The Conditional Volatility Premium on Currency Portfolios*

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Abstract

Our paper examines conditional risk-return relations in a cross-section of currency portfolios, while modeling economic states using a large number of underlying risk factors. We identify a time-varying relationship between currency returns and volatility risk: investors require a positive risk premium in many, but by no means all, time periods or investment strategies. We find that value and momentum portfolios obtained a positive risk premium during the financial crisis. Important economic states underpinning exchange rate risks include the US and global business cycles. Finally, we uncover that the risk-return relation on the momentum portfolio is counter-cyclical.

Keywords: Systematic Risk; Currency Carry Trade; Momentum; Value; Conditional Factor Model; Currency Variability

JEL codes: C12, C58, F3, G11, G15

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1. Introduction

Central to asset pricing research is testing the empirical relationship between systematic risk and return, given that investors require compensation if risk is priced. When risk is modeled by volatility and assumed to have a time invariant relationship to excess return, Sharpe ratios are state independent. This state independence assumption is open to question. In addition and despite its centrality to asset pricing, the literature has not converged on a consensus on the nature of the link between returns and risk factors, such as volatility. For stock market returns, French et al. (1987), Merton (1987), Scruggs (1998), Ghysels et al. (2005), and Guo and Whitelaw (2006) present positive risk-return relations for example, while Campbell (1987), Glosten et al. (1993) and Ang et al. (2006) report a negative empirical relationship between returns and risk, in the form of return volatility. The former studies indicate investors require a risk premium for additional volatility, while the latter indicates that agents are not averse to additional asset price variability.[1]

Our work extends the risk-return trade-off test to the under explored area of currency portfolios. Asset pricing studies usually focus upon U.S. stock market returns (e.g. Ang et al., 2006; Guo and Whitelaw, 2006), but testing the risk and return nexus using alternative asset classes provides illuminating results. A burgeoning literature has recently implemented portfolio approaches for the currency market. These approaches sort currencies based upon a narrower set of cross-sectional differences, and these portfolios are advantageous since currency specific risk components are averaged out (e.g. Lustig and Verdelhan, 2007; Lustig et al., 2011; Menkhoff et al. 2012a). Currency carry trades are widely investigated and currency carry portfolios have systematic risk exposure to market and macroeconomic uncertainty (Atanasov and Nitschka, 2014; Dobrynskaya, 2014; Lettau et al., 2014; Berg and Mark, 2018; Byrne et al., 2018; Orlov, 2019).

[1]Bansal and Yaron (2004) is a prominent early model motivating long run risks or uncertainty shocks as having risk premiums. See also the expanding literature on volatility risk premiums, e.g. Bali and Engle (2010), Bansal et al. (2014), and Della Corte et al., (2016a, 2020). These studies often differentiate between realized and option implied volatility, while our work focuses upon modeling the underlying factors driving currency volatility.

Our study's first contribution is to focus on currency portfolios when examining the link between risk and return for several investment strategies. Some studies investigate risk and return relationships for a narrower set of portfolios, for example the currency carry portfolios. Christiansen et al. (2011) and Menkhoff et al. (2012a) report that global currency volatility is associated with cross-sectional pricing models, while Bakshi and Panayotov (2013) explore the relationship in a time-series context. We also focus upon time-series relationships and extend the study of Bakshi and Panayotov (2013) to a wider array of currency portfolios, not only the currency carry but also value and momentum investment strategies. Hence, our work goes beyond the carry strategy for currency portfolios, as we extend the examinations of currency risk and return to several currency investment strategies. Important work by Asness et al. (2013) argues that value and momentum are observed in all asset classes including currency markets.[2] Menkhoff et al. (2012b) and Eriksen (2019) report that high average returns of currency momentum portfolios cannot be explained by traditional risk factors, although they do not specifically investigate the risk-return relationship in a time-series context. It is worthwhile, therefore, to ask the following question: What do the higher average returns of momentum portfolios imply for the risk-return trade-off?

