the variability of the permanent component of the pricing kernel across countries. This risk premium is very similar the currency risk premium using the short rate in equation (9). However, when long-term bonds are used, the risk premium depends only on the permanent shocks to the pricing kernel in foreign and domestic countries.

Finally, In my empirical analysis, I also consider a differences in excess returns of infinite period bonds, without foreign currency exposures. The expected log-return of this return difference can be expressed directly from equation (15) as:

Cross-Currency Term Risk Premium:

$$\mathrm{E}_t\left[\left(r^{i,\infty}_{t+1} - r^i_t\right) - \left(r^{\infty}_{t+1} - r_i\right)\right] = L_t(M^{i,T}_{t+1}) - L_t(M^T_{t+1}). \qquad (18)$$

Without currency exposures, this is equivalent to the return on a long-short strategy of purchasing long-term foreign bonds, borrowing at the foreign short rate and comparing the return to that of the same long-short strategy conducted using domestic bonds. In this case, the differences in excess returns of infinite period bonds provide information about the total variability of the pricing kernels after excluding variability explained by the permanent components.

Collectively, the risk premia on holding foreign short-term and long-term bonds reflects cross-country differences in permanent and transitory shocks to the pricing kernel. Examining the relationships across bonds, with or without currency exposure, is informative about the differences in the entropy pricing kernels across countries. Moreever, it should be noted that such interpretations are only valid under a complete financial markets. Nonetheless, I turn to the empirical investigation of historically realized risk premia in the following section. Notably, since this is a reduced-form model, the framework is silent as to the exactly which variable would be informative about empirically observed risk premia, other than that the predicting variable should also be related to future entropy of pricing kernels.

3 Returns on Currency Investing

Most currency investment portfolio studied in the finance literature involves investments in the short rates. When I examine currency investments reaching further back in history, I can obtain a more extensive data sample if I consider investments in other types of foreign assets, such as long bonds. I begin in this section by generalizing the empirical framework used in the literature to allow for foreign investments in assets other than the short rates.

3.1 Foreign Exchange Returns

For each currency i, I obtain the end-of-period exchange rate in terms of the dollar price of one unit of foreign currency, S_t^i. I define the gross foreign exchange (FX) return over the next period as $R_{t+1}^{FX,i} = \frac{S_{t+1}^i}{S_t^i}$. Given any gross investment return in a foreign currency, R_{t+1}^i, total investment return with currency appreciation, denoted $R_{t+1}^{Tot,i}$, is

$$R_{t+1}^{Tot,i} = \frac{S_{t+1}^i}{S_t^i} R_{t+1}^i. \tag{19}$$

The literature typically defines the excess foreign exchange return on currency i, denoted Π^i_{t+1}, as

$$\Pi^i_{t+1} = \frac{S^i_{t+1}}{S^i_t}\frac{R^i_{t+1}}{R^{US}_{t+1}}. \tag{20}$$

This return is the future value of taking one USD to purchase $1/S^i_t$ units of foreign currency i and investing in an asset with a total return of R^i_{t+1}, relative to the future value from an equivalent investment made in the US with a return of R^{US}_{t+1}. Following the literature, the US is treated as the 'home' currency for now, and robustness to changing the base currency is addressed later.

The existing literature uses the short rates (risk-free rate) as investment returns and run their analysis at monthly or annual frequency data. In logarithmic term, excess foreign exchange return is:

$$\pi^i_{t+1} = \Delta s^i_{t+1} + (r^i_{f,t} - r^{US}_{f,t}). \tag{21}$$

In cases where forward rates exist and covered interest rate parity can be expected to hold, log excess foreign exchange return can be rewritten as

$$\pi^i_{t+1} = f^i_{t+1} - s^i_t, \tag{22}$$

where f^i_{t+1} is the log one-period forward foreign exchange rate.

The literature often directly examine this difference between the forward rate and the spot rate since the forward rate implicitly embeds the short-term interest rate (Hansen and Hodrick, 1980; Fama, 1984). Using the forward rate implicitly assumes that covered interest rate parity holds, and has the advantage that daily frequency data is available for computing volatility (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012b; Accominotti, Cen, Chambers, and March, 2019) and bid-ask spread data is available for estimating transaction costs.[7]

[7] Accominotti, Cen, Chambers, and March (2019) extend this approach and obtain spot and forward exchange market data extending back to December 1919 across 19 currencies. Similarly,

To obtain longer historical data across a broader set of currencies, I recognize that the investment asset used for R^i_{t+1} does not need to be restricted to short rates. For instance, in the literature testing the validity of Purchasing Power Parity (PPP), the investment asset is a basket of real assets. In my study, I use the return on longer-maturity bonds as the investment return. There are various disadvantages to using bond returns, such as the fact that bond returns might have additional premia embedded in them for sovereign default risk or illiquidity. Moreover, I generally do not observe bond returns but have to estimate them from recorded yields.[8] Nevertheless, I accept these disadvantages and examine currency investment portfolios using long bonds to extend the data sample.

3.2 Computation of Bond Returns

Unlike bond yields, bond returns are generally unavailable for most countries. The US Dollar is a notable exception, for which Center for Research in Securities Prices (CRSP), Ibbotson, and Bloomberg calculate bond returns. Similar to my method below, Swinkels (2019) and Swinkels (2023) extract bond returns from changes in bond yields but use) bond duration and convexity to approximate bond returns. Koijen, Moskowitz, Pedersen and Vrugt (2018) also employ a similar approximation for bond return but only incorporates bond duration. Global Financial Data (GFD) produces a total bond return series for every country, but their methodology is not documented. I compute bond returns from their bond yields rather than rely on an

Doskov and Swinkels (2015) obtain short rate data extending back to 1901 across 20 currencies. Lothian and Wu (2011) are able to extend the short rate data back to 1800, but only for three currencies.

[8] Some papers, such as Lothian and Wu (2011), ignore the difference between bond returns and bond yields and proceed to use bond yields itself as an approximation of bond returns. This method ignores the capital gains component of returns, which can be substantial.

undocumented process.[9]

In Section 2, the link between bond returns and pricing kernels was established based on hypothetical infinite maturity zero-coupon bonds, $r^{i,\infty}_{t+1}$. For the empirical analysis, I calculate the returns on a coupon paying 10-year bond. In my dataset, I observe the yield, $y^{(n)}_t$, on some n-period coupon paying bond. If an investor holds a bond over a single period from time t to time $t+1$, the return on the bond is generally not equal to the bond yield because there will be capital gains associated with holding a longer-term bond over a shorter time interval. Practitioners refer the expected component of this capital gains as the 'roll yield' and often refer to repeatedly holding longer-term bond over shorter time interval as 'riding the yield curve'.

To simplify my notations, I define bond present value (BPV), in terms of percentage of par, of an n-period bond paying coupon at a rate of c discounted at rate y as

$$BPV(n,c,y) \overset{def}{=} \frac{c}{(1+y)} + \cdots + \frac{c+1}{(1+y)^n}. \tag{23}$$

This function has the well-known property that $BPV(\cdot) = 1$ whenever $c = y$ (Malkiel, 1962). For the special case of a perpetuity, $BPV(\infty, c, y) = c/y$. At time t, the price of the bond is

$$P^{(n)}_t = BPV(n,c,y^{(n)}_t) = \frac{c}{(1+y^{(n)}_t)} + \cdots + \frac{c+1}{(1+y^{(n)}_t)^n}. \tag{24}$$

However, at time $t+1$, the ex-coupon price of this bond, which is now an $n-1$ period bond, is

$$P^{(n-1)}_{t+1} = \frac{c}{(1+y^{(n-1)}_{t+1})} + \cdots + \frac{c+1}{(1+y^{(n-1)}_{t+1})^{n-1}}. \tag{25}$$

[9] Notably, Lustig, Stathopoulos, and Verdelhan (2019) use the GFD total bond return series, which may explain some of the differences seen with their empirical results.

By adding the coupon back in, the cum-coupon value can be rewritten as

$$\begin{aligned} P_{t+1}^{(n-1)} + c &= c + \frac{c}{(1+y_{t+1}^{(n-1)})} + \cdots + \frac{c+1}{(1+y_{t+1}^{(n-1)})^{n-1}} \\ &= BPV(n, c, y_{t+1}^{(n-1)})(1+y_{t+1}^{(n-1)}). \end{aligned} \tag{26}$$

Therefore, the total gross return of this bond over time t and $t+1$ is

$$R_{t+1} = \frac{P_{t+1}^{(n-1)} + c}{P_t^{(n)}} = \frac{BPV(n, c, y_{t+1}^{(n-1)})}{BPV(n, c, y_t^{(n)})}(1+y_{t+1}^{(n-1)}). \tag{27}$$

Note that equation (27) can be approximated using Modified Duration, as in Koijen, Moskowitz, Pedersen and Vrugt (2018) and Swinkels (2019). As an illustration, the total gross return for a perpetuity reduces to

$$R_{t+1} = 1 + \underbrace{\left(\frac{1/y_{t+1}^{\infty}}{1/y_t^{\infty}} - 1\right)}_{\text{capital gains}} + \underbrace{y_t}_{\text{yield}}. \tag{28}$$

In this case, the first term is the capital gains of holding a perpetuity and the second term is the single period yield of the bond.

Since most bonds are not perpetuities, I estimate total bond returns by making two assumptions. First, I assume that there exists a hypothetical par bond at time t with coupon, $c = y_t^{(n)}$. Second, I assume that yield curves at the longer-maturities are flat, such that the $n-1$ period yield is equal to the n period yield: $y_{t+1}^{(n-1)} = y_{t+1}^{(n)}$. With these two assumptions, I can drop the $n-1$ and n superscripts and equation (26) becomes

$$R_{t+1} = BPV(n, y_t, y_{t+1})(1+y_{t+1}). \tag{29}$$

With some manipulations and using the fact that $BPV(n, y_{t+1}, y_{t+1}) = 1$, total gross return on the bond can now be rewritten as

$$R_{t+1} = 1 + \underbrace{(BPV(n, y_t, y_{t+1}) - 1)}_{\text{capital gains}} + \underbrace{y_t}_{\text{yield}} + \eta_{t+1}, \tag{30}$$

where $\eta_{t+1} \equiv \frac{y_{t+1}-y_t}{(1+y_{t+1})^n}$. As with a perpetuity, the first term $(BPV(n, y_t, y_{t+1}) - 1)$ is the capital gains of holding a par bond over a single period, and y_t is the single period yield of the bond. The additional term, η_{t+1}, appears due to the assumption I made equating the yields of $n-1$ and n period bonds, and this term disappears as $n \to \infty$. To ensure that bond returns computed using equation (30) produces returns consistent with bond returns calculated using other methods, Appendix A compares the bond return series using in this paper to bond return series used in other papers.

3.3 Base Currency

In the formulation presented in Section 3.1, the base currency is denominated in terms of the US dollar (USD). For my analysis, it is particularly important not to have my empirical design be anchored to any single currency since no one currency was a dominant currency throughout my entire sample that goes back as far as 1788. In fact, the US dollar did not even exist until the Coinage Act of 1792.[10] . Therefore, I design an empirical analysis such that it is base-currency neutral.

Total returns on any investment from Equation (19) can be converted to any currency, FX*. Suppose that $S_t^{i,*}$ denotes the FX* price of one unit of foreign currency. Then total gross investment return in terms of FX* is

$$R_{t+1}^{Tot*,i} = \frac{S_{t+1}^{i,*}}{S_t^{i,*}} R_t^i. \tag{31}$$

Assuming that cross-currency arbitrage holds, such that $S_t^{i,*} = S_t^i / S_t^*$, the total investment return can be rewritten as:

$$R_{t+1}^{Tot*,i} = \frac{S_{t+1}^i / S_{t+1}^*}{S_t^i / S_t^*} R_t^i = \frac{R_{t+1}^{Tot,i}}{S_{t+1}^* / S_t^*}. \tag{32}$$

[10] Prior to the introduction of the US dollar, my data provider uses the equivalent Pennsylvania Shilling to fill in the data.

In log-terms, this is simply,

$$r_{t+1}^{Tot*,i} = r_{t+1}^{Tot,i} - \Delta s_{t+1}^{*}. \tag{33}$$

Hence, converting a US dollar return to any other currency is simply a matter of subtracting off a constant, Δs_{t+1}^{*}, at each point in time. Empirically, this term is absorbed by time fixed effects in a panel regression.

Moreover, this empirical design allows me to leave the US dollar in my sample as a data point rather than remove it altogether as it is often done in the literature. In the literature, the term 'dollar-neutral' does not mean that the US dollar is given equal footing as other currencies, but rather the US dollar is removed entirely from the analysis. In my analysis, the US dollar remains in the sample as the trivial investment with the gross return of $R_{t+1}^{US} = 1$ and excess return of $\Pi_{t+1}^{US} = 1$. This maintains symmetry across all currencies by retaining the option to invest in the US.

3.4 Equal-Weighted and Signal-Weighted Portfolio Returns

Returns on currency investment portfolios are constructed by varying the weights, $\omega_{t,i}$, on currency i according to some observable signal, $x_{t,i}$, at time t. Portfolios that capture a variety of currency investment strategies, such as the carry trade, momentum strategy, and value investing, are constructed by varying the signal. The gross return at time $t+1$ on a portfolio, P, is denoted:

$$\Pi_{t+1}^{P} = \sum_{i} \omega_{t,i} \Pi_{t+1}^{i}. \tag{34}$$

Equal-weighted long side portfolios use $\omega_{t,i} = \frac{1}{n_t^L}$, for an integer n_t^L equal to the number of currencies in the long portfolio, if the currency is in the portfolio and zero otherwise. A typical carry-trade includes currencies with the highest one-third of interest rates. Similarly, equal-weighted short side portfolio uses $\omega_{t,i} = \frac{-1}{n_t^S}$, for an integer n_t^S equal to the number of currencies in the short portfolio. In all cases, I maintain $n_t^L = n_t^S$ for all t. Note that weights sum to positive (negative) one for long side (short side) portfolios. Returns on long side portfolios are compared to returns on equal-weighted portfolios that simply invests evenly across all currencies.[11] Alternatively, long-short portfolios capture the difference in returns between long side portfolios and short side portfolios.

While equal-weighted portfolios are often studied in the literature and used in practice, these portfolios are not particularly conducive for relating them to formal statistical analysis. In fact, portfolios need not be equal-weighted.[12] As an alternative, I study signal-weighted portfolios where portfolio weights, $\omega_{t,i}$, which maintain the property that they are a function of some signal, $x_{t,i}$, and long (short) portfolios retain the property that the weights sum to positive (negative) one. These signal-weighted portfolios have a natural mapping to regressions.[13] Ang and Chen (2017), Menkhoff, Sarno, Schmeling, and Schrimpf (2017), and Hassan and Mano (2019) also study currency portfolios using weights that depend on the strength of the signals.

Given a signal, $x_{t,i}$, define cross-sectionally demeaned signal as $x_{t,i}^m = x_{t,i} - \bar{x}_t$, where $\bar{x}_t$ is the cross-sectional average of $x_{t,i}$ across i at time t. I define a signal-weighted long-short portfolio as the portfolio with the weights such that, $\omega_{t,i} = x_{t,i}^m / k_t$, where k_t is the average mean deviation of $x_{t,i}$ for those greater than the cross-sectional average $\bar{x}_t$. By construction, weights on long-short signal-weighted portfolios sum to zero. Similar to equal-weighted portfolios, signal-weighted long (short) portfolios take only the positive (negative) weights and maintain that weights

[11] It is more common to use returns in excess of the short rate of the base currency, but using an even investment across all currencies makes the benchmark currency-neutral.

[12] For example, Koijen, Moskowitz, Pedersen and Vrugt (2018) uses rank-weighted portfolios.

[13] Fama (1976) provides a discussion of the interpretation of Fama and MacBeth (1973) regressions as portfolio returns, while Hassan and Mano (2019) a provide a decomposition of portfolio returns into regressions in the context of currency investments.

sum to positive (negative) one.

Cross-sectionally demeaned signal, $x^m_{t,i}$, has the advantage that it is easily related to well-known regressions because they are mean-zero at each point in time, t. For example, typical ordinary least squares (OLS) panel regression of gross currency investment returns, Π^i_{t+1}, on cross-sectionally demeaned signal, $x^m_{t,i}$, has the regression estimate for coefficient, β^{Panel}, of

$$\hat{\beta}^{\text{Panel}} = \frac{1}{SSx} \sum_{t,i} x^m_{t,i} \Pi^i_{t+1} = \frac{1}{SSx} \sum_t \sum_i x^m_{t,i} \Pi^i_{t+1}, \tag{35}$$

where $SSx = \sum_{t,i} (x^m_{t,i})^2$. Comparing this expression to equation (34), one can see that the average return on a signal-weighted portfolio is proportional to the regression coefficient from a panel regression, upto a time-varying scalar, k_t.[14] Similarly, oft used Fama-MacBeth regression in finance has the regression coefficient, β^{FM}, with an estimate of $\hat{\beta}^{\text{FM}} = \frac{1}{T} \sum_t \hat{\beta}^t$, where for each t,

$$\hat{\beta}^t = \frac{1}{SSx_t} \sum_i x^m_{t,i} \Pi^i_{t+1}, \tag{36}$$

where $SSx_t = \sum_i (x^m_{t,i})^2$ for each t. Once again, one can see that the average return on the signal-weighted portfolio is proportional to the regression coefficient from a Fama-MacBeth regression, upto a time-varying scalar, $\frac{k_t}{SSx_t}$. In another word, a time-weighted average return on a signal-weighted portfolio is equivalent to a panel regression, which is also equivalent to a Fama-MacBeth regression for some time-varying weighting scheme.