Moreover, currency value portfolios are often associated with mean reversion to purchasing power parity, an important way to understand exchange rate fluctuations (e.g. Taylor, 2002; Imbs et al., 2005; Boudoukh et al., 2016; Menkhoff et al., 2017). Although most studies focus on a time-series and single currency context, our work represents the first attempt to connect currency value portfolios to an intertemporal risk-return relationship. Furthermore, most professional fund managers take exposure to one of three currency strategy risks, as reported by Pojarliev and Levich (2010), hence it is important to understand the link between risk and return in the three strategies.[3] In contrast to Menkhoff

[2]Kroencke et al. (2014), and Barroso and Santa-Clara (2015) present empirical results that including value and momentum currency portfolios diversify the risk of currency investors' portfolios.

[3]Three currency investing strategies are categorised as carry, momentum, and value: carry seeks to exploit the difference between high and low yielding currencies; momentum exploits trends in currency

et al. (2012a) and Menkhoff et al. (2017), we explore the intertemporal relation and it is more useful for investors in terms of risk management, since they do not observe the risk associated with their portfolios in the next month and frequently use past volatility as a risk proxy. Furthermore, we investigate four new currency portfolios: dollar carry trade (Lustig et al., 2014), global imbalances (Della Corte et al., 2016b), "good" carry trade (Bekaert and Panayotov, 2020), and correlation risk in the FX market (Mueller et al., 2017).

The standard approach in asset pricing studies is to examine risk and return in portfolios using unconditional methods. The second contribution we make is to take into account a time-varying relation between conditional volatility and expected returns. A theoretical asset pricing model conditional upon economic states, was proposed by Backus and Gregory (1993). In contrast to unconditional models, conditional models employ information up to the current time and reflect changes in economic states (Jagannathan and Wang ,1996; Cochrane, 1996; Lettau and Ludvigson, 2001). The advantage of the conditional models is that it allows a time-varying relationship between asset returns and risk. Risk-return trade-offs have been widely investigated using the conditional models in the stock market literature (e.g. Whitelaw, 2000; Rossi and Timmermann, 2010; Ghysels et al., 2014; Adrian et al., 2019).[4] Whitelaw (2000) builds a general equilibrium model with a regime-switching consumption process and generates a time-varying and non-linear relation between volatility and expected returns in the stock market. Rossi and Timmermann (2010) find a non-monotonic relation between conditional volatility and expected returns in the stock market, and Ghysels et al. (2014) present work indicating that the positive risk-return relation is not observed in a "flight-to-quality" regime. In recent work, Adrian et al. (2019) find that expected returns on stock and bond markets depend upon the level of VIX and the relationships are nonlinear. To investigate the time-varying relationship

returns; and value seeks to a currency which is inexpensive in terms of the fundamental price.

[4]For research conditional asset pricing models more generally see *inter alia* Ferson and Schadt (1996), Lewellen and Nagel (2006) and Gagliardini et al. (2016).

between returns and risk, our study adopts a time-varying conditional factor model proposed by Ang and Kristensen (2012), which allows for smooth changes in coefficients. In the FX market, Baillie and Kim (2015) and Sakemoto (2019) observe that utilising macro indicators results in smooth changes in risk.

The third contribution of our work on the volatility risk premium is to employ an empirical factor model to summarize more broadly macroeconomic and financial market information. This is important since economic states affect the relationship between conditional volatility and expected returns, see Backus and Gregory (1993), and Backus et al. (2001). To capture economic states, we focus upon the common component of macro and financial information since it is non-diversifiable and linked to the business cycle (Jurado et al., 2015), while idiosyncratic information can be diversified. Furthermore, narrow macro indicators like consumption may suffer from measurement errors, with an unknown relationship between macro indicators and asset returns. Investors also extract macro-finance information broadly when implementing their investment strategies. Ludvigson and Ng (2007) construct several empirical factors that summarise macro indicators and uncover a positive risk-return relation for U.S. stocks. This factor model is also useful in predicting currency carry returns (Filippou and Taylor, 2017). In contrast to the previous literature, our study predicts conditional FX market volatility by a factor model, not currency portfolio returns. Moreover, our aim is to examine the risk-return relationship with currency portfolios, rather than predict FX volatility.