[14] This can further be shown to be equivalent to running a panel regression on non-demeaned signal $x_{t,i}$ with time-fixed effects.

4 Data

For my empirical analysis, I collect data from GFD. Whereas most other research in this literature obtains data from Datastream, which provides forward exchange data at higher frequencies and with bid-ask spreads, GFD has the advantage of offering a longer historical coverage of data over a broader cross-section of currencies. Lustig and Verdelhan (2007), Ang and Chen (2017), and Lustig, Stathopoulos, and Verdelhan (2019) are examples of works in the literature that have also used GFD data to analyze currency returns.[15]

I obtain two sets of historical interest rate data: short-term interest rates (short rates) and the interest rate on longer maturity bonds (long bonds). Each of these series is obtained at the monthly frequency from GFD for as much history as possible. For the short rate, I first seek out the '3-month Treasury Bill Yield' for each currency in GFD, which goes back to the mid-20th century for most currencies, and as far back as 1900 for the British Pound (GBP). I then seek out the central bank discount rate to complete the data, which is available for a much longer history. For the GBP, this series begins in 1694, when the Bank of England was established. I start the dataset as of 1854:01, when interest rates for at least six currencies become available to ensure a broad enough cross-section. In instances where a country did not historically exist, its primary predecessor is used, such as the Kingdom of Prussia for Germany.[16]

For historical foreign exchange rates, I obtain values of one US dollar for each currency from GFD across time. The data provider has made adjustments for foreign exchange conversions, such as the conversion of 100 old French francs for 1 new

[15] GFD also provides total return indices on long-term bonds, but their methodology in undocumented. Appendix A compares using GFD total return indices to other methods.

[16] In the earliest periods, such as the 18th century, data provided is the yield on the most comparable instrument, such as the dividend yield on a highly secure bank stock such as the Million Bank for England or the East India Company for India.

French franc, much in the same way stock prices are adjusted for stock splits. When foreign exchange rate versus the US dollar is unavailable, when possible, it is inferred from GBP foreign exchange rate or the Dutch guilder (NLG) foreign exchange rate, assuming no currency triangular arbitrage.[17] For currencies that entered the Euro, the data series end on 1998:12, with the exception of German Deutschemark (DEM), which I splice in with the Euro.

I focus on one-year holding period returns, so twelve months of foreign exchange returns and interest rates must be available for a currency to be in my sample. To eliminate potential outliers due to periods of hyperinflation, I remove periods when a currency experienced an absolute one-year foreign exchange return of more than 80%.[18] This screen reduces the impact of hyperinflationary periods with minimal look-ahead bias but does not remove it altogether.

4.1 Descriptive statistics

I create two data samples, the first using short rates and the second using long bonds, and focus on one-year holding period returns. For currencies that entered the Euro with the exception of DEM, the sample ends on 1997:12, with a one-year return ending on 1998:12. For all other currencies, the sample ends on 2016:06, with a one-year return ending on 2017:06. Figure 1 shows the number of currencies represented in my samples across time. The short rate sample begins with 6 currencies represented in 1854:12, but steadily rises to include 21 currencies by the late the 1920s. The

[17] Some additional missing data on the foreign exchange rate is inferred from the Swedish krona (SEK) foreign exchange rate available from the Riksbank (Lobell, 2010).

[18] As an example, the hyperinflationary period of the German Weimar Republic is generally agreed to have lasted from August 1922 to December 1923. My screen removes DEM from the sample only from July 1923 and retains the earliest part of the hyperinflationary period. DEM reenters the sample in December 1924 with the one-year return ending on December 1925.

long bond sample begins with 8 currencies represented in 1788:09 and expands, with occasional drops, to include 21 currencies by the 1890s. This sample remains at 21 currencies with occasionally drops around the period following World War II. Both samples fall to 13 currencies when the Euro is introduced and legacy currencies are removed.

Table 1 presents descriptive statistics of interest rate data in my sample. For each currency, I report means and volatilities in annual percentage terms, as well as the first month of observations. For the majority of currencies, I can obtain longer historical data by using the long bonds, rather than using only the short rates. The two exceptions are the Finnish markka (FIM) and the Swiss franc (CHF). In almost every country, the average long-term interest rate has been higher than the average short-term interest rate, and the typical yield curve has been upward-sloping throughout history. The one exception has been in India, where the yield curve has been relatively flat on average. On the other end of the spectrum, Spain has historically exhibited the highest long-term bond rate. Much of this can be attributed to the high yield on bonds issued by the Spanish crown during the early 19th century when the Spanish government defaulted on its debt payments. This period also accounts for the high variability of long-term bond yields in Spain. Fortunately, the Spanish experience is the exception rather than the rule. In other countries, long-term bond yields were much less variable and often less variable than the short-term interest rate.

5 Carry Trade Over the Recent Centuries

I now investigate the historical returns on investments made in foreign currencies and bonds over the recent centuries. I begin by summarizing individual currency investment returns and then analyzing the carry trade. I later turn to foreign currency investment returns made using other predictive variables. The analysis presented in this section focuses on cross-sectional predictability while Appendix C presents time-series predictability along the lines of Fama (1984).[19]

5.1 Individual Currency Investment Returns

For each currency, I begin by computing total currency investment returns according to equation (19), where investment return R^i_{t+1} is either the short rate or the long bonds held over twelve-months periods as estimated by equation (30). I use twelve months holding period as the base case specification, but use shorter holding periods as a robustness check. Table 2 shows the summary statistics of net investment returns, $R^i_{t+1} - 1$, net foreign exchange rate returns, $\frac{S^i_{t+1}}{S^i_t} - 1$, and net total returns, $R^{Tot,i}_{t+1} - 1$. When long bonds are used, the table also reports the capital gains component, with the estimation adjustment term η_t included. Columns labeled 'Short Rate Sample' use the short rate as the investment vehicle, while the columns labeled 'Long Bond Sample' use the long bonds as the investment vehicle.

In my data, short rates have been relatively stable compared to other variables, as shown by their low volatilities (standard deviations). The Swiss franc (CHF) has had one of the most stable short rates (volatility of 1.88%) and has also had the lowest average short rates (average of 2.82%). On the other hand, the Portuguese escudo (PTE) has had the most volatile short rates (volatility of 5.39%), as well as one of the highest average short rates (average of 6.26%). Generally speaking, lower average short rates have been associated with more stable short rates, with a correlation between them of 0.66.

On the other hand, foreign exchange returns have historically been more volatile

[19] Unlike the carry trade, tests of Uncovered Interest Rate Parity are typically studied by investigating time-series variations between currency pairs. Hassan and Mano (2019) discusses this distinction in further detail.

and accounted for the bulk of the volatility of total returns when short rates are used as the investment vehicle. From the point of view of the US dollar, the most volatile investment currency has been the German mark (DEM), while by construction, the least volatile investment currency has been the US dollar (USD), followed by the Canadian dollar (CAD), the Swedish kroner (SEK) and the Indian rupee (INR). The Swiss franc (CHF) appreciated the most in this sample, followed by Dutch guilder (NLG) and then the US dollar (USD) while the Austrian shilling (ATS) and the Portuguese escudo (PTE) depreciated the most. Interestingly, currencies with the highest volatility relative to the US dollar have depreciated the most, with a correlation of -0.61 between average volatility and average currency appreciation. Taken together, although the high-yielding New Zealand dollar (NZD) produced the overall highest total investment returns, this has been the exception rather than the rule. Hassan and Mano (2019) decompose the carry trade into two components, a ‘static trade’ and a ‘dynamic trade’, and find that the static carry trade accounts for the bulk of the carry trade. In this initial overview, however, there is no indication of a static carry trade where countries with the highest overall yield across time produce the highest total investment return. The correlation between average total return and the short rate is only 0.05.

When I use the long bonds as the investment vehicle, patterns similar to that with the short rates emerge, except that investment returns are much more volatile due to the capital gains component. Investment returns from long bonds are still more stable than currency returns, with some notable exceptions. In particular, returns on Spanish bonds have been extremely volatile, particularly during the early 19th century. This volatility was also accompanied by very high returns on Spanish bonds, which was subject to default risk at the time. Even with the Spanish bonds removed, more volatile bonds have exhibited higher average returns with a correlation of 0.65 between average return and volatility. Much of this pattern is attributable to the bond yield components since average capital gains are generally close to zero. Overall, capital gains add volatility to investment returns but do not seems to contribute significantly to overall investment returns.

Patterns among currency returns remain similar with the highest volatility currencies producing the greatest currency depreciation, with a correlation between average volatility and an average appreciation of -0.45. While the Spanish bonds provided the highest carry and the highest total investment returns, if I exclude them, there is still no indication of a static carry trade and the correlation between average total investment return and the long-term bond rate is only -0.02.

5.2 Carry Trade Over the Modern Sample

With these currency investment returns in hand, I first confirm the integrity of my data by reproducing the well-known carry trade in the literature before examining the extended historical sample.[20] The literature has primarily focused on the floating exchange rate period since 1973, which I refer to as the 'Modern Sample'. I follow the portfolio formation process described in Section 3.4 and begin with monthly-rebalanced equal-weighted long-short portfolios using the short-rate as the investment vehicle. Monthly-rebalanced equal-weighted portfolio is the most often used specification in the literature. I vary the portfolio formation process to ensure that these results are robust to specification of the portfolio formation process.

Panel A of Table 3 shows the characteristics of these monthly-rebalanced equal-weighted portfolio returns. Long-short portfolios using the short rate has produced an average return of 3.42% per year with a volatility of 6.45% during this modern period.

[20] The literature has generally focused on using only the G10 currencies to investigate the carry trade, whereas this paper uses a wider set of currencies. Appendix B presents further robustness check using only the G10 currencies to reproduce the known results in the literature.

This is a Sharpe ratio of 0.530, which is comparable to that of earlier research.[21] Since there are 44.5 years of returns, this Sharpe ratio is equivalent to a t-statistic of 3.54 using ordinary standard errors. In this sample, there is only a little evidence of negative skewness with a coefficient of skewness of 0.64 and a minimum one-month return of -9.93% return, indicating that crash risk is not a significant factor in this sample. The long-short portfolio return is decomposed into the long side and the short side by comparing each side to returns on an equal-weighted portfolio that invest evenly across all currencies in both the long side and the short.[22] The decomposition is presented under the columns labeled 'Long Side' and 'Short Side' and show that each side has similar characteristics during the Modern Sample. If anything, it is the long side currency investment that has contributed slightly greater return, with a comparable level of volatility. Interestingly, the Sharpe ratios are not significantly different across the long side and short side. In the context of the reduced-form model presented in Section 2 and equation (9), the results suggests that when a currency has low short rate, it must reflects greater entropy of that country's pricing kernel relative to countries with higher short rate.

I first vary the investment vehicle to long-term bonds in columns labeled 'Long Bond Portfolios' in Panel A to see if using an alternative investment vehicle affects the carry trade during the Modern Sample. During this period, long-short portfolios using the long bonds has produced an average return of 2.52% per year with a volatility of 6.43% for a Sharpe ratio of 0.392. Interestingly, even though individual long

[21] Some research report higher Sharpe ratios using a wider cross-section of currencies (Lustig, Roussanov and Verdelhan, 2011) or specifying a currency portfolio that is not neutral with respect to all currencies (Burnside, Eichenbaum, Kleshchelski and Rebelo, 2011). Later, I explicitly examine the robustness of dollar carry trade presented by Lustig, Roussanov and Verdelhan (2014).

[22] Some articles in the literature report excess return relative to USD risk-free rate, which is not currency-neutral. Other articles report absolute portfolio returns, which is difficult to interpret because it is not feasible to obtain zero returns.

bonds are riskier with greater volatility due to exposures to capital gains, portfolios of currency investments with long-term bonds are not any riskier than portfolios of currency investments using short rates. However, the average return and consequent Sharpe ratio of 0.392 are somewhat lower using long bonds than with short rates. But they are still economically significant and statistically significant with a t-statistic of 2.61.

This result is in contrast to Lustig, Stathopoulos, and Verdelhan (2019), who report insignificant carry trade returns using long bonds over the Modern Sample. However, I form portfolios based on the yields of the long bonds, rather than on the short rate or the slop of the yield curve. Koijen, Moskowitz, Pedersen and Vrugt (2018) also report positive carry premia among long bonds. In the context of the reduced-form model and equation (17), positive premia on long-bond carry trade can be interpreted as low long bond rate reflects higher entropy of the permanent component of that country's pricing kernel.

Panel B of Table 3 illustrates the portfolio characteristics when carry trade portfolios are annually-rebalanced at the end of each December, instead of monthly rebalancing. Since historical data is more reliable at the annual frequency and transaction costs associated with excessively frequent rebalancing is a potential concern, I use annually-rebalanced portfolios as the main specification later in the extended historical sample. Most research on carry trade that use the forward rate focus on one-month forwards and incorporate bid-ask spread on a new forward contract on a monthly basis. Nevertheless, I begin by checking that the well-researched carry trade is not affected by less frequent rebalancing. Indeed, qualitative results do not materially change with annual-rebalancing, but is subject to less transaction cost concerns. With equally-weighted portfolios, annually-rebalanced portfolios are generally riskier with slightly lower returns. Sharpe ratios are 0.373 and 0.356, using short rates and long bonds, respectively, which remain economically and statistically significant. It remains the case that the long side of the carry trade portfolios contributes just as much, if not greater proportion of returns, than the short side of the carry trade portfolios. Moreover, it remains the case that there is not a significant evidence of negative skewness or extreme negative returns, whether the short rates or the long bonds are used.

Finally, I consider signal-weighted carry trade portfolio returns in Panel C of Table 3. Unlike equal-weighted portfolios, signal-weighted portfolios place greater portfolio weight on more extreme yields, akin to regression analysis. The resulting portfolio is qualitatively similar to equal-weighted portfolios presented in Panel B, with some notable features. Overall returns are slightly higher, but they have higher volatility, which results in Sharpe ratios of 0.391 and 0.361, depending on whether short rates or long bonds are used as the investment vehicle. Long-short portfolios exhibit slightly less negative skewness, of which much of the change seems to be coming from the long side portfolio rather than the short side portfolio.

Table 4 provides some indications of how similar these portfolios are by presenting the correlations among portfolio returns over the Modern Sample. Not too surprisingly, annually-rebalanced equal-weighted and annually-rebalanced signal-weighted portfolios are strongly correlated with correlations of 0.954 and 0.929 for short rate portfolios and long bond portfolios, respectively. On the other hand, currency portfolios using short rates are slightly distinct from currency portfolios using long bonds. The correlation of returns between equal-weighted short rate currency investment portfolio and that of the long bond portfolio is 0.884, which further drops with annual rebalancing to 0.857 and 0.838 for equal-weighted portfolios and signal-weighted portfolios.

Overall, these tables show that my dataset created from GFD replicates empirical results consistent with that found in the existing literature. Moreover, the qualitative results of the carry trade are not affected by various specification changes. Namely, the carry trade is robust to using short rate or long bonds as the investment vehicle and is not limited to using forward rates. Furthermore, the carry trade can be constructed using annually-rebalanced portfolios, which mitigates transaction cost concerns. Finally, the carry trade can be signal-weighted rather than equal-weighted. With these concerns out of the way, I now examine extended historical samples spanning a much longer time.

5.3 Carry Trade Returns Over Recent Centuries

I use the period from 1855 to 2017 as the 'Main Sample' and use an extended period starting in 1789 as the 'Extended Sample' using long bonds. In this extended sample, I focus on annually rebalanced equally-weighted long-short portfolios of using both the short rate and the long bond as the investment vehicle. In the robustness section, I also consider using annually rebalanced signal-weighted portfolios and monthly panel regressions.

I begin by plotting cumulative returns across the entire sample in Figure 2. The cumulative returns are normalized to equal one hundred USD at the end of 1854. This plot shows some preliminary indication that while there are some time-variations in the riskiness of currency investment portfolios, the carry trade would have consistently produced positive risk premia throughout. For instance, before 1854, portfolios were significantly more volatile, but the returns were noticeably higher on average. The portfolio returns were extremely stable during the following period until the start of the World Wars and became significantly volatile during the wars. There is one particularly notable period immediately following World War II and the introduction of the fixed exchange rate regime under the Bretton Woods Agreement during the post-war reconstruction efforts. Doskov and Swinkels (2015) note this period as an influential observation, while Accominotti, Cen, Chambers, and Marsh (2019) attribute the low carry trade return to the change from floating exchange regime to fixed exchange regime. During the post-war period, portfolio returns were once again very stable. Most notably, currency investment portfolio returns remained positive throughout the entire sample.