To preview our results, we find that the relationship between conditional volatility and expected returns is time-varying on currency momentum and value portfolios. Importantly, we do not find formal evidence of a link between returns and risk on the currency momentum and value portfolios with constant parameter models. When we reflect changes in economic states and adopt the time-varying model, we observe that the risk-return parameters occasionally change signs, indicating that agents require positive compensation for risk in some periods but not in others. Moreover, the risk-return parameters increase during the recent financial crisis on the currency momentum and the currency value portfolios, and these indicate that average high returns of the momentum and the value portfolios are explained by the standard risk-return relationship. Our empirical findings are also associated with those of Guiso et al. (2018) who use Italian investors' survey data in 2007 and 2009, and observe that investors' risk aversion increased after the financial crisis.

The paper is organized as follows: Section 2 introduces our theoretical model. Section 3 describes the currency volatility and currency portfolios. Section 4 then lays out the econometric methods implemented in our paper, and Section 5 describes the data. Section 6 presents empirical results, Section 7 conducts the further analysis and Section 8 concludes.

2. A theoretical framework

While making essentially an empirical contribution, this paper adopts a no-arbitrage asset pricing model to investigate the relationship between FX volatility and expected returns on currency portfolios. According to the asset market view, exchange rates are related to country pricing kernels.[5] Following Backus et al. (2001) and Lustig et al. (2011, 2014), the logarithm of the stochastic discount factor in currency i at $t+1$, m^i_{t+1}, is determined by a global state variable, z_{t+1}:

$$m^i_{t+1} = a^i + b^i z_{t+1} + u^i_{t+1} \tag{1}$$

where a^i is a parameter, b^i is the factor loading, and u^i_{t+1} is the idiosyncratic iid gaussian shock.[6] Backus et al. (2001) proposition 1 states that if there are no arbitrage opportunities, the change in the exchange rate (Δs^i_{t+1}) between two currencies, say United States dollar (USD) and British pound (GBP), is equal to the difference between their stochastic discount factors, respectively m_{t+1} and m^i_{t+1}. Therefore exchange rates are a function of

[5] For other applications and discussions of the asset market view of exchange rates, see also Brandt et al. (2006), Maurer et al. (2019), Lustig and Verdelhan (2019), and Burnside and Graveline (2020).

[6] For instance, we consider global industrial production or global inflation as examples of the global state variable which affects all stochastic discount factors. Backus et al. (2001) do not include the idiosyncratic shock, while this difference does not affect our conclusion.

the global state variable z_{t+1}, based upon Equation (1):

$$\Delta s^i_{t+1} = m_{t+1} - m^i_{t+1} = a - a^i + (b - b^i)z_{t+1} + u_{t+1} - u^i_{t+1} \tag{2}$$

where the two idiosyncratic shocks u_{t+1} and u^i_{t+1} are iid with the variance σ^2_u.

Furthermore, the conditional variance of the change in the exchange rate is also the difference between the two stochastic discount factors, and written as:

$$var_t(\Delta s^i_{t+1}) = (b - b^i)^2 var_t(z_{t+1}) + 2\sigma^2_u. \tag{3}$$

Using Equation (3), we obtain the aggregate conditional variance of the change in the exchange rate:

$$\sigma_{FX,t} = \frac{1}{K}\sum_{i=1}^{K} var_t(\Delta s^i_{t+1}) = (\frac{1}{K}\sum_{i=1}^{K}(b - b^i)^2)var_t(z_{t+1}) + 2\sigma^2_u. \tag{4}$$

This is an affine transformation of the state variable $var_t(z_{t+1})$ from Equation (3). Following Lustig and Verdelhan (2007), the risk premium of the currency portfolio is described as the covariance between the expected return of the currency portfolio and the logarithm of the stochastic discount factors:

$$E_t(r^i_{t+1}) = -cov_t(\Delta s^i_{t+1}, m_{t+1}) = \beta^i var_t(z_{t+1}) + \sigma^2_u \tag{5}$$

where $\beta^i = b(b - b^i)$ corresponds to the estimated coefficient of the regression between conditional variance and expected returns. The parameter β^i is positive or negative based upon the underlying link between the stochastic discount and state factors. Thus, to examine conditional risk-return trade-offs for currency portfolios, and whether the volatility risk premium is positive, we implement an empirical variant of Equation (5) in the following analysis.

3. Currency portfolios and volatility

This section describes the currency volatility and portfolios data used in our study. To examine trade-offs for a wide range of currency returns, we construct several currency portfolios. These include, carry, momentum, value, "good" carry, dollar carry trade, global imbalances, and global correlation risk.

3.1. *Currency excess return and volatility*

This study computes a currency excess return using spot and forward rates and assuming U.S. investors. The currency excess return $r_{i,t}$ for currency i at time t is defined as:

$$r_{i,t} = \frac{F_{i,t-1} - S_{i,t}}{S_{i,t}} \tag{6}$$

where $F_{i,t-1}$ is the one-month forward price of foreign currency i per unit of USD and this price is agreed at $t-1$ and delivered at t, and $S_{i,t}$ is the spot price of foreign currency i at t. Following Lustig et al. (2011), we take into account transaction costs using bid-ask prices.

We adopt global FX volatility as our measure of volatility in intertemporal risk-return trade-off tests. We follow Menkhoff et al. (2012a) and global FX volatility, σ_{FX}, in day d is obtained as:

$$\sigma_{FX,d} = \sum_{i=1}^{K_d} \left(\frac{|r_{i,d}|}{K_d} \right) \tag{7}$$

where $|r_{i,d}|$ is the absolute value of $r_{i,d}$, and K_d is the number of currencies on day d. Next, monthly global FX volatility in month t, $\sigma_{FX,t}$, is calculated as:

$$\sigma_{FX,t} = \frac{1}{T_t} \sum_{d=1}^{T_t} \sigma_{FX,d} \tag{8}$$

where T_t is the total number of trading days in month t. The monthly global FX volatility $\sigma_{FX,d}$ is employed in the later analysis.

3.2. *Carry strategy*

We begin with carry trade portfolios which are constructed based upon forward discounts. This strategy exploits deviations from uncovered interest rate parity, previously explored in the literature (e.g. Lustig et al., 2011; Menkhoff et al., 2012a; Bakshi and Panayotov, 2013). A high interest rate currency generates a higher return than a low interest rate currency because the interest rate difference is not offset by the change in the spot exchange rate. Following Lustig et al. (2011), a forward discount $FD_{i,t}$ is computed as the difference between forward and spot rates at time t:

$$FD_{i,t} = \frac{F_{i,t} - S_{i,t}}{S_{i,t}}. \tag{9}$$

When $FD_{i,t}$ is positive, this means that the interest rate in the foreign country i is higher than that in U.S., since we assume that the covered interest rate parity condition is satisfied (e.g. Akram et al., 2008).[7] In carry portfolios, investors go long (short) in currencies in which there are high (low) forward discounts. This study considers strategies at a monthly frequency. At the end of each month, two currencies are in the long position and two currencies are in the short position.[8]

In addition to the standard carry approach, we adopt the "good" carry trade strategy proposed by Bekaert and Panayatov (2020). They find that only a limited number of "good" currencies avoid negative skewness and exhibit higher Sharpe ratios. Following Bekaert and Panayatov (2020), we employ GBP, New Zealand dollar (NZD) and Swedish krona (SEK).