I investigate the sources of carry trade portfolio returns in detail by decomposing portfolio returns across time and into components of returns. I divide the sample into seven major time periods of roughly 22 years each: Early Second Industrial Revolution (1855-1879), Classic Gold Standard Era (1880-1913), World Wars Era (1914-1949), Bretton Woods Era (1950-1972)[23] , Pre-Euro Floating Exchange Regime (1973-1998), and Post-Euro Floating Exchange Regime (1998-2017). I also decompose portfolio returns into a component that is attributable to foreign exchange returns ('FX Returns') and the remainder attributable to the yield on the short rate ('Carry Returns'). For each return component, I also report its standard deviation ('Vol').

Table 5 presents the results of this exercise for annually rebalanced equal-weighted currency investment portfolios based on short rates. As already indicated in Figure 2, Table 5 also shows that currency investment portfolio returns were positive during each of the subsamples, except during the World Wars Era. There were significant differences in the volatility of these portfolios across time. The Classic Gold Standard Era, when currencies were primarily pegged to the value of gold, produced one of the lowest volatility of returns. As a result, this period resulted in the highest return carry trade portfolio with a Sharpe ratio of 1.200. The World Wars Era was accompanied by the greatest volatility and the lowest Sharpe ratio. This period was followed by the fixed-exchanged rate regime of the Bretton Woods Era that produced

[23] Bretton Woods Agreement was introduced in 1946, but there were still significant adjustments to fixed exchange rate pegs of European currencies until September of 1949. Hence I use 1950 as the beginning of the Bretton Woods Era.

one of the lowest returns, but like the Classic Gold Standard Era, the volatility of currency investment portfolios was very low and contributed to a very high Sharpe ratio of 0.714. The oft studied Floating Exchange Regime produced high carry trade returns, particularly in the period after the Euro was introduced. The overall picture is that equal-weighted currency investment portfolios based on short rates produced consistently positive returns across different periods, with a single exception, but significantly differed in its volatility depending on the exchange-rate regime and the stability of the global economy.

The average FX returns has generally been negative and much of the currency investment returns would have come from capturing the yield component of returns ('carry returns'). On the other hand, much of the risk associated with currency investment would have come from FX returns rather than from the yield component. These characteristics are consistent throughout the subsamples. Overall, much of the positive returns associated with currency investing would have come from capturing the yield differential among short rates, while accepting the risk of currency fluctuations. Whereas the UIP Hypothesis would have predicted that such interest rate differentials would have led to adverse changes in currencies, such changes did not ever materialize during the recent centuries. As shown in Equation 9, countries with higher short rates are associated higher entropy of the pricing kernel and generate a positive risk premium.

Table 6 presents the results for the equal-weighted currency investment portfolios based on long bonds. Since I can obtain a longer sample for long bonds, this table adds the eighth period at the beginning: Age of Revolution (1789-1854). With long bonds, I can further decompose currency investment returns into a third component attributable to capital gains on holding long-term bonds, ('Cap Gains'). As with the short-rates, I observe similar patterns across time. Overall, carry trade portfolio returns were consistently positive across periods when long bonds are used as the investment vehicle. However, the riskiness of the portfolio varied depending on the exchange-rate regime and the stability of the global economy. As before, the World Wars Era was associated with one of the most volatile periods for currency portfolios, only to be surpassed by the volatility of the Age of Revolution. The least volatile period is still the Bretton Woods Era, which led to the period with the highest Sharpe ratio for the carry trade with long bonds.

Similar to the case with short-rates, investing in higher yield bonds was not met with depreciation in currencies, and it was also not met with capital losses in the values of long bonds. If anything, the capital gains component of returns was positive and would have added further to currency investment portfolio returns. Furthermore, the capital gains component was volatile and added risk to the portfolio returns. During the Age of Revolution, long term bonds were highly volatile, but became less volatile during the Early Second Industrial Revolution and much less so in the following periods. Overall, when long bonds are used, the strategy of capturing yield differential while accepting the risk of currency fluctuations and the risk of capital losses would have provided additional returns and positive Sharpe ratios. Compared to Lustig, Stathopoulos, and Verdelhan (2019), who fail to find a positive premium using short rates or the slope of yield curve as a predictor, I find robust evidence of risk premium associated with long bond carry trade using long-term yields as the predictor. As shown in Equation 17, countries with higher long-term yields are associated higher entropy of the pricing kernel and generate a positive risk premium.

5.4 Robustness of Carry Trade Returns Across Time

The previous section established that the carry trade, both in terms of using the short rate or the long bond, would have produced significant positive risk premia throughout the recent centuries, except for the period surrounding the economic turmoils associated with the World Wars and the recoveries from them. I now investigate the robustness of this result with respect to the specification of the analysis.

I begin by computing the returns on signal-weighted portfolios described earlier in Section 3.4 over the extended data sample. In addition, to allow for appropriate statistical inference, I run panel regressions of the form:

$$\Pi^i_{t+\Delta t} = \alpha_t + \sum_{\text{Era}} \beta_{\text{Era}} \mathbf{1}_{t \in \text{Era}} x_{t,i} + \epsilon_{t,i}, \tag{37}$$

where $x_{t,i}$ is either the short rate, $r^i_{f,t}$, or long-term bond yield, $y_{t,i}$. The indicator functions, $\mathbf{1}_{t \in \text{Era}}$, equal 1 for observations in each sub-period. Unlike equal-weighted portfolios, both signal-weighted portfolios and panel regressions place greater weight on extreme observations that deviate more from the means. As discussed in Section 3.4, the average returns on signal-weighted portfolios, coefficient estimates of panel regressions with time fixed effects, and coefficient estimates of Fama-MacBeth regressions are all related to each other up to a time-varying scalar.[24]

Equation (37) is first estimated as a panel regression with time fixed-effects, which absorbs the effects of time-varying means. Hence in this specification, the results are driven by cross-sectional variations at each point in time. The regression framework easily allows for the use of overlapping observations where holding period, Δt, might be longer than the frequency of observations of time, t. When running regressions, I consider 12-month holding periods as before but use all monthly observations rather than portfolios formed only in December. Using overlapping observations will mechanically understate standard errors because two subsequent observations are related to one another due to the overlap. Moreover, standard errors might also be overstated because some currency pairs are naturally related to one another and are not genuinely independent observations. In order to control for these two effects, the

[24] Petersen (2009) offers detailed discussions of the differences between Fama-MacBeth regressions and panel regressions with clustered standard errors.

standard errors are computed using two-way clustering by time and by currencies following Petersen (2009) and Thompson (2011).[25] As a further robustness check of the specifications, I also run monthly Fama-MacBeth regressions. Since standard errors based on overlapping observations are still a concern with this method, I produce Newey-West standard errors following Newey and West (1987).[26]

Table 7 shows the robustness of the short rate carry trade to these specifications. Panel A shows the returns on signal-weighted short rate carry trade portfolios over recent centuries. Over the whole sample, the average return of 2.14% per year with a volatility of 9.52% is comparable to that of the equal-weighted short rate carry trade shown in Table 5. The Sharpe ratio is essentially unchanged at 0.225. Within each period, neither the average returns nor volatilities are substantially changed. It remains the case that the short rate carry trade did not produce positive returns during the World Wars Era but experienced significantly reduced volatility during the Classic Gold Standard Era and Bretton Woods Era. As a result, short rate carry trade was most significant in terms of Sharpe ratios during these two periods when currencies were not freely floating, regardless of using equal-weighted portfolios or signal-weighted portfolios.

Examining regression results allows for making more careful statistical inference than casually looking at average returns and Sharpe ratios. The estimates of panel regressions with time fixed-effects and clustered standard errors are denoted $\hat{\beta}^{\text{Panel}}$ and shown in Panel B of Table 7. The column labeled 'Whole Sample' shows the regression result of equation (37) without changing the indicator function across

[25] While the two-way clustering method is commonly used in empirical asset pricing, this method assumes that cross-autocorrelations are equal to zero. Hence, if there is a lead-lag effect across currencies, the standard errors would still be overstated.

[26] To further alleviate concerns associated with overlapping observations, I also ran annual non-overlapping regressions using observations only in December, and the results were not materially different.

periods. A coefficient estimate of 0.367 indicates that when short rate of a currency is higher by 1% relative to that of other currencies, on average, the total investment return in the short rate of that currency was greater by 0.367%. Put another way, given an increased short rate carry of 1% return, an average of 0.367% return was not lost to currency depreciation. This estimate is statistically significant at the 1% level, even after controlling for both clustering by time and by currency.

The remaining columns of Panel B show the coefficient estimate with indicator functions for each period, which can be interpreted as time-varying short rate carry trade. Consistent with the portfolio results, the panel regression estimates show that there was no risk premium associated with short rate carry during the World Wars Era. Curiously, despite the modest Sharpe ratio of 0.389 shown in Panel A over the Early Second Industrial Revolution, the panel regression estimate for this period is not statistically significant. Part of this can be explained by the fact that the short rate carry trade is less pronounced when overlapping data is used during this period, but it is also due to the more conservative inference made with two-way clustered standard errors.

As an additional specification check, the estimates from Fama-MacBeth regressions are denoted $\hat{\beta}^{\text{FM}}$ and shown in Panel C. Across the whole sample, the coefficient estimate is 0.308 and remains statistically significant using Newey-West standard errors. The remaining columns of Panel C show the coefficients estimates from Fama-MacBeth regressions over each period and are equivalent to the estimates from the panel regressions with indicator functions. Consistent with panel regression results, Fama-MacBeth regressions also fail to detect statistically significant short rate carry trade returns during the Early Second Industrial Revolution and the World Wars Era.

Table 8 repeats the robustness checks to varying specifications for the long bond carry trade. Panel A shows the returns on signal-weighted long bond carry trade portfolios, which are similar in terms of Sharpe ratios to that of equal-weighted long bond carry trade portfolios shown in Table 6. However, both average returns and volatilities are significantly higher in the extended sample that covers the Age of Revolution. Similar to the short rate carry trade, the long bond carry trade was also not positive during the World Wars Era. The lack of long bond carry trade during this time period is confirmed by the panel regression results in Panel B and Fama-MacBeth regression results in Panel C. However, unlike the short rate carry trade, the regression results support a statistically significant long bond carry trade during the Age of Revolution and the Early Second Industrial Revolution. The regression point estimates are larger for long bond carry trade, but harder to interpret, that those for the short rate carry trade. The point estimate from the panel regression of 1.851 for the whole sample in Panel B indicates that given an increased long-term bond yield of 1% is associated with more than one-for-one total investment return, some of which is due to carry and lack of currency depreciation, but also due to capital gains as future yields fall. Compared to the short rate carry trade, the regression point estimates are generally higher for the long bond carry trade across periods, but converges during the Modern Sample.

Overall, my extension of the study of the carry trade indicates that the carry trade is robust to using the long bonds and extending the sample to longer time, but with some exceptions. In particular, neither the short rate carry trade nor the long bond carry trade appears to have produced positive returns during the World Wars Era. While Accominotti, Cen, Chambers, and Marsh (2019) argue that it was the transition to fixed exchange rate that leads to reduced carry trade returns, such an argument doesn't explain the robust carry trade returns around the Classic Gold Standard Era or the lack of change in returns when exchange rates become floating once again. If anything, fixed exchange rate eras, such as the Classic Gold Standard Era or the Bretton Woods Era, led to reduced volatility of exchange rates and ultimately made both the short rate carry trade and the long bond carry trade more prominent in terms of Sharpe ratios. Various specification tests of this also show that the carry trade is robust to focusing on just the long side or the short, using signal-weighted portfolios, using overlapping data in a regression analysis, and using clustered standard errors. Whereas Lustig, Stathopoulos, and Verdelhan (2019) find the lack of long bond premium puzzling for explaining the results in a theretical model, I find there is no puzzle to be explained when other variables are used to predict returns.

6 Other Currency Investment Portfolios

With extended data sample of the short rates and long bonds over the recent centuries, I can also investigate the robustness of other currency investment strategies based on additional signals studied in the literature. I begin by examining the robustness of currency investment strategies that use the slope of the yield curve as the predictor. Then I examine a version of the carry trade that places the US dollar in a central position, called the dollar carry trade. Finally, I examine the robustness of the momentum effect and the reversal effect among currencies.

6.1 Currency Investing Based on Term Spread (Slope)

Ang and Chen (2017) shows that in addition to the level of interest rates, the slope of the yield curve, or the term spread, has predictive power over future currency investment returns. That study provides empirical evidence that a relatively flat yield curve in currency compared to other currencies predicts positive future currency returns. Ang and Chen (2017) offers an interpretation that the term spread reflects a latent risk factor. Since the extension of the data includes both short-term interest rates and long-term interest rates, it is natural to check the robustness of this result to the extended historical sample. Moreover, whereas Ang and Chen (2017) only considers using the short rate as the investment vehicle, I can now use long bonds as the investment vehicle instead, as well as currency-hedged long bond positions.

Yield curve slope trades are based on the term spreads. When short rates are the investment vehicles, the currency term spread trade goes long currencies with the lowest term spread and short currencies with the steepest yield curve. Similarly, when long bonds are the investment vehicles, I consider going long currencies with the steepest yield curve. The latter strategy is studied by Lustig, Stathopoulos, and Verdelhan (2019) as well. As before, I construct annually-rebalanced equally-weighted portfolios and run monthly overlapping panel regressions with two-way clustered standard errors for robustness tests.

Figure 3 shows cumulative returns on currency term spread trades throughout the whole sample. Both short rate and long bond portfolios generally exhibit positive returns throughout the sample. Even though they are individually increasing, the two portfolios are naturally complementary and exhibit strongly negatively correlated returns because they are constructed using opposite signals. Indeed, negative returns exhibited by the long bond portfolio during the 1920s is accompanied by positive returns in the short rate portfolio. However, during the Classic Gold Standard Era and the Bretton Woods Era when currencies were fixed, the two portfolios seem to behave independently, and both produced positive returns. Panels A and B of Table 9 show detailed statistics of these two portfolios across different periods. Consistent with the plots, both portfolios exhibit positive returns across all sub-periods, except for the long bond currency term spread portfolio over the World Wars Era and Post-Euro Floating Exchange Regime. Consistent with other strategies studied, portfolio returns were less volatile during the fixed exchange regimes, which produce high Sharpe ratios during these periods. The fact that investing in short rates based on term spread, the lack of positive returns using long bonds is documented as a puzzle by Lustig, Stathopoulos, and Verdelhan (2019).

The negative correlation between the short rate and the long bond currency term spread trades suggests consdering the currency-hedged long bond portfolios using the term spread as the predictor. This portfolio goes long long bonds and goes short short rates when the term spread in a currency is steep relative to others. Similarly, the portfolio would go short long bonds and go long short rates when the term spread is relatively flat. From Section 2, equation (18) shows that differences in currency-hedged long bonds returns could arise from differences in the entropies of the non-permanent shocks to the pricing kernel.Panel C of Table 9 shows the portfolio returns on this currency hedged long-term bond carry trade. This trade produces positive returns throughout every sub-period. In some periods, this spread produces the highest Sharpe ratio of all strategies considered thus far. This strategy is also investigated by Koijen, Moskowitz, Pedersen and Vrugt (2018) who use the yield difference between 10-year bonds and 2-year bonds, but over a shorter sample.

As a robustness test, Panel D of Table 9 shows the coefficient estimates from panel regressions for currency term spread trade using short rates, long bonds, and currency hedged long bonds. Consistent with Ang and Chen (2017), the short rate currency term spread trade is significantly positive during the Modern Sample. Before the Modern Sample, coefficients are generally positive but not statistically significant. For the long bond currency term spread trade, the regression coefficients vary greatly from strongly positive during the Early Second Industrial Revolution and Bretton Woods Era, to negative during the Post-Euro period.[27]

The most interesting result is for the currency-hedged long bond carry trade. The panel regression coefficient is consistently positive and statistically significant

[27] Results using Fama-MacBeth regressions with Newey-West standard errors are not shown but are similar.

throughout all periods. The average coefficient across all periods is 1.204 (unreported), which can be interpreted as whenever the term spread of a currency is higher by 1%, investing in that currency's long bond by financing it with that currency's short rate yields a return on average of 1.204%. Part of this is due to the higher yield, but it is also partly due to the fact that flattening yield curves lead to capital gains in long bonds. Overall, currency-hedged long-term bond carry trade is extremely robust and produced positive risk premia throughout the sample. Based on the interpretation from Section 2, the results suggest that there are cross-sectional differences in the entropies of pricing kernels not explained by permanent shocks to the pricing kernels. In short, both transitory and permanent shocks to the pricing kernel are reflected in the observed currency portfolio returns.

6.2 Dollar Carry Trade

Lustig, Roussanov, and Verdelhan (2014) and Hassan and Mano (2019) examine a variation of the carry trade that focuses explicitly on the level of the USD short rate relative to that of the average of all other currency's short rates. This strategy goes long all other currencies and goes short USD whenever the average global short rates are above the US short rate. Similarly, the strategy goes long USD whenever the US short rate is high relative to that of other currencies. Lustig, Roussanov, and Verdelhan (2014) show that this strategy delivered substantial returns from 1983 to 2010, even after controlling for transaction costs by using forward contracts. They argue that the relative level of the US short rate is related to the US economic cycle, and interpret the high excess return on this portfolio strategy as a risk premia in currency markets for macroeconomic risk. Hassan and Mano (2019) reexamine the potentially unique role of the US dollar in a regression framework and find some support.

Using the same methodology I used for the normal carry trades, I examine the robustness of the dollar carry trade to earlier historical samples. One problem with this exercise is that the short rate for the US can only be obtained going back to 1914:11 in my data source.[28] Fortunately, using long bonds allows historical data to reach as far back as 1788:09. When using long bonds, dollar carry trade portfolios are constructed using the yield on the long-term US bond rate relative to the average of all other currency's long-term bond rates. With both investment assets, I focus on annually-rebalanced equal-weighted portfolios. Results based on monthly rebalancing or signal-weighting are similar but not shown. For robustness, I also present results based on overlapping monthly panel regressions.

Table 10 shows the returns on dollar carry trade over the extended time sample. Panel A presents the dollar carry trade using the short rate going back to 1914. Consistent with the literature, the dollar carry trade produced positive returns during the Modern Sample, albeit with only moderate Sharpe ratios. During the fixed-exchange regime of Bretton Woods Era, the return on the dollar carry trade was modest at only 0.89% per year, but this was a period of very low volatility in currency exchanges. Overall, the Bretton Woods Era would have produced the dollar carry trade with the highest Sharpe ratio. However, as with the normal carry trades, the World Wars Era remains the exception. During this period, the dollar carry trade would not have produced a positive risk premium. If anything, the dollar carry trade would have been negative. Hence, it may have be the case that the dollar carry trade doesn't hold up to the robustness test of using an extended sample. Alternatively, it may also have been the case that the underlying economic mechanisms at work was different during the period surrounding the World Wars Era.

[28] The 3-month US Treasury bill rate is available on (FRED) from 1934. Before this, other short-term US Treasury securities and the discount rate of the Federal Reserve Bank of New York is used.

Panel B of Table 10 shows results using long bonds in place of short rates, which extends the data sample for the US dollar significantly. The long bond sample shows weak returns on the dollar carry trade in the most recent half of the Modern Sample in the Post-Euro Floating Exchange Regime. As with the normal carry trade, returns would have been smaller during the Bretton Woods Era and the Classic Gold Standard Era, but the reduced currency volatility of the period would have made the Sharpe ratios of the dollar carry trade attractive. In fact, the long bond dollar carry trade would have been positive in all other periods except during the World Wars Era and the Early Second Industrial Revolution. Figure 4 plots the cumulative returns on both the dollar carry trade using the short rate and the long bond and provides a clear view on when the dollar carry trade failed to produce positive returns. The points in time when the dollar carry trade produced significantly negative returns correspond to the US Civil War period and World Wars period. Hence rather than economic cycles, the performance of dollar carry trade might be more tied to periods of extreme economic turmoils.

As a final robustness check, I run monthly overlapping panel regressions with two-way clustered standard errors. In the case of the dollar carry trade, the independent variable, $x_{t,\mathrm{USD}}$, equal one (negative one) if the US dollar interest rate is greater (lower) than the average interest rate of all other currencies. For all other currency i, $x_{t,i}$ equals positive (negative) $\frac{1}{n_t}\%$ if the US dollar interest rate is lower (greater) than the average interest rate of all other currencies, where n_t is the number of currencies excluding US dollar in the sample at time t. As with before, this variable is interacted with an indicator function for each period.

Panel C of Table 10 presents the results from the panel regressions for the short rate dollar carry trade and for the long bond dollar carry trade. Results using Fama-MacBeth regressions with Newey-West standard errors are not shown but are similar. The coefficient estimate of 0.609 for the short rate dollar carry over the whole sample can be interpreted as when the US dollar interest rate is above average, investing in the US dollar produced an average of 0.609% return per year. The coefficients with the period interaction terms show time variation in the short rate dollar carry trade. Consistent with the portfolio results, the panel regression using short rates shows that dollar carry trade produced positive returns during the Modern Sample and extended back to the Bretton Woods Era, but not back to the World Wars Era. The coefficients on the long bond dollar carry trade show qualitatively similar results, but with a higher overall impact. As before, dollar carry trade produced negative returns around the Early Second Industrial Revolution, which contained the US Civil War, and the World Wars Era.

Overall, these results suggest that the dollar carry trade is fairly robust except during periods of extraordinary economic turmoil, which is similar to the lack of robustness of the normal carry trade during such times. This lack of robustness might help explain the mechanism underlying both carry trades. It is plausible that the risk premium associated with the dollar carry trade is associated only with periods when the US dollar plays a central role in the global economy. Further investigation is left for future research.

6.3 Currency Momentum and Reversal (Value)

The momentum effect and the reversal (value) effect are two additional currency investment strategies that have been studied in the literature that can also be readily be examined in my expanded sample. Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) and Asness, Moskowitz, and Pedersen (2013) both report strong momentum effect in the Modern Sample during which currencies that have appreciated the most in the past twelve months tend to continue to exhibit have high investment returns. Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) report that this effect is most potent when the holding period is over the next one month, which is consistent with the strategy studied in Asness, Moskowitz, and Pedersen (2013). The latter study also documents a reversal effect, where currencies with low long-term past returns tend to revert to higher returns. Menkhoff, Sarno, Schmeling, and Schrimpf (2017) report similar results based on past 5-year currency appreciation, relative to changes in purchasing power.[29] Since low past returns given relatively unchanged fundamentals are similar to low valuation of currencies, these reversal effects are sometimes referred to as 'value' effects. These studies are all based upon observations during the Modern Sample. In this section, I investigate the robustness of momentum and reversal effects in currencies over extended periods.

In studying the momentum effect, I follow Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) and focus on a one-month holding period, which they found to exhibit the strongest momentum effect, by considering monthly-rebalanced portfolios and monthly overlapping panel regressions. I use past twelve month FX returns, excluding the carry, as the sorting variable, which Menkhoff et als. (2012a) found to be stronger than using past total investment returns.[30] Figure 5 shows the cumulative returns on currency momentum based on using both the short rate and the long bond as the investment vehicle. This figure indicates a generally positive return to momentum investing in currencies since 1855 when the short rate sample begins. Unlike the carry trade, currency momentum would have remained robust during the World Wars Era. However, when we extend the data sample back to the

[29] There is also a vast literature examining the Purchasing Power Parity (PPP) throughout history, but that literature focuses on time-series variation in currency pairs rather than cross-sectional variations across multiple currencies at a point in time.

[30] An alternative method would be to create a strategy based on past total investment returns that include both past carry and past capital gains of the investment asset. However, this would confound the results from the carry trade and from any momentum and reversal effects of long-term bonds.

Age of Revolution using long bonds, the resulting plot casts doubt on the robustness of currency momentum strategy throughout the entire sample.

Panel A of Table 11 examines the robustness of the monthly-rebalanced equal-weighted momentum strategy across time. While the currency momentum effect has existed in the Modern Sample, it appears that the effect has been negligible during the most recent Post-Euro Floating Exchange Regime. However, in all other periods, currency momentum has exhibited positive Sharpe ratios. Even during the Bretton Woods Era and the Classic Gold Standard Era, when overall momentum return was low, coupled with low volatility of this era meant that momentum offered reasonable returns for the amount of risk taken. Curiously, the World Wars Era was the period that produced the highest momentum returns in terms of Sharpe ratios. Panel B of Table 11 re-examines the momentum effect using the long bond as the investment asset instead. The results are largely consistent with that of currency momentum using the short rate. Consistent with Figure 5, Panel B reflects the fact that the momentum effect was negative during the Age of Revolution.

Panel C of Table 11 shows the results based on monthly panel regressions with two-way clustered errors. The combined regression results suggest that short rate currency momentum may not be very robust. Based on the short rate as the investment vehicle, currency momentum effect over the whole sample is only statistically significant at the 10% level. In fact, the only period when the momentum effect was statistically significant was during the World Wars Era. Panel C also shows the results based on currency momentum investing in long bonds. The currency momentum investing can be shown to have been significant during the first half of the Modern Sample, but it is offset by the statistically significant negative effect during the Early Second Industrial Revolution. Over the whole sample, the long bond momentum effect can not be shown to have been statistically significant.

Finally, I examine currency reversal trade over my extended data sample. Annually-rebalanced equal-weighted portfolios are formed according to the past five years of FX returns. This formation is equivalent to the currency reversal strategy studied by Asness, Moskowitz, and Pedersen (2013) rather than currency value strategy studied by Menkhoff, Sarno, Schmeling, and Schrimpf (2017) which uses real returns in foreign exchange. As before, I consider investments in both short rate and long bonds.

Figure 6 shows the cumulative returns on currency reversal. Both short rate currency reversal and long bond currency reversal have only been positive since around 1980, when most prior studies begin their data. There has been period of relatively flat returns when currencies were not freely floating, but the general trend in returns to currency reversal has been negative. Table 12 examines returns on currency reversal portfolios deeper. Panels A and B show the returns using short rates and long bonds, respectively, and tell results similar to that of the figure.

The only period during which currency reversal produced significantly positive returns was during the latter part of the Modern Sample. Returns were relatively flat during the Classic Gold Standard Era and the Bretton Woods Era. Similar to the carry trades, if anything, returns were negative during the World Wars Era. Monthly overlapping panel regressions in Panel C confirm these findings. Some periods such as the Early Second Industrial Revolution and the Classic Gold Standard Era, do manage to produce statistically significant coefficients on currency reversal, but the overall effect throughout the whole sample is not statistically different from zero. While it is possible that the results would differ under other specifications of currency value that accounts for inflation and changes in purchasing power, this evidence based on a long history of currency reversal does not bode well for the robustness of currency value strategies.

7 Conclusion

I investigate in this paper the robustness of currency investment strategies using an extended data sample that spans over two centuries and uses long-term bonds as well as short-term rates as the investment vehicle. Using portfolio returns and panel regression analysis, I find that the carry trade returns would have been robust across time, whether short rates or long bonds are used, except for the period surrounding the World Wars. The dollar carry trade also has been robust except for these periods plus the period surrounding the US Civil War. While there is limited support for the currency momentum effect, using a longer sample shows that currency reversal effect does not exist. Finally, an examination of currency investments based on slopes of the yield curve suggests that currency-hedged long bond investments produce very high excess returns.

Some surprising stylized facts emerge from this study. In contrast to Lustig, Stathopoulos, and Verdelhan (2019), long bond currency investments exhibit robust positive returns when predictable variables other than short rate or term spread are used. Overall, there is no evidence of a downward term structure of currency carry trade risk premia and the empirical results can be interpreted as reflecting varying entropy of pricing kernels across countries. My results are consistent with Koijen, Moskowitz, Pedersen, and Vrugt (2018) and Baltussen, Swinkels, and van Vliet (2021) who find strong carry trade premia across a wide variety of asset classes, including long bonds. Across various periods, fixed exchange rate regimes do not make currency effects like the carry trade go away. If anything, since these periods exhibit lower currency exchange rate volatility, fixed exchange rate regimes are associated with higher carry returns on a risk-adjusted basis. Rather than economic cycles, it seems to be the case that it is the periods of major economic turmoil associated with World Wars that make these currency effects go away.

While this paper offers some additional understanding of the patterns of the cross-section of currency returns over the recent centuries, this line of research is still far from complete. In particular, this study investigates only cross-country variations in currencies and did not investigate cross-time variations in currency investment returns, as is done in studies of the PPP and UIP hypotheses. While these returns across currency investments can be interpreted in a complete financial market framework as reflecting variations in both permanent and transitory shocks in the pricing kernel, this understanding is only within a reduced-form model framework. I leave for future research, additional investigation of the underlying economic drivers behind these observations and shocks to the pricing kernels.

References

[1] Alvarez, F. and Jermann, U.J., 2005, "Using asset prices to measure the persistence of the marginal utility of wealth," *Econometrica*, 73(6), 1977-2016.

[2] Accominotti, O., Cen, J., Chambers, D., and Marsh, I., 2019, "Currency regimes and the carry trade", *Journal of Financial and Quantitative Analysis*, 54(5), 2233-2260.

[3] Asness, C.S., Moskowitz, T.J., and Pedersen, L.H., 2013, "Value and momentum everywhere", *The Journal of Finance*, 68(3), 929-985.

[4] Ang, A. and Chen, J.S., 2017, "Yield curve predictors of foreign exchange returns", working paper, University of California, Davis.

[5] Backus, D.K., Foresi, S., and Telmer, C.I., 2001, "Affine term structure models and the forward premium anomaly," *Journal of Finance*, 56(1), 279-304.

[6] Backus, D.K., Chernov, M., and Zin, S., 2014, "Sources of entropy in representative agent models," *Journal of Finance*, 69(1), 51-99.

[7] Baltussen, G., Swinkels L., and van Vliet, P., 2021, "Global factor premiums", *Journal of Financial Economics*, 142(3), 1128-1154.

[8] Bansal, R., 1997, "An exploration of the forward premium puzzle in currency markets," *Review of Financial Studies*, 10(2), 369-403.

[9] Bekaert, G. and Panayotov, G., 2020, "Good carry, bad carry", *Journal of Financial and Quantitative Analysis*, 55(4), 1063-1094.

[10] Burnside, C., Eichenbaum, M., Kleshchelski, I., and Rebelo, S., 2011, "Do peso problems explain the returns to carry trade?", *Review of Financial Studies*, 24(3), 853-891.

[11] Cochrane, J., 2000, *Asset Pricing*, Princeton University Press.

[12] Croce, M.M. and Colacito, R., 2011, "Risks for the long run and the real exchange rate," *Journal of Political Economy*, 119(1), 153-181.

[13] Davis, J.L., Fama, E.F., and French, K.R., 2000, "Characteristics, covariances, and average returns: 1929 to 1997", *The Journal of Finance*, 55(1), 389-406.

[14] Dimson, E., Marsh, P., and Stauton, M., 2013 "Global investment returns sourcebook", Credit Suisse Research Institute.

[15] Doskov, N. and Swinkels, L., 2015, "Empirical evidence on the currency carry trade, 1900-2012", *Journal of International Money and Finance*, 51, 370-389.

[16] Fama, E.F., 1976, *Foundations of Finance*, Basic Books.

[17] Fama, E.F., 1984, "Forward and spot exchange rates", *Journal of Monetary Economics*, 14(3), 319-338.

[18] Fama, E.F. and MacBeth, J.D., 1973, "Risk, return, and equilibrium: empirical tests", *Journal of Political Economy*, 81(3), 607-636.

[19] Golez, B. and Koudijs, P., 2018, "Four centuries of return predictability", *Journal of Financial Economics*, 127(2), 248-263.

[20] Greenwood, R., Hanson, S.G., Stein, J.C., and Sunderam, A., 2023, "A Quantity-Driven Theory of Term Premia and Exchange Rates", *Quarterly Journal of Economics*, 138(4), 23272389.

[21] Hansen, L.P. and Hodrick, R.J., 1980, "Forward exchange rates as optimal predictors of future spot rates: An econometric analysis", *The Journal of Political Economy*, 88(5), 829-853.

[22] Hassan, T.A. and Mano, R.C., 2019, "Forward and spot exchange rates in a multi-currency world", *The Quarterly Journal of Economics*, 134(1), 397-450.

[23] Jordà, Ò., Knoll, K., Kuvshinov, D., Schularick, M., and Taylor, A.M., 2019, "The rate of return on everything, 1870-2015", *The Quarterly Journal of Economics*, 134(3), 1225-1298.

[24] Koijen, R.S., Moskowitz, T.J., Pedersen, L.H., and Vrugt, E.B., 2018, "Carry", *Journal of Financial Economics*, 127(2), 197-225.

[25] Linnainmaa, J.T. and Roberts, M.R., 2018, "The history of the cross section of stock returns", *Review of Financial Studies*, 31(7), 2606-2649.

[26] Lobell, H., 2010, "Foreign exchange rates 1804-1914", in Edvinsson, R., Jacobson, T. and Waldenstrm (Eds.), *Exchange rates, prices, and wages, 1277-2008*, 291-339, Sveriges Riksbank and Ekerlids Frlag.