3.3. *Momentum strategy*

A momentum strategy uses past return as a characteristic, instead of a forward discount. We employ the past three months cumulative currency excess return. Kroencke et al. (2014) and Barroso and Santa-Clara (2015) also adopt this definition, since Menkhoff et al. (2012b) report that momentum has persistence, but that including more than the past three months do not provide a higher return. In momentum portfolios, long (short)

[7]After the global financial crisis, the covered interest rate parity is not satisfied (Du et al, 2018; Chatziantoniou et al., 2020). This fact, however, does not impact our main conclusion. We employ a rolling regression approach, and hence can exclude the results derived from the recent data.

[8]We also go long (short) in three currencies in the Appendix.

currencies have high (low) past excess returns.

3.4. *Value strategy*

A value strategy exploits information of a fundamental value: and if the price of currency i is undervalued compared with what is considered its fundamental value, then investors invest in the currency i. This strategy focuses upon deviation from purchasing power parity (PPP), and a value of the exchange rate has a mean-reversion property in the long-run (e.g. Taylor, 2002; Boudoukh et al., 2016). The fundamental value is computed as the cumulative five year change of the real exchange rate, as in Kroencke et al. (2014) and Barroso and Santa-Clara (2015). The fundamental value $VA_{i,t}$ is computed as:

$$VA_{i,t} = \frac{S_{i,t-3} CPI_{i,t-60} CPI_{US,t-3}}{S_{i,t-60} CPI_{i,t-3} CPI_{US,t-60}} \tag{10}$$

where $CPI_{i,t-3}$ is the price level of consumer goods in country i at $t-3$, and $CPI_{US,t-3}$ is the price level in the U.S. We follow Kroencke et al. (2014) and employ a three month lag to avoid overlaps between momentum and value strategies. Further, Barroso and Santa-Clara (2015) document that a lag value is appropriate since there is a time shift involved in the observation of price levels. If $VA_{i,t}$ is higher (lower) than one, then this it indicates that the currency is overvalued (undervalued), and thus is in the short (long) position.

3.5. *Dollar carry trade*

The dollar carry trade is based upon the Average Forward Premium (AFD) which is calculated as the average forward discount on foreign currency against the U.S. dollar (Lustig et al., 2014). We go long in foreign currencies when AFD is above the U.S. short-term interest rate and go short otherwise.

3.6. *Global imbalances*

Global imbalance (IMB) portfolios are proposed by Della Corte et al. (2016b). This factor is based upon the theory that net debtor countries are riskier than net creditor countries, and hence these countries' currencies provide risk premia. In particular, the net debt countries which are funded by foreign currencies are riskier than those are funded by their own currencies. The global imbalance factor is constructed in two steps (Della Corte et al. 2016b). Firstly, currencies are separated into two baskets based upon the net foreign asset to gross domestic product ratio (nfa).[9] Secondly, currencies are sorted within each nfa basket, based upon the share of foreign liabilities in domestic currency (ldc).[10] Finally the nfa and ldc sorted currencies are put into five portfolios. Portfolio 1 includes high nfa and high ldc countries, which are robust against negative financial shocks, while portfolio 5 does low nfa and low ldc countries, which are risky and provide risk premia. Therefore, the global imbalance factor is calculated as the return spread between portfolios 5 and 1.

3.7. *Global correlation risk*

This paper also considers the importance of global correlation risk (ΔFXC) for currency returns. This strategy focuses upon a FX correlation that has counter-cyclicality. A portfolio that has low exposure to the correlation risk provides a higher return, since the portfolio does not work as a hedge during recessions. Following Mueller et al. (2017), we calculate this empirical risk factor as follows. First, a conditional correlation between FX spot rate returns is obtained and the rolling window size is three months (66 days). Second, we sort all G10 FX pairs (base currency is the U.S. dollar) into deciles based on conditional correlations and take the difference between the average correlation in the top decile and that in the bottom decile. This is called as the cross-sectional dispersion in conditional FX

[9]The data of foreign assets and liabilities, and gross domestic product are shared by Lane and Milesi-Feretti (2004, 2007).