[27] Lothian, J.R. and Taylor, M.P., 1996, "Real exchange rate behavior: The recent float from the perspective of the past two centuries", *The Journal of Political Economy*, 104(3), 488-509.

[28] Lothian, J.R. and Wu, L., 2011, "Uncovered interest-rate parity over the past two centuries", *Journal of International Money and Finance*, 30(3), 448-473.

[29] Lustig, H. and Verdelhan, A., 2007, "The cross section of foreign currency risk premia and consumption growth risk", *American Economic Review* 97(1), 89-117.

[30] Lustig, H., Roussanov, N., and Verdelhan, A., 2011, "Common risk factors in currency markets", *Review of Financial Studies*, 24(11), 3731-3777.

[31] Lustig, H., Roussanov, N., and Verdelhan, A., 2014, "Countercyclical currency risk premia", *Journal of Financial Economics*, 111(3), 527-553.

[32] Lustig, H., Stathopoulos, A., and Verdelhan, A., 2019, "The term structure of currency carry trade risk premia", *American Economic Review*, 109(12), 4142-4177.

[33] Malkiel, B.G., 1962, "Expectations, bond prices, and the term structure of interest rates", *The Quarterly Journal of Economics*, 76(2), 197-218.

[34] Menkhoff, L., Sarno, L., Schmeling, M. and Schrimpf, A., 2012a, "Currency momentum strategies", *Journal of Financial Economics*, 106(3), 660-684.

[35] Menkhoff, L., Sarno, L., Schmeling, M., and Schrimpf, A., 2012b, "Carry trades and global foreign exchange volatility", *The Journal of Finance*, 67(2), 681-719.

[36] Menkhoff, L., Sarno, L., Schmeling, M., and Schrimpf, A., 2017, "Currency value", *The Review of Financial Studies*, 30(2), 416-441.

[37] Newey, W.K. and West, K.D., 1987, "A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix", *Econometrica*, 55(3), 703-708.

[38] Petersen, M.A., 2009, "Estimating standard errors in finance panel data sets: comparing approaches", *The Review of Financial Studies*, 22(1), 435-480.

[39] Piazzesi, M., 2010, "Affine term structure models," in Ait-Sahalia, Y. and Hansen, L. P., eds, *Handbook of Financial Econometrics*, Elsevier, Amsterdam, 691-766.

[40] Schwert, G.W., 1990, "Stock returns and real activity: A century of evidence", *The Journal of Finance*, 45(4), 1237-1257.

[41] Swinkels, L., 2019, "Historical Data: International monthly government bond returns", Erasmus University Rotterdam, https://doi.org/10.25397/eur.8152748.v6.

[42] Swinkels, L., 2023, "Historical Data: International monthly government bond returns", Dataset, Erasmus University Rotterdam, https://doi.org/10.25397/eur.8152748.

[43] Thompson, S.B., 2011 "Simple formulas for standard errors that cluster by both firm and time", *Journal of Financial Economics* 99(1), 1-10.

[44] Verdelhan, A., 2010, "A habit-based explanation of the exchange rate risk premium," *Journal of Finance*, 65(1), 123-145.

[45] Zviadadze, I., 2017, "Term Structure of Consumption Risk Premia in the Cross Section of Currency Returns", *The Journal of Finance*, 72(4), 1529-1566.

Table 1: Historical Interest Rate Data

Country	Currency	Short Rates Mean	Short Rates StDev	Short Rates Start	Long Bonds Mean	Long Bonds StDev	Long Bonds Start
Australia	AUD	5.12	3.81	1920:07	5.43	2.73	1857:06
Austria	ATS	4.79	1.96	1860:07	6.05	1.96	1813:11
Belgium	BEF	4.44	2.60	1858:06	5.13	2.12	1831:12
Canada	CAD	4.34	3.88	1934:03	5.04	2.45	1853:01
Denmark	DKK	5.28	3.92	1864:01	5.49	3.13	1788:09
Finland	FIM	5.47	1.77	1867:01	7.81	2.84	1896:01
France	FRF	4.41	2.93	1854:01	5.85	4.44	1788:09
Germany/Euro	DEM	4.17	3.89	1854:01	5.37	2.02	1788:09
India	INR	5.55	2.99	1873:12	5.48	2.80	1864:10
Italy	ITL	6.15	3.68	1861:01	6.70	3.11	1807:11
Japan	JPY	4.49	2.49	1882:10	5.55	2.34	1870:05
Netherlands	NLG	3.54	2.04	1854:01	5.16	2.84	1788:09
New Zealand	NZD	5.88	4.40	1923:01	5.33	2.86	1861:10
Norway	NOK	4.54	2.48	1854:01	5.02	2.28	1822:03
Portugal	PTE	6.03	5.04	1885:01	7.15	3.98	1806:01
South Africa	ZAR	6.25	4.68	1913:01	6.51	3.87	1860:12
Spain	ESP	5.35	3.29	1870:01	11.45	10.67	1788:09
Sweden	SEK	4.68	2.93	1856:11	5.48	2.93	1788:09
Switzerland	CHF	2.79	1.89	1854:01	3.84	1.28	1893:01
United Kingdom	GBP	4.34	3.17	1854:01	4.67	2.64	1788:09
United States	USD	3.44	2.91	1914:11	4.77	2.33	1788:09

This table reports means and standard deviations of interest rate data used. Short rates are the yields on three-month government bill rates or the closest available instrument. Long bonds are the 10-year government bonds or the closest available instrument. ISO 4217 code is used for currency code. The start of the sample is also reported. For currencies that entered the Euro with the exception of DEM, the sample ends with 1998:12. For all other currencies, the sample ends with 2017:06.

Table 2: Summary Statistics

	Short Rate Sample						Long Bond Sample							
	Yield		FX Return		Total Return		Yield		Cap Gains		FX Return		Total Return	
Currency	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
AUD	5.25	3.98	-0.34	10.87	4.86	11.72	5.65	5.74	0.25	5.05	-0.11	11.29	5.44	12.56
ATS	4.85	1.97	-2.13	16.83	2.68	18.01	6.37	6.81	0.29	6.49	-1.80	15.48	4.53	18.07
BEF	4.54	2.67	-0.52	12.77	4.00	13.67	5.27	4.87	0.15	4.35	-0.42	11.75	4.88	13.92
CAD	4.46	4.01	-0.21	5.42	4.23	6.69	5.28	5.30	0.27	4.69	0.08	7.53	5.35	9.27
DKK	5.44	4.16	-0.32	10.41	5.11	11.88	5.71	6.74	0.25	5.86	-0.38	13.73	5.36	16.18
FIM	5.59	1.79	-2.33	13.20	3.13	14.09	7.96	10.53	0.18	9.90	-2.93	15.20	4.97	20.45
FRF	4.51	3.01	-1.75	15.76	2.68	16.68	6.54	16.05	0.76	13.86	-1.86	15.44	4.85	25.73
DEM	4.00	1.73	-1.71	17.94	2.22	18.73	5.96	6.58	0.64	6.33	-0.94	14.69	4.91	17.10
INR	5.69	2.87	-1.93	8.98	3.58	9.23	5.41	4.94	-0.08	4.02	-1.92	8.91	3.34	10.07
ITL	6.35	3.89	-2.23	16.38	3.92	17.50	6.90	7.59	0.21	6.76	-1.58	14.20	5.31	17.47
JPY	4.57	2.54	-1.26	15.18	3.27	16.03	6.22	6.41	0.74	6.04	0.26	10.04	6.58	13.28
NLG	3.60	2.01	0.71	10.76	4.34	11.41	5.33	9.79	0.20	9.09	0.72	9.17	6.09	13.79
NZD	6.07	4.58	-0.40	12.94	5.67	14.61	5.55	6.25	0.25	5.42	-0.12	12.12	5.46	14.35
NOK	4.63	2.54	0.11	11.38	4.76	12.36	5.27	5.13	0.27	4.66	0.50	11.03	5.80	12.73
PTE	6.26	5.39	-3.23	14.61	2.69	15.73	7.64	11.37	0.56	10.32	-1.60	13.45	6.08	18.79
ZAR	6.49	4.92	-2.56	12.19	3.62	12.93	6.40	6.39	-0.10	4.92	-1.51	11.91	4.82	14.46
ESP	5.50	3.26	-1.51	15.04	3.90	16.07	13.42	33.89	2.16	29.47	-0.73	10.12	12.69	36.00
SEK	4.78	3.02	-0.13	8.92	4.62	9.64	5.45	7.29	-0.01	6.71	-0.48	9.53	4.97	12.74
CHF	2.82	1.88	1.58	10.86	4.44	11.41	4.14	4.84	0.33	4.49	1.34	9.94	6.07	12.10
GBP	4.44	3.24	-0.33	10.14	4.09	11.12	4.83	5.13	0.18	4.38	-0.18	8.95	4.63	10.56
USD	3.51	2.97	0.00	0.00	3.51	2.97	5.36	7.41	0.64	6.49	0.00	0.00	5.36	7.41

This table shows the summary statistics of 12-months investment returns. Columns under ‘Short Rate Sample’ and ‘Long Bond Sample’ report summary statistics for when short rates and long bonds are used, respectively. Columns labeled ‘Yield’ show means and standard deviations of twelve-months yield on short rates and long bonds. Returns on short rate are 3-months interest rates compounded for 12-months. Returns on long bonds are approximated as per Section 3.2 and include capital gains and adjustment term in the column labeled ‘Cap Gains’. Columns labeled ‘FX Return’ show means and standard deviations of twelve-months returns on foreign exchange over the sample period. Columns labeled ‘Total Return’ show the averages the products of investment returns and foreign exchange returns. All values are in annual percentages.

Table 3: Carry Trade: Modern Sample (1973-2017)

	Short Rate Portfolios			Long Bond Portfolios		
	Long-Short	Long Side	Short Side	Long-Short	Long Side	Short Side
Panel A: Monthly-Rebalanced Equal-Weighted Portfolio Returns						
Average Return	3.42%	1.92%	1.50%	2.52%	1.34%	1.18%
Volatility	6.45%	3.55%	3.50%	6.43%	3.81%	3.16%
Sharpe Ratio	0.530	0.541	0.428	0.392	0.350	0.374
Skewness	(0.64)	(0.30)	(0.80)	(0.43)	(0.35)	(0.39)
Minimum	-9.93%	-3.86%	-6.33%	-7.28%	-3.90%	-3.67%
Maximum	5.86%	4.16%	3.53%	5.71%	4.05%	3.27%
Panel B: Annually-Rebalanced Equal-Weighted Portfolio Returns						
Average Return	3.04%	1.76%	1.28%	3.28%	1.77%	1.52%
Volatility	8.14%	3.94%	4.81%	9.21%	5.21%	4.70%
Sharpe Ratio	0.373	0.446	0.266	0.356	0.339	0.323
Skewness	(0.55)	0.06	(0.82)	(0.47)	(0.44)	(0.54)
Minimum	-24.30%	-8.14%	-16.16%	-20.86%	-11.19%	-12.79%
Maximum	23.93%	12.56%	11.36%	20.32%	12.68%	12.09%
Panel C: Annually-Rebalanced Signal-Weighted Portfolio Returns						
Average Returns	3.51%	2.21%	1.30%	4.26%	2.79%	1.47%
Volatility	8.99%	5.67%	4.15%	11.81%	8.67%	4.54%
Sharpe Ratio	0.391	0.390	0.313	0.361	0.322	0.325
Skewness	(0.16)	0.44	(1.20)	(0.20)	(0.13)	(0.40)
Minimum	-24.34%	-9.23%	-15.11%	-27.58%	-24.41%	-13.24%
Maximum	26.90%	17.33%	9.57%	31.05%	24.57%	12.53%

This table reports summary statistics of returns on equal-weighted (Panels A and B) and signal-weighted (Panel C) long/short carry trade portfolios over 1973:01 to 2017:06. Each portfolio is formed according to the yield on the investment vehicle and rebalanced each month (Panel A) or each December (Panels B and C). The equal-weighted portfolios go long currencies with the highest one-third of the yields and go short currencies with the lowest one-third of the yields. The signal-weighted portfolios go long currencies with above average yields and go short currencies with below average yields, such that all positive weights sum to one and all negative weights sum to negative one. Returns are decomposed to the long side return and the short side return relative to an equal-weighted portfolio of currencies on either side. Minimum and maximum values are one-month holding period returns in Panel A, while all other values are annualized values.

Table 4: Correlations of Carry Trade Portfolio Returns

	Monthly EW Short-Rate	Monthly EW Long-Bond	Annual EW Short-Rate	Annual EW Long-Bond	Annual SW Short-Rate	Annual SW Long-Bond
Monthly EW Short-Rate	1.000					
Monthly EW Long-Bond	0.884	1.000				
Annual EW Short-Rate	0.943	0.902	1.000			
Annual EW Long-Bond	0.818	0.903	0.857	1.000		
Annual SW Short-Rate	0.930	0.882	0.954	0.833	1.000	
Annual SW Long-Bond	0.788	0.843	0.804	0.929	0.838	1.000

This table reports correlations between returns on various carry trade portfolio returns over the Modern Sample (1973-2017). Each portfolio is formed according to the yield on the investment vehicle and rebalanced each month ('Monthly') or each December ('Annual'). The equal-weighted ('EW') portfolio go long currencies with the highest one-third value of the yields and go short currencies with the lowest one-third value of the yields. The signal-weighted ('SW') portfolio go long currencies with above average yields and go short currencies with below average yields, such that all positive weights sum to one and all negative weights sum to negative one.

Table 5: Short Rate Carry Trade over Recent Centuries

		Sub-Periods					
	Whole Sample	1855-1879 Early Second Industrial Revolution	1880-1913 Classic Gold Standard Era	1914-1949 World Wars Era	1950-1972 Bretton Woods Era	1973-1998 Pre-Euro Floating Exchange Regime	1999-2017 Post-Euro Floating Exchange Regime
Average Returns	2.07%	2.80%	2.40%	-0.04%	2.06%	2.16%	4.30%
Volatility	8.61%	7.13%	2.00%	14.31%	2.88%	5.59%	10.90%
Sharpe Ratio	0.240	0.392	1.200	(0.003)	0.714	0.387	0.395
FX Returns	-1.34%	0.89%	0.17%	-2.53%	-0.98%	-4.53%	-1.02%
Vol (FX)	8.39%	6.89%	1.78%	13.86%	2.69%	5.57%	10.16%
Carry Returns	3.52%	1.83%	2.23%	2.58%	3.08%	7.22%	5.37%
Vol (Carry)	2.16%	0.71%	0.67%	0.74%	0.35%	2.11%	0.69%

This table decomposes returns on annually-rebalanced equal-weighted long-short short rate carry trade over recent centuries. Each portfolio is formed according to the yield on the short rate, using the short rate as the investment vehicle, and rebalanced each December. Sample periods are split across major periods in history across columns. Average returns, volatilities and Sharpe ratios are computed within each sub-period. Total investment returns are also split into currency returns (‘FX returns’) and yields on short rates (‘Yield’). Averages and standard deviations (‘Vol’) of component returns are computed within each sub-period.

Table 6: Long Bond Carry Trade Returns over Recent Centuries

		Sub-Periods						
	Whole Sample	1789-1854 Age of Revolution	1855-1879 Early Second Industrial Revolution	1880-1913 Classic Gold Standard Era	1914-1949 World Wars Era	1950-1972 Bretton Woods Era	1973-1998 Pre-Euro Floating Exchange Regime	1999-2017 Post-Euro Floating Exchange Regime
Average Returns	5.28%	13.30%	2.76%	2.47%	-1.42%	3.51%	2.27%	4.74%
Volatility	16.07%	25.63%	4.75%	3.68%	10.87%	4.37%	8.35%	10.42%
Sharpe Ratio	0.328	0.519	0.557	0.672	(0.131)	0.803	0.272	0.455
FX Returns	-1.67%	-0.41%	-0.90%	-0.23%	-4.59%	-0.68%	-5.28%	-0.46%
Vol (FX)	7.26%	8.67%	3.28%	1.95%	9.44%	2.26%	6.02%	9.69%
Carry Returns	4.79%	8.40%	3.16%	1.87%	2.43%	2.86%	6.11%	4.62%
Vol (Carry)	4.10%	5.69%	1.27%	0.78%	0.78%	0.43%	1.57%	0.88%
Cap Gains	2.38%	5.51%	0.52%	0.86%	0.89%	1.44%	2.26%	0.83%
Vol (Cap Gains)	11.57%	20.52%	3.16%	2.11%	3.83%	3.45%	4.76%	4.23%

This table decomposes returns on annually-rebalanced equal-weighted long-short long bond carry trade over recent centuries. Each portfolio is formed according to the yield on the long bond, using the long bond as the investment vehicle, and rebalanced each December. Sample periods are split across major periods in history across columns. Average returns, volatilities and Sharpe ratios are computed within each sub-period. Total investment returns are also split into currency returns ('FX returns'), yields on long bonds ('Yield'), and capital gains on long bonds ('Cap Gains'). Averages and standard deviations ('Vol') of component returns are computed within each sub-period.

Table 7: Robustness of Short Rate Carry Trade

	Whole Sample	Sub-Periods: 1855-1879 Early Second Industrial Revolution	1880-1913 Classic Gold Standard Era	1914-1949 World Wars Era	1950-1972 Bretton Woods Era	1973-1998 Pre-Euro Floating Exchange Regime	1999-2017 Post-Euro Floating Exchange Regime
Panel A: Signal-Weighted Portfolio Returns							
Average Returns	2.14%	3.13%	2.62%	-0.79%	2.34%	2.15%	5.48%
Volatility	9.52%	8.06%	2.65%	15.56%	2.80%	6.05%	11.98%
Sharpe Ratio	0.225	0.389	0.988	(0.051)	0.836	0.355	0.458
Panel B: Panel Regression Coefficients							
$\hat{\beta}^{\text{Panel}}$	0.367**	0.155	0.731**	-0.290	0.651**	0.311*	0.823**
	(0.092)	(0.298)	(0.069)	(0.484)	(0.137)	(0.124)	(0.117)
Panel C: Fama-MacBeth Regression Coefficients							
$\hat{\beta}^{\text{FM}}$	0.308**	0.109	0.708**	-0.342	0.624**	0.310**	0.750**
	(0.117)	(0.249)	(0.091)	(0.461)	(0.093)	(0.086)	(0.211)

This table shows the robustness of short rate carry trade. Sample periods are split across major periods in history across columns. Panel A shows the returns on annually-rebalanced signal-weighted long-short short rate carry trade. Each portfolio is formed according to the yield on the short rate, using the short rate as the investment vehicle, and rebalanced each December such that portfolio weights are proportional deviations from cross-sectional means. Average returns, volatilities and Sharpe ratios are computed within each sub-period. Panel B shows estimates from panel regressions of 12-months currency investment returns with time fixed-effects and interaction terms for sub-periods, as described in equation (37). Standard errors are shown in parenthesis and are two-way clustered by time and by currency. Panel C provides estimates from Fama and MacBeth (1973) regressions for each sub-period, with Newey-West standard errors. Estimates of constant terms are not shown. Double asterisk (**), asterisk (*) and plus (+) represent statistical significance at the 99%, 95%, and 90% confidence levels, respectively. The total number of observations is 33,321 across time and across currencies.

Table 8: Robustness of Long Bond Carry Trade

		Sub-Periods						
	Whole Sample	1789-1854 Age of Revolution	1855-1879 Early Second Industrial Revolution	1880-1913 Classic Gold Standard Era	1914-1949 World Wars Era	1950-1972 Bretton Woods Era	1973-1998 Pre-Euro Floating Exchange Regime	1999-2017 Post-Euro Floating Exchange Regime
Panel A: Signal-Weighted Portfolio Returns								
Average Returns	11.25%	29.19%	4.74%	5.06%	0.62%	6.50%	2.60%	6.66%
Volatility	37.54%	64.20%	9.78%	8.97%	15.90%	8.28%	9.76%	14.23%
Sharpe Ratio	0.300	0.455	0.485	0.564	0.039	0.785	0.267	0.468
Panel B: Panel Regression Coefficients								
$\hat{\beta}^{\text{Panel}}$	1.851**	2.225**	1.252**	1.934**	0.564	1.647**	0.479*	0.886**
	(0.167)	(0.228)	(0.104)	(0.511)	(0.363)	(0.218)	(0.221)	(0.147)
Panel C: Fama-MacBeth Regression Coefficients								
$\hat{\beta}^{\text{FM}}$	0.901**	1.352**	0.896**	1.334**	-0.081	1.314**	0.311*	0.738*
	(0.099)	(0.179)	(0.214)	(0.232)	(0.394)	(0.161)	(0.145)	(0.295)

This table shows the robustness of long bond carry trade. Sample periods are split across major periods in history across columns. Panel A shows the returns on annually-rebalanced signal-weighted long-short long bond carry trade. Each portfolio is formed according to the yield on the long bond, using the long bond as the investment vehicle, and rebalanced each December such that portfolio weights are proportional deviations from cross-sectional means. Average returns, volatilities and Sharpe ratios are computed within each sub-period. Panel B shows estimates from panel regressions of 12-months currency investment returns with time fixed-effects and interaction terms for sub-periods, as described in equation (37). Standard errors are shown in parenthesis and are two-way clustered by time and by currency. Panel C provides estimates from Fama and MacBeth (1973) regressions for each sub-period, with Newey-West standard errors. Estimates of constant terms are not shown. Double asterisk (**), asterisk (*) and plus (+) represent statistical significance at the 99%, 95%, and 90% confidence levels, respectively. The total number of observations is 45,122 across time and across currencies.

Table 9: Currency Term Spread (Slope) Trade over Recent Centuries

	1855-1879 Early Second Industrial Rev.	1880-1913 Classic Gold Standard Era	1914-1949 World Wars Era	1950-1972 Bretton Woods Era	1973-1998 Pre-Euro Floating Exchange Regime	1999-2017 Post-Euro Floating Exchange Regime
Panel A: Currency Term Spread Trade Using Short Rate						
Average Returns	0.58%	1.70%	2.12%	0.79%	1.90%	2.75%
Volatility	5.24%	2.03%	9.64%	1.99%	4.74%	9.36%
Sharpe Ratio	0.110	0.836	0.220	0.396	0.400	0.294
Panel B: Currency Term Spread Trade Using Long Bonds						
Average Returns	2.89%	1.67%	-0.26%	2.84%	1.63%	-0.30%
Volatility	7.39%	4.15%	10.02%	4.01%	6.83%	9.31%
Sharpe Ratio	0.391	0.402	(0.026)	0.710	0.239	(0.033)
Panel C: Currency Term Sread Trade Using Hedged Long Bonds						
Average Returns	3.47%	3.37%	1.86%	3.63%	3.53%	2.45%
Volatility	4.67%	3.20%	4.31%	2.95%	3.88%	3.10%
Sharpe Ratio	0.742	1.053	0.430	1.230	0.908	0.789
Panel D: Panel Regression Coefficients						
Short Rates	-0.164*	0.437+	0.512	0.234	0.616**	2.243**
	(0.076)	(0.215)	(0.563)	(0.255)	(0.134)	(0.632)
Long Bonds	1.254**	1.210+	0.865	1.257*	0.274	-0.869
	(0.104)	(0.695)	(0.561)	(0.482)	(0.201)	(0.814)
Hedged Long Bonds	1.090**	1.647**	1.411**	1.497**	0.891**	1.374**
	(0.052)	(0.510)	(0.160)	(0.319)	(0.114)	(0.377)

This table examines robustness of currency term spread (slope) trade over recent centuries, based on the term spread. Sample periods are split across major periods in history across columns. Panel A (B) shows the returns on annually-rebalanced equally-weighted currency yield curve slope trade using short rates (long bonds). Panel C shows the returns on annually-rebalanced equally-weighted currency yield curve slope trade that goes long long bonds and short short rates (hedged long bonds). Panel D shows estimates from panel regressions of 12-months currency investment returns with time fixed-effects and interaction terms for sub-periods, as described in equation (37). Estimates of constant terms are not shown. Standard errors are shown in parenthesis and are two-way clustered by time and by currency. Double asterisk (**), asterisk (*) and plus (+) represent statistical significance at the 99%, 95%, and 90% confidence levels, respectively. The total number of observations is 32,280 across time and across currencies.

Table 10: Dollar Carry Trade over Recent Centuries

		Sub-Periods						
	Whole Sample	1789-1854 Age of Revolution	1855-1879 Early Second Industrial Revolution	1880-1913 Classic Gold Standard Era	1914-1949 World Wars Era	1950-1972 Bretton Woods Era	1973-1998 Pre-Euro Floating Exchange Regime	1999-2017 Post-Euro Floating Exchange Regime
Panel A: Dollar Carry Trade Using Short Rate								
Average Returns	0.70%				-1.74%	0.89%	2.89%	2.01%
Volatility	10.96%				14.13%	1.97%	11.06%	10.39%
Sharpe Ratio	0.064				(0.123)	0.454	0.262	0.193
Panel B: Dollar Carry Trade Using Long Bonds								
Average Returns	2.57%	6.38%	-1.28%	0.75%	-1.52%	2.90%	5.87%	0.42%
Volatility	11.67%	14.98%	6.64%	1.56%	14.05%	4.01%	11.25%	11.74%
Sharpe Ratio	0.220	0.426	(0.192)	0.484	(0.108)	0.723	0.521	0.036
Panel C: Panel Regression Coefficients								
Short Rates	0.609*				-1.678*	0.901**	2.676**	1.726**
$\hat{\beta}^{\text{Panel}}$	(0.279)				(0.767)	(0.249)	(0.418)	(0.583)
Long Bonds	2.093**	5.232*	-1.049+	0.661*	-1.620*	2.727**	4.278**	0.796
$\hat{\beta}^{\text{Panel}}$	(0.622)	(1.898)	(0.560)	(0.283)	(0.711)	(0.390)	(0.482)	(0.505)

This table examines robustness of dollar carry trade over recent centuries. Sample periods are split across major periods in history across columns. Panel A shows the returns on annually-rebalanced equally-weighted dollar carry trade using short rates. Average returns, volatilities and Sharpe ratios are computed within each sub-period. Panel B shows the returns on annually-rebalanced equally-weighted dollar carry trade using long bonds. Panel C shows estimates from panel regressions of 12-months currency investment returns with time fixed-effects and interaction terms for sub-periods, as described in equation (37), for the short rate sample and for the long bond sample. Estimates of constant terms are not shown. Standard errors are shown in parenthesis and are two-way clustered by time and by currency. Double asterisk (**), asterisk (*) and plus (+) represent statistical significance at the 99%, 95%, and 90% confidence levels, respectively. The total number of observations is 23,291 across time and across currencies.

Table 11: Currency Momentum Trade over Recent Centuries

	Whole Sample	Sub-Periods: 1789-1854 Age of Revolution	1855-1879 Early Second Industrial Revolution	1880-1913 Classic Gold Standard Era	1914-1949 World Wars Era	1950-1972 Bretton Woods Era	1973-1998 Pre-Euro Floating Exchange Regime	1999-2017 Post-Euro Floating Exchange Regime
Panel A: Currency Momentum Trade Using Short Rate								
Average Returns	3.50%		3.87%	0.60%	9.25%	0.65%	3.97%	-0.01%
Volatility	10.00%		16.15%	2.70%	13.63%	2.13%	7.15%	7.78%
Sharpe Ratio	0.350		0.240	0.221	0.679	0.307	0.556	(0.002)
Panel B: Currency Momentum Trade Using Long Bonds								
Average Returns	1.81%	-1.29%	1.95%	0.28%	8.61%	0.86%	4.14%	-0.10%
Volatility	10.57%	13.10%	14.74%	2.12%	12.77%	2.04%	7.21%	7.82%
Sharpe Ratio	0.171	(0.098)	0.132	0.133	0.674	0.420	0.575	(0.012)
Panel C: Panel Regression Coefficients								
Short Rates	0.022+		-0.057+	-0.011	0.037*	-0.005	0.015+	-0.002
	(0.012)		(0.029)	(0.012)	(0.018)	(0.013)	(0.007)	(0.007)
Long Bonds	0.021	0.046+	-0.072*	-0.016	0.048*	-0.003	0.016*	-0.002
	(0.012)	(0.023)	(0.029)	(0.013)	(0.021)	(0.014)	(0.007)	(0.007)

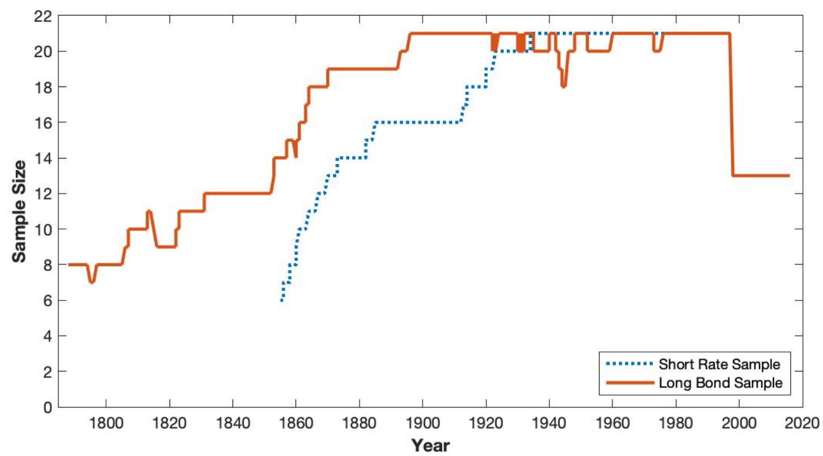
This table examines robustness of currency momentum trade over recent centuries, based on FX returns over the past twelve months. Sample periods are split across major periods in history across columns. Panel A shows the returns on monthly-rebalanced equally-weighted currency momentum trade using short rates. Average returns, volatilities and Sharpe ratios are computed within each sub-period. Panel B shows the returns on monthly-rebalanced equally-weighted currency momentum trade using long bonds. Panel C shows estimates from panel regressions of one month currency investment returns with time fixed-effects and interaction terms for sub-periods, as described in equation (37), for the short rate sample and for the long bond sample. Estimates of constant terms are not shown. Standard errors are shown in parenthesis and are two-way clustered by time and by currency. Double asterisk (**), asterisk (*) and plus (+) represent statistical significance at the 99%, 95%, and 90% confidence levels, respectively. The total number of observations is x,xxx across time and across currencies.

Table 12: Currency Reversal (Value) Trade over Recent Centuries

	Whole Sample	Sub-Periods: 1789-1854 Age of Revolution	1855-1879 Early Second Industrial Revolution	1880-1913 Classic Gold Standard Era	1914-1949 World Wars Era	1950-1972 Bretton Woods Era	1973-1998 Pre-Euro Floating Exchange Regime	1999-2017 Post-Euro Floating Exchange Regime
Panel A: Currency Reversal (Value) Trade Using Short Rate								
Average Returns	-0.27%		0.86%	0.52%	-4.77%	-0.22%	-0.05%	5.32%
Volatility	9.96%		12.70%	2.49%	14.58%	2.36%	6.25%	10.88%
Sharpe Ratio	(0.027)		0.068	0.207	(0.327)	(0.091)	(0.008)	0.489
Panel B: Currency Reversal (Value) Trade Using Long Bonds								
Average Returns	0.60%	2.85%	-0.33%	0.33%	-3.74%	-0.37%	0.34%	5.08%
Volatility	17.25%	28.40%	14.88%	2.74%	13.36%	3.33%	8.60%	11.82%
Sharpe Ratio	0.035	0.100	(0.022)	0.119	(0.280)	(0.110)	0.040	0.430
Panel C: Panel Regression Coefficients								
Short Rates	-0.017		0.149**	0.075**	-0.072*	0.007	0.012	0.126**
	(0.018)		(0.038)	(0.024)	(0.033)	(0.017)	(0.027)	(0.034)
Long Bonds	0.006	0.083	0.143**	0.091**	-0.075*	0.013	0.004	0.139**
	(0.024)	(0.068)	(0.045)	(0.024)	(0.034)	(0.027)	(0.030)	(0.042)

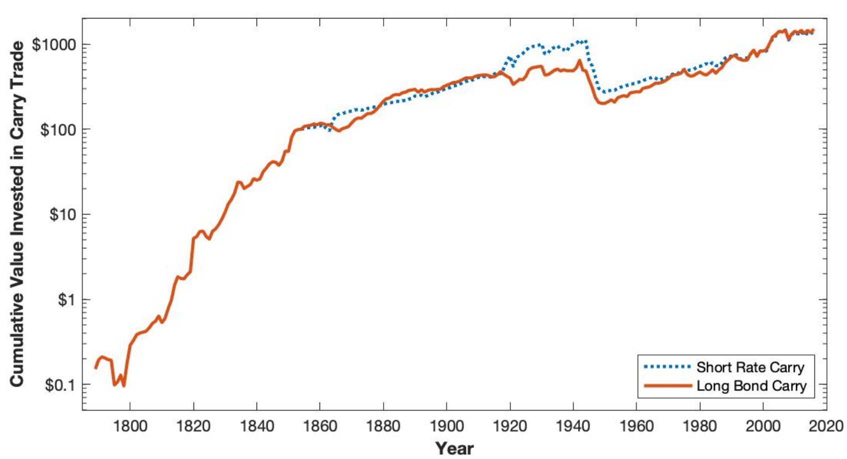
This table examines robustness of currency reversal (value) trade over recent centuries, based on FX returns over the past 5 years. Sample periods are split across major periods in history across columns. Panel A shows the returns on annually-rebalanced equally-weighted currency reversal trade using short rates. Average returns, volatilities and Sharpe ratios are computed within each sub-period. Panel B shows the returns on annually-rebalanced equally-weighted currency reversal trade using long bonds. Panel C shows estimates from panel regressions of 12-months currency investment returns with time fixed-effects and interaction terms for sub-periods, as described in equation (37), for the short rate sample and for the long bond sample. Estimates of constant terms are not shown. Standard errors are shown in parenthesis and are two-way clustered by time and by currency. Double asterisk (**), asterisk (*) and plus (+) represent statistical significance at the 99%, 95%, and 90% confidence levels, respectively. The total number of observations is x,xxx across time and across currencies.