[10]Data of the proportion of external liabilities denominated in foreign currency are constructed by Lane and Shambaugh (2010) and Benetrix et al. (2015).

correlation (FXC). Third, we pick up FXC at each end of month and take the innovation part of FXC (ΔFXC). Fourth, we construct three currency portfolios based upon factor betas on ΔFXC. The factor betas are estimated by regressing on currency excess returns on ΔFXC, and the rolling window size is 36 months. Finally, the global correlation risk portfolio is constructed by taking the return difference between portfolios 1 and 3.

4. Empirical methodology

This section describes the econometrics methods used to test risk-return trade-offs in FX markets, and to identify the time varying parameter for variance risk. We employ a factor model to summarise a large information set based upon many macroeconomic indicators. Regressing FX volatility onto common factors, we obtain predicted FX volatility. Furthermore, we use a conditional factor model that allows for a change in risk-return relationship.

4.1. *Factor model*

We begin by explaining the way in which we obtain common information, which underpins our volatility measure. The common information across macroeconomic data sets is extracted by principal components. Define $\mathbf{X}$ to be the $T \times N$ standardized macroeconomic time series matrix with elements, $x_{j,t}$, $j = 1, \ldots, N$, $t = 1, \ldots, T$, and N indicates the number of macroeconomic time series and T does that of time series observations. Each macroeconomic time series, $x_{j,t}$, is decomposed into a common factor, f_t, and an idiosyncratic component, $\epsilon_{j,t}$, as:

$$x_{j,t} = \Lambda_j f_t + \epsilon_{j,t} \tag{11}$$

where Λ_j is the loading on the common factor.

Given the estimated common factors in Equation (11), we employ a factor model to obtain conditional volatility, since adopting many conditional variables faces a dimensionality problem. Following Ludvigson and Ng (2007), FX volatility, $\sigma_{FX,t+1}$, is regressed onto a common factor f_t and an error term e_{t+1}:

$$\sigma_{FX,t+1} = \phi f_t + e_{t+1}. \tag{12}$$

Once we estimate the parameters ϕ, we obtain predicted FX volatility $\hat{\sigma}_{FX,t+1}$.

4.2. *Time-varying conditional factor model*

Next, we describe a nonparametric approach to estimate a time-varying conditional factor model. Let $r_{i,t+1}$ be the excess return of currency portfolio i at time $t+1$, and $\sigma_{FX,t}$ is FX volatility. The excess return is represented by the following conditional factor model:

$$ret_{i,t+1} = \alpha_{i,t+1} + \beta_{i,t+1}\sigma_{FX,t} + \epsilon_{i,t+1} \tag{13}$$

where $\alpha_{i,t+1}$ is the time-varying conditional alpha and $\beta_{i,t+1}$ is the time-varying factor loading (beta) for portfolio i. The error term $\epsilon_{i,t+1}$ has conditional expectation $E[\epsilon_t \mid \sigma_{FX,t}, \beta_{i,t+1}] = 0$ and conditional variance $E[\epsilon_{i,t+1}^2 \mid \sigma_{FX,t}, \beta_{i,t+1}] = \Omega_{t+1}$. Following Ang and Kristensen (2012), we introduce τ when estimating a kernel regression, and $\alpha_{i,\tau}$ and $\beta_{i,\tau}$ at any point τ in the interval $1 \leq \tau \leq T$ are obtained by minimizing the following local kernel-weighted least-squared residuals:

$$[\hat{\alpha}_{i,\tau}, \hat{\beta}_{i,\tau}] = \arg\min_{(\alpha,\beta)} \sum_{t=1}^{T-1} K_{h_iT}(t-\tau)(ret_{i,t+1} - \alpha_i - \beta_i\sigma_{FX,t})^2 \tag{14}$$