Figure 1: Number of Currencies Used



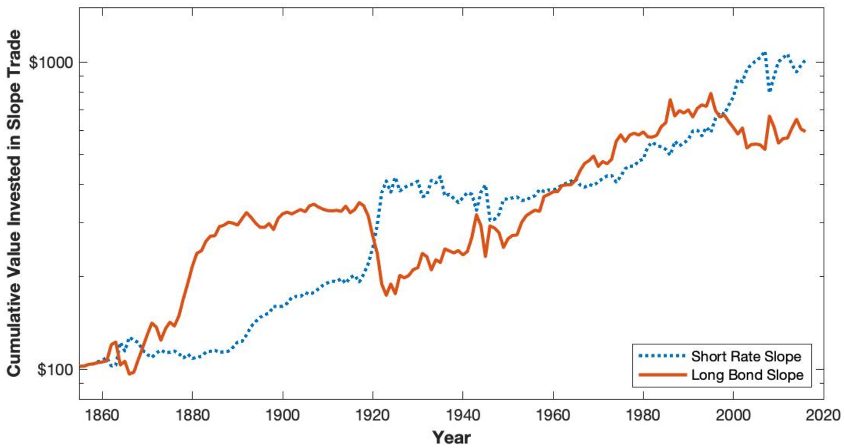
This plot shows the number of observations available in each of my samples. In addition to currency returns, the short rate sample uses short-term interest rates and the long bond sample uses long-term interest rates. For the short rate sample, data starts on 1854:01, and for the long bond sample, data starts on 1788:09. Data ends on 2017:06 in both samples.

Figure 2: Cumulative Returns on the Carry Trade



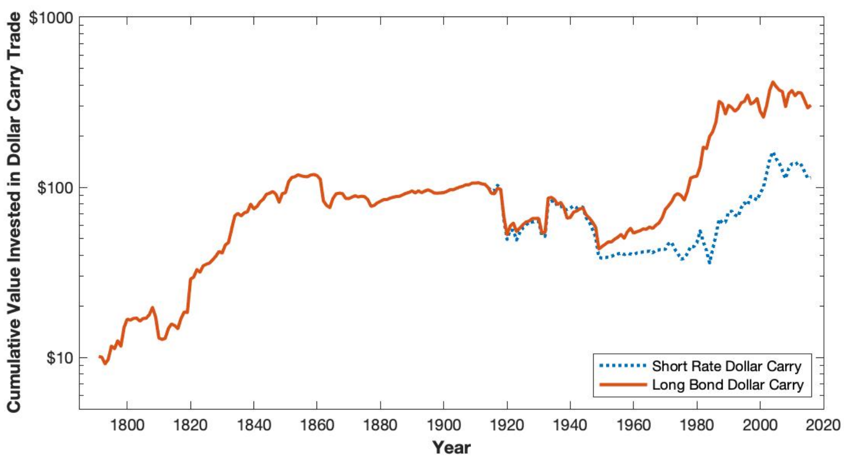
This plot shows the cumulative returns on long/short carry trade returns, normalized to $100 investment made in 1854. Each portfolio is formed according to the yield on the investment vehicle and rebalanced each December ('Annual'). The equal-weighted portfolios go long currencies with the highest one-third value of the yields and go short currencies with the lowest one-third value of the yields.

Figure 3: Cumulative Returns on Term Spread (Slope) Trade



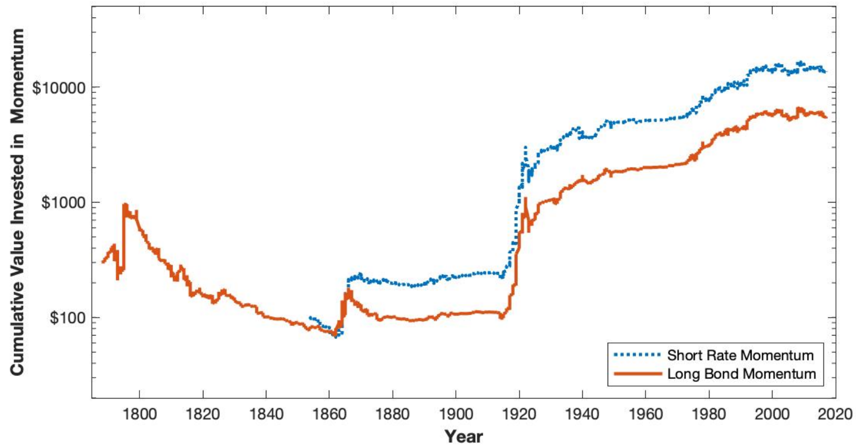
This plot shows the cumulative returns on long/short currency investment returns based on the yield term spread (slope) normalized to $100 investment made in 1854. Each portfolio is formed according to the slope of the yield curve and rebalanced annually each December. The equal-weighted portfolios go long currencies with the highest one-third value of the term spread and go short currencies with the lowest one-third value of the term spread.

Figure 4: Cumulative Returns on the Dollar Carry Trade



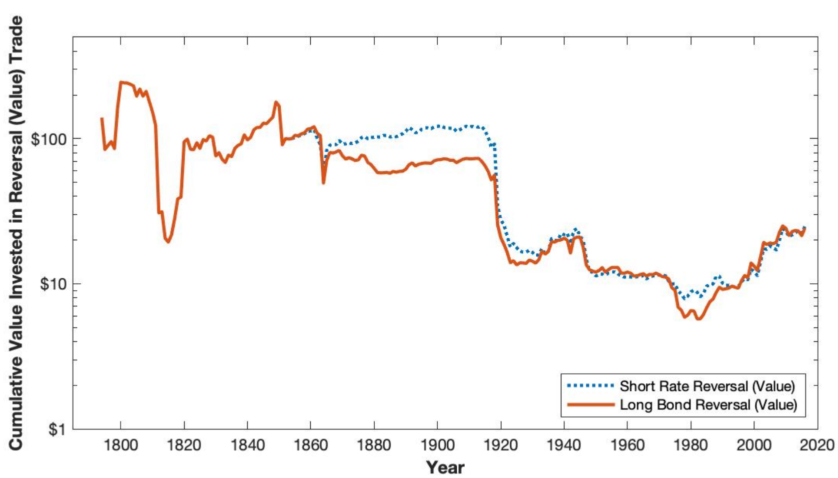
This plot shows the cumulative returns on the dollar carry trade returns normalized to $100 investment made in 1914. The dollar carry trade portfolio goes long (short) the US dollar (USD) when the yield on the USD investment instrument is greater (less) than the average of all other currencies and goes short (long) the equal-weighted portfolio of all other currencies.

Figure 5: Cumulative Returns on Currency Momentum



This plot shows the cumulative returns on long/short currency momentum returns normalized to \$100 investment made in 1854. Each portfolio is formed according to FX returns over the past twelve months and rebalanced monthly. The equal-weighted portfolios go long currencies with the highest one-third value of past FX returns and go short currencies with the lowest one-third value of past FX returns.

Figure 6: Cumulative Returns on Currency Reversal (Value)



This plot shows the cumulative returns on long/short currency reversal (value) returns normalized to \$100 investment made in 1854. Each portfolio is formed according to FX returns over the past 5 years and rebalanced annually each December. The equal-weighted portfolios go long currencies with the highest one-third value of past FX returns and go short currencies with the lowest one-third value of past FX returns.

Appendix

A Data Quality Analysis of Bond Return Series

In this section, I ensure the accuracy of long bond return series calculated from long-term bond yields using equation (30).

A1 Reconciling Bond Return Calculations

To begin, I compare bond returns for 10-year US dollar (USD) bonds obtained from various other data sources to ensure that bond returns are accurately computed in my data. Center for Research in Security Prices (CRSP) makes available bond returns going back to 1941:5 under their US Treasury and Inflations Series. For the 10-year index, CRSP selects the long-term bond with maturity closest to 10 years and computes monthly bond returns based on historical quotes. Swinkels (2023) offers updated data spanning 1947 to 2022 on a monthly frequency publicly available, along with additional international bond returns calculated from publicly available bond yield data. Data used by Lustig, Stathopoulos, and Verdelhan (2019) are available through the data and code availability policy of the American Economic Association and are originally obtained from Global Financial Data (GFD). Finally, total bond return indices are downloaded directly from GFD at the end of 2023.[1]

Table A1 treats CRSP as a benchmark and shows summary statistics of 10-year US bond returns from various data sources. Panel A begins with the Modern Sample, starting on 1975:1 and ending on 2015:12, which is the sample period used in Lustig, Stathopoulos, and Verdelhan (2019) and is the shortest among the datasets being considered. Across all datasets, average bond returns are very close, but volatilities differ slightly. The correlations with CRSP are all extremely high at nearly 0.97 across all datasets. These slight differences are likely due to variations between methodologies, but the close similarities in these statistics attest that the methods generate very comparable results.

Even though the analysis in Lustig, Stathopoulos, and Verdelhan (2019) focused on the period after 1975, their dataset contains older data gathered from GFD reaching back to 1900. The data on USD bonds go back to 1947:1 in Swinkles (2023). This allows for a comparison of bond returns used across different sources during the Bretton Woods era from 1947:1 to 1974:12 in Panel B of Table A1. During this period, all data series continue to produce extremely close average bond returns with only slight differences in volatilities.

Overall, the analysis in this subsection demonstrates that returns computed using the method in this paper based on equation (30) yields very similar results as other methods.[2] CRSP computes returns directly from historical quotes. Swinkels (2019) extracts bond returns from changes in bond yields but uses bond duration and convexity to approximate bond returns. Lustig, Stathopoulos, and Verdelhan (2019) uses total return data calculated by GFD in 2016. Despite these different methods, they produce very similar bond return series.

[1] Koijen, Moskowitz, Pedersen and Vrugt (2018) also calculate bond returns to achieve their analysis, but their source data is not published.

[2] While I do not have access to use data from Ibbotson or Bloomberg, Swinkels (2019) reports his US bond return series has R-squareds that imply a correlation of 0.967 with data series from Ibbotson over 1962 to 2005, and a correlation of 0.972 with data series from Bloomberg over 1973 to 2018. This indicates his data series is also very close to data series from Ibbotson and Bloomberg.

A2 Comparing Bond Returns Across Datasets

Armed with assurances that the different datasets and their methodologies produce extremely close results, Table A2 compares the bond return data for 10-year bonds in G-10 currencies over 1975:1 to 2015:12. Swinkels (2023) does not produce bond returns for NZD or CHF. Panel A shows the summary statistics of the data series used in this paper along with correlations with data from other sources.[3] Across currencies, the correlations of the bond return series between this paper and Swinkels (2023) are generally above 0.96, with the exception of JPY and GBP at 0.853 and 0.905, respectively. In an unreported result, these correlations increase to 0.965 and 0.979 for JPY and GBP, respectively, over a shorter sample of 1999:1 to 2015:12. The correlations for other currencies are above 0.98 in this later period. Remarkably, the correlation of USD bond returns is exceptionally highly at 0.999.

Outside USD, the correlations of bond return series between this paper and Lustig, Stathopoulos, and Verdelhan (2019) are generally less than perfect, which may explain some of the differences between our results. The correlations are less than 0.9 for most G10 currencies (DEM, JPY, NOK, SEK, CHF, and GBP). However, these correlations increase when compared to data series from GFD accessed more recently. In this case, only JPY and CHF have correlations of less than 0.9. In an unreported result, these correlations increase to 0.894 and 0.924 for JPY and CHF, respectively, over the more recent 1999:1 to 2015:12 sample. Since these return series are calculated based on the same long-term bond yield data from GFD, the differences can only be explained by differences in computational methodologies. Unfortunately, GFD does not publish their methodologies to make further investigation possible. Panel B of Table A2 compares data used in Swinkels (2023) to these datasets, and the results are similar. The correlations are less than 0.9 for most currencies, and also improve if more recently downloaded data from GFD is used.

Finally, Panels C and D of Table A2 show summary statistics of data series used in Lustig, Stathopoulos, and Verdelhan (2019) and data recently recalculated from GFD. The only difference between these two data series is the timing of when the database was accessed. In half of the cases, the data are exactly identical or very close to identical with correlations greater than 0.999, as expected. However, there are some significant differences that should not be there. Most notably, the correlations of NOK and SEK are very low at only 0.434 and 0.559, respectively. For GBP bond returns the correlation between the two data series is only 0.620. Surprisingly, the average returns and volatilities are very different. The average return of GBP bond returns is 0.76% per month with an annualized volatility of 4.98%, but increases to 0.93% per month with volatility of 11.27% in the recent download from GFD.[4] In a conversation with GFD, they confirm that the underlying source of data for these data series has been changed with data they felt are more accurate.

Overall, the analysis of bond return series across various datasets confirms the accuracy of the methodology used in this paper and illustrates potential concerns over using undocumented methods. Bond returns series for USD are very close across papers with different methods and with commercial databases. However, there are some differences among international bond returns with the data used in this paper being most similar to the data in Swinkles (2023). Most strikingly, data

[3] G10 currencies are defined ex-post as the top ten most heavily trade currencies as of 2023: Australian dollar (AUD), Canadian dollar (CAD), Euro/German mark (EURU/DEM), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Swedish krona (SEK), Swiss franc (CHF), Pound sterling (GBP), and United States dollar (USD). German mark is spliced to the Euro prior to 1999.

[4] Furthermore, the bond return series for GBP in Lustig, Stathopoulos, and Verdelhan (2019) goes back to only 1932:12 but is available all the way back to the 1700's in GFD

downloaded from Global Financial Data changed over time and may explain some of the differences in results.

B Carry Trades Among G10 Currencies

The majority of the literature on currency investing focuses on the G10 currencies because they are the world's most liquid currencies. Therefore, data for these currencies are the most accurate and the most readily available, and there is the least concern about market frictions. However, these ten currencies are selected on an ex-post basis during the modern sample and are subject to look-ahead bias. Moreover, with a longer historical perspective, dominant currencies change over time. Hence, this paper focuses on using all available currencies rather than a subset.

Nevertheless, this appendix illustrates how the main results change when only the ex-post G10 currencies are used. Table B1 repeats Table 3 to reproduce the well-known carry trade results during the Modern Sample among only the G10 currencies. This table shows the characteristics of monthly-rebalanced equal-weighted portfolio returns. The results are comparable to that in Panel A of Table 3. The overall Sharpe ratio of long-short portfolios using the short rate is lower at 0.348 rather than 0.530, but this level of Sharpe ratio is consistent with what the literature reports. By using the long bonds, there continue to be risk premium with a Sharpe ratio of 0.359 even among just the G10 currencies. Not surprisingly, overall volatility and the range of returns are significantly larger since each portfolio contains only three currencies and is less diversified.

Table B2 presents the robustness of short rate carry trade to the expanded sample starting in 1855 among the G10 currencies. Panel A shows the equal-weighted portfolio returns and is comparable to the results in Table 5. The average carry trade returns are similar when only the G10 currencies are used (2.26% vs. 2.07%), but overall volatility is significantly greater (13.80% vs. 8.61%), resulting in a lower Sharpe Ratio (0.164 vs. 0.240). Naturally, volatility is greater within each sub-period as well, but average equal-weighted carry trade returns are generally positive within each sub-period. A notable exception is, once again, during the World Wars Era when the average carry trade return was not significantly different from zero. Panel B of Table B2 presents the signal-weighted portfolio returns using the G10 currencies and is comparable to the results in Panel A of Table 7. As with equal-weighted portfolios, average returns are roughly similar across the whole sample and within each subsample, but volatility is unilaterally greater with fewer currencies, resulting in lower Sharpe ratios. Panel C formalizes the statistical analysis with panel regressions with two-way clustered standard errors. Except for the World Wars Era, the short rate carry produced a positive risk premium throughout the recent centuries, with statistical significance in most sub-periods.

This section concludes with Table B3 illustrating the robustness of long bond carry trade among the G10 currencies. Panels A and B show characteristics of equal-weighted and signal-weighted portfolio returns, respectively. These results are comparable to the results in Table 6 and Panel A of 8. With long bond returns, limiting the sample to G10 currencies results in significantly reduced volatility of both equal-weighed and signal-weighted portfolios. Most of this can be attributed to excluding the most volatile long bond returns shown in the summary statistics of Table 2, such as the Spanish bonds. Nevertheless, average long bond carry trade portfolios are positive throughout the sample and in every subperiod, except for the World Wars Era. Panel C provides formal statistical analysis with a panel regression, which indicates that long-bond carry trade produced a positive risk premium in every sub-period, except for the World Wars Era, and extended as early as 1789.