where $K_{h_iT} = K(z/(h_iT))/(h_iT)$ with $K(\cdot)$ being a kernel with bandwidth $h_i > 0$ We choose the Gaussian kernel, which is widely used in the finance literature (see, e.g., Ang and Kristensen, 2012; Adrian et al., 2015). $\hat{\alpha}_{i,\tau}$ and $\hat{\beta}_{i,\tau}$ are obtained by solving Equation (14). We need to choose bandwidths to solve Equation (14). Kristensen (2012), and Ang and Kristensen (2012) employ a "plug-in" method to select the bandwidths, since cross-validation procedures may provide extremely small bandwidths.[11]

[11] See Kristensen (2012), and Ang and Kristensen (2012).

5. Data

5.1. *Currency data*

This study uses daily spot and one-month forward rates against the U.S. dollar and these were obtained from Datastream. Following Kroencke et al. (2014) and Bakshi and Panayotov (2013), we employ the G-10 currencies, since they are the most liquid and are widely used in currency investment strategies. Currency portfolios are rebalanced at the end of every month. The full time series span is from December 1983 to April 2017.[12]

5.2. *U.S. and global macroeconomic data*

U.S. and global macroeconomic data are central to our analysis as these are used to construct our empirical factor model. We employ 88 U.S. macroeconomic indicators, as in Ludvigson and Ng (2007). The groups of series included are: income, consumption, employment, production, housing starts, producer and consumer prices, interest rates, money supply, and stock markets. In addition to the U.S. data set, this study employs global macroeconomic data series, and Filippou and Taylor (2017) address the idea that the global data are important for exchange rate markets. The global data series are obtained from G-10 countries[13] and we employ 57 macroeconomic indicators: employment, production, producer and consumer prices, interest rates, foreign reserves, and stock markets.[14] The U.S. and the global data series are mainly downloaded from the Federal Reserve Bank of St. Louis, and extend from January 1984 to September 2016.[15] We linearly interpolate some quarterly values to obtain data at the monthly frequency, as in Vissing-Jørgensen

[12]To compute real exchange rates, the Consumer Price Index is obtained from OECD/Main Economic Indicators.

[13]G10 currencies are constructed by the Australian dollar, Canadian dollar, Danish krone, Swiss franc, British pound, Japanese yen, Norwegian krone, New Zealand dollar, Swedish krona, and euro. We replace the Deutsche mark with the euro prior to 1999.

[14]We do not include trade balance data since they cover a relatively shorter period compared with other global data. However, we include the trade balance data, it did not impact our results.

[15]As predicted FX volatility is used in Equation (12), currency portfolio returns extend by September 2016.

and Attanasio (2003). U.S. factors are denoted by F_j and global factors are denoted by G_j. All data series are transformed based upon unit root tests and standardized to estimate factor models.

6. Empirical results

To assess relationships between risk and return, we present empirical evidence in this section. First, we report the summary statistics of the currency portfolios in Section 6.1. and the result of the unconditional model that employs realized FX volatility as risk in Section 6.2. Second, we estimate FX volatility using a large number of macroeconomic indicators in Section 6.3. Third, we investigate the risk-return relationship using the estimated FX volatility in Section 6.4. Finally, we present our main results that adopting the time-varying conditional model and how the risk-return relationship varies over time for each currency portfolio in Section 6.5.

6.1. *Descriptive statistics*

We begin our empirical results section with summary statistics for each currency trade. Table 1 shows that average annualized excess return, annualized standard deviation, return skewness, return kurtosis, monthly maximum values, monthly minimum values and Sharpe ratios. An average annual excess return of the carry portfolio which goes long in two currencies and goes short in two currencies is 2.99%. The carry portfolio shows negative skewness, which is a typical characteristic of carry portfolios (e.g. Brunnermeier et al., 2009; Bakshi and Panayotov, 2013). In contrast