With only the G10 currencies, the overall message for the short-rate carry trade and long-bond carry trade remains the same. The carry trade is robust to using long bonds and robust over a much longer horizon. Even if the sample is restricted to currencies that are ex-post most liquid, empirical evidence suggests risk premium is earned for currency investing, which can be interpreted as arising from differences in entropies of overall pricing kernels or entropies of the permanent component of the pricing kernels. If anything, evidence for the robustness of long bond carry trade is stronger because the most volatile long bonds are excluded by focusing on the ex-post G10 currencies.

C Time Series Regressions

While the literature in asset pricing has generally been interested in the cross-sectional predictability of currency investing, such as through the carry trade, the literature in international finance has focused on the time-series predictability of foreign exchange returns. The two are related but distinct. Cross-sectional predictability is concerned with understanding which currency will likely reflect a return premium at each point in time. In contrast, time-series predictability keeps fixed a currency and is concerned with understanding when this currency is likely to produce returns. Hassan and Mano (2019) provides a full decomposition of the relationship between the two.

This paper has focused on investigating cross-sectional predictability, but we can also explore the time-series predictability. Interpretation of risk premia in terms of reflecting differences in entropies of pricing kernels, presented in equations (9), (17), and (18) remain unchanged. We can run panel regressions that focus on the time-series predictability by replacing the time fixed-effects with currency fixed-effects. We can also continue to incorporate indicator variables for each sub-period as in equation (37) and run regressions of the form:

$$\Pi^i_{t+\Delta t} = \alpha_i + \sum_{\text{Era}} \beta^{\text{TS}}_{\text{Era}} \mathbf{1}_{t\in\text{Era}} x^m_{t,i} + \epsilon_{t,i}, \tag{C1}$$

where $x^m_{t,i}$ is either the cross-sectionally demeaned short rate, $r^i_{f,t}$, or the cross-sectionally demeaned long-term bond yield, $y_{t,i}$. Recall that cross-sectionally demeaned signal is $x^m_{t,i} = x_{t,i} - \bar{x}_t$, where $\bar{x}_t$ is the cross-sectional average of $x_{t,i}$ across i at time t, from which signal-weighted portfolios are constructed.

If the independent variables were computed relative to their US dollar equivalent, the panel regression would correspond to the predictability regressions that consider interest rates relative to the US dollar, as in Fama (1984). Using the average is similar to the Fama regression but looks instead at foreign exchange appreciations relative to the average foreign exchange rate (instead of the US dollar) and interest rate differential relative to the average interest rate (instead of the US dollar rate). Comparison to the average exchange rate instead of the US dollar has the advantage that longer panel data is available since the data for the US short rate only goes back to 1914:11. In this formulation, uncovered interest rate parity (UIP) corresponds for $\beta^{TS} = 0$. In contrast, if foreign exchange rate changes are unpredictable random walks, then $\beta^{TS} = 1$. By considering currency risk premium relative to the US dollar, Fama (1984) reports that $\beta^{TS} \approx 2$.

Table C1 presents the results of panel regressions with currency fixed-effects. Panel A uses 12-month currency investment returns with short rates as the investment vehicle. Using the whole sample, the coefficient estimate is 0.448 and is only marginally statistics different from zero. Within each sub-period, estimates of β^{TS} fluctuate between zero and one. The estimates are closer to one during the fixed exchange rate regimes of the Classic Gold Standard Era and the Bretton Woods Era, suggesting that foreign exchange rates appeared closer to random walks when exchange rates were fixed. However, the results are mixed during the Modern Sample with β^{TS} closer to zero during the floating exchange regime before the introduction of the Euro, but closer to one after the introduction of the Euro. Panel B repeats the regression but uses only the G10 currencies. The coefficient estimates are generally the same with fewer currencies, but standard errors are greater. Panels C and D repeat this exercise but use long bonds as the investment vehicle and long-term bond yields as the predictors. This specification does not have the same interpretation of UIP tests as using the short rates, but they are still informative. With long bonds, the time-series regression coefficients are generally greater than and often closer to 2, similar to Fama's (1984) findings with short rates. With long-term yields, periods of high yields relative to other times indicate that future returns on long bonds are greater than expected, indicating high long-term yields forecast decreases in future long-term yields that generate such returns. Since the focus of this paper is cross-sectional relations, further analysis of time-series relations is left for future research.

Table A1: Reconciling US Bond Return Data

	CRSP	This paper	Swinkels (2023)	LSV (2019)	GFD (2023)
Panel A: 1975-2015, Modern Sample					
Average Return	7.80%	7.75%	7.86%	7.95%	7.90%
Volatility	7.96%	7.81%	8.42%	8.44%	8.47%
Correl w/ CRSP		0.970	0.971	0.969	0.968
Panel B: 1947-1974, Bretton Woods Era					
Average Return	2.67%	2.75%	2.63%	2.78%	2.64%
Volatility	5.62%	4.18%	4.93%	4.71%	4.60%
Correl w/ CRSP		0.975	0.975	0.973	0.972

This table reports summary statistics of monthly total returns on the 10-year US Dollar (USD) bonds across various datasets. The column labeled 'CRSP' is based on the data series from the Center for Research in Security Prices. The column labeled 'This paper' is the data series used in this paper. Columns labeled 'Swinkels (2023)' and 'LSV (2019)' are from Swinkels (2023) and Lustig, Stathopoulos, and Verdelhan (2019), respectively. The column labeled 'GFD (2023)' is based on the total return index downloaded from the Global Financial Data in 2023. Average returns are annualized, and volatilities are the annualized standard deviations of returns. Rows labeled 'Correl w/ CRSP' show the correlation of each data series with the data series from CRSP. Panel A shows results for 1975:1 to 2015:12, roughly corresponding to the Modern Sample used in the paper. Panel B shows results for an earlier period of 1947:1 to 1974:12, which roughly corresponds to the Bretton Woods Era in the paper.

Table A2: Comparing G10 Bond Return Data

	AUD	CAD	DEM	JPY	NZD	NOK	SEK	CHF	GBP	USD
Panel A: This Paper										
Average Return	9.76%	8.71%	7.35%	5.58%	9.34%	8.67%	8.96%	5.03%	10.36%	7.75%
Volatility	6.93%	7.36%	5.62%	6.08%	9.01%	5.70%	6.78%	4.54%	8.38%	7.81%
Correl w/ Swinkels	0.997	0.962	0.964	0.853		0.963	0.982		0.905	0.999
w/ LSV	0.992	0.949	0.885	0.836	0.923	0.479	0.625	0.715	0.697	0.997
w/ GFD	0.992	0.949	0.947	0.836	1.000	0.919	0.912	0.715	0.927	0.997
Panel B: Swinkles (2023)										
Average Return	9.88%	8.11%	7.55%	5.71%		8.72%	9.15%		10.20%	7.86%
Volatility	7.43%	6.72%	5.93%	6.15%		5.99%	7.18%		8.77%	8.42%
Correl w/ LSV	0.993	0.913	0.900	0.891		0.491	0.630		0.717	0.998
w/ GFD	0.993	0.913	0.962	0.891		0.876	0.890		0.807	0.998
Panel C: Lustig, Stathopoulos, and Verdelhan (2019)										
Average Return	9.95%	8.99%	7.18%	5.97%	9.47%	8.30%	8.14%	4.84%	9.15%	7.95%
Volatility	7.52%	7.55%	6.26%	6.82%	9.15%	5.35%	5.43%	3.32%	4.98%	8.44%
Correl w/ GFD	1.000	1.000	0.938	1.000	0.922	0.434	0.559	1.000	0.620	0.999
Panel D: Global Financial Data (2023)										
Average Return	9.95%	8.99%	7.51%	5.97%	9.48%	8.51%	8.27%	4.84%	11.15%	7.90%
Volatility	7.52%	7.55%	5.91%	6.82%	9.45%	6.05%	5.63%	3.32%	11.27%	8.47%

This table reports summary statistics of monthly total returns on the 10-year bonds for G10 currencies across various datasets. Panel A shows the results of the data used in this paper. Panels B and C show results for data used in Swinkels (2023) and Lustig, Stathopoulos, and Verdelhan (2019). Panel D uses the total return index downloaded from the Global Financial Data in 2023. Average returns are annualized, and volatilities are the annualized standard deviations of returns. The row labeled 'Correl w/ Swinkels' shows correlations of each data series with corresponding data series from Swinkels (2023) Rows labeled 'w/ LSV' show the correlations with data series from Lustig, Stathopoulos, and Verdelhan (2019). Rows labeled 'w/ GFD' show the correlation with data based on total return indices downloaded from the Global Financial Data in 2023. The sample period is 1975:1 to 2015:12 for all panels.

Table B1: Carry Trade: Modern Sample Among G10 Currencies (1973-2017)

	Short Rate Portfolios			Long Bond Portfolios		
	Long-Short	Long Side	Short Side	Long-Short	Long Side	Short Side
Average Return	2.91%	1.96%	0.95%	3.66%	2.91%	0.75%
Volatility	8.35%	4.42%	4.65%	10.18%	5.47%	5.60%
Sharpe Ratio	0.348	0.442	0.205	0.359	0.532	0.134
Skewness	(0.67)	(0.50)	(0.59)	(0.75)	(0.74)	(0.61)
Minimum	-11.10%	-5.42%	-6.21%	-16.41%	-10.28%	-6.91%
Maximum	7.44%	4.04%	4.20%	9.12%	5.70%	4.56%

This table reports summary statistics of returns on equal-weighted long/short carry trade portfolios over 1973:01 to 2017:06 using among G10 currencies. Each portfolio is formed according to the yield on the investment vehicle and rebalanced each month. The equal-weighted portfolios go long currencies with the highest one-third of the yields and go short currencies with the lowest one-third of the yields. Returns are decomposed to the long side return and the short side return relative to an equal-weighted portfolio of currencies on either side.

Table B2: Robustness of Short Rate Carry Trade Among G10 Currencies

		Sub-Periods					
	Whole Sample	1855-1879 Early Second Industrial Revolution	1880-1913 Classic Gold Standard Era	1914-1949 World Wars Era	1950-1972 Bretton Woods Era	1973-1998 Pre-Euro Floating Exchange Regime	1999-2017 Post-Euro Floating Exchange Regime
Panel A: Equal-Weighted Portfolio Returns							
Average Returns	2.26%	5.08%	1.24%	0.97%	2.94%	0.92%	3.89%
Volatility	13.80%	20.87%	2.87%	20.52%	3.88%	10.05%	10.66%
Sharpe Ratio	0.164	0.243	0.432	0.047	0.756	0.091	0.365
Panel B: Signal-Weighted Portfolio Returns							
Average Returns	1.81%	4.92%	1.76%	-1.88%	2.96%	1.07%	4.56%
Volatility	13.37%	17.37%	4.29%	20.82%	3.54%	10.16%	10.87%
Sharpe Ratio	0.135	0.283	0.410	(0.090)	0.834	0.106	0.419
Panel C: Panel Regression Coefficients							
$\hat{\beta}^{\text{Panel}}$	0.485*	0.422	0.631**	-0.296	0.773**	0.413*	1.135**
	(0.158)	(0.593)	(0.061)	(0.950)	(0.121)	(0.186)	(0.232)

This table shows the robustness of short rate carry trade over recent centuries among only G10 currencies. Sample periods are split across major periods in history across columns. Panel A shows the returns on annually-rebalanced equal-weighted long-short short rate carry trade. Each portfolio is formed according to the yield on the short rate, using the short rate as the investment vehicle, and rebalanced each December. Average returns, volatilities and Sharpe ratios are computed within each sub-period. Panel B shows the returns on annually-rebalanced signal-weighted long-short short rate carry trade, where portfolio weights are proportional deviations from cross-sectional means. Panel C shows estimates from panel regressions of 12-months currency investment returns with time fixed-effects and interaction terms for sub-periods, as described in equation (37). Standard errors are shown in parenthesis and are two-way clustered by time and by currency. Double asterisk (**), asterisk (*) and plus (+) represent statistical significance at the 99%, 95%, and 90% confidence levels, respectively. The total number of observations is 15,726 across time and across currencies.

Table B3: Robustness of Long Bond Carry Trade Among G10 Currencies

		Sub-Periods						
	Whole Sample	1789-1854 Age of Revolution	1855-1879 Early Second Industrial Revolution	1880-1913 Classic Gold Standard Era	1914-1949 World Wars Era	1950-1972 Bretton Woods Era	1973-1998 Pre-Euro Floating Exchange Regime	1999-2017 Post-Euro Floating Exchange Regime
Panel A: Equal-Weighted Portfolio Returns								
Average Returns	2.06%	3.97%	3.34%	1.03%	-2.07%	3.53%	1.35%	3.17%
Volatility	10.69%	12.34%	8.31%	2.63%	13.78%	7.66%	12.91%	8.74%
Sharpe Ratio	0.192	0.322	0.402	0.392	(0.150)	0.462	0.105	0.363
Panel B: Signal-Weighted Portfolio Returns								
Average Returns	2.42%	3.12%	3.21%	1.03%	-1.30%	6.05%	2.34%	4.30%
Volatility	11.07%	10.98%	4.54%	5.69%	14.85%	12.43%	13.28%	10.56%
Sharpe Ratio	0.219	0.285	0.708	0.182	(0.088)	0.487	0.176	0.407
Panel C: Panel Regression Coefficients								
$\hat{\beta}^{\text{Panel}}$	1.237**	2.186**	1.031**	0.398*	0.583	1.612**	0.751*	1.418**
	(0.303)	(0.597)	(0.386)	(0.186)	(0.670)	(0.300)	(0.340)	(0.306)

This table shows the robustness of long bond carry trade over recent centuries among only G10 currencies. Sample periods are split across major periods in history across columns. Panel A shows the returns on annually-rebalanced equal-weighted long-short long bond carry trade. Each portfolio is formed according to the yield on the long bond, using the long bond as the investment vehicle, and rebalanced each December. Average returns, volatilities and Sharpe ratios are computed within each sub-period. Panel B shows the returns on annually-rebalanced signal-weighted long-short long bond carry trade, where portfolio weights are proportional deviations from cross-sectional means. Panel C shows estimates from panel regressions of 12-months currency investment returns with time fixed-effects and interaction terms for sub-periods, as described in equation (37). Standard errors are shown in parenthesis and are two-way clustered by time and by currency. Double asterisk (**), asterisk (*) and plus (+) represent statistical significance at the 99%, 95%, and 90% confidence levels, respectively. The total number of observations is 21,599 across time and across currencies.

Table C1: Time-Series Regressions

	Whole Sample	1789-1854 Age of Revolution	1855-1879 Early Second Industrial Revolution	1880-1913 Classic Gold Standard Era	1914-1949 World Wars Era	1950-1972 Bretton Woods Era	1973-1998 Pre-Euro Floating Exchange Regime	1999-2017 Post-Euro Floating Exchange Regime
		Sub-Periods						
Panel A: Short Rate Time-Series Predictability								
$\hat{\beta}^{\text{TS}}$	0.448+		0.191	0.958**	0.081	0.718**	0.332	0.945**
	(0.225)		(0.303)	(0.166)	(0.784)	(0.189)	(0.298)	(0.259)
Panel B: Short Rate Time-Series Predictability Among G10 Currencies								
$\hat{\beta}^{\text{TS}}$	0.440		0.352	1.029**	1.046	0.907**	0.140	1.119*
	(0.446)		(0.478)	(0.156)	(0.952)	(0.234)	(0.589)	(0.482)
Panel C: Long Bond Time-Series Predictability								
$\hat{\beta}^{\text{TS}}$	2.075**	2.397**	1.606**	2.838**	1.042**	1.990**	0.675	1.243**
	(0.267)	(0.180)	(0.098)	(0.809)	(0.350)	(0.282)	(0.424)	(0.210)
Panel D: Long Bond Time-Series Predictability Among G10 Currencies								
$\hat{\beta}^{\text{TS}}$	0.971*	1.106*	1.472**	1.423	2.116**	1.939**	0.279	1.419*
	(0.423)	(0.397)	(0.315)	(1.570)	(0.735)	(0.389)	(0.848)	(0.701)

This table shows coefficient estimates from panel regressions of 12-months currency investment returns with currency fixed-effects and interaction terms for sub-periods as described in equation (C1) among G10 currencies. Dependent variables are 12-months returns in using short rates as the investment vehicle in Panel A and using long bonds in Panel B. Independent variables are 12-months lagged cross-sectionally demeaned short-term interest rates in Panel A and 12-months lagged cross-sectionally demeaned long-term bond yield in Panel B. Standard errors are shown in parenthesis and are two-way clustered by time and by currency. Estimates of constant terms are not shown. Double asterisk (**), asterisk (*) and plus (+) represent statistical significance at the 99%, 95%, and 90% confidence levels, respectively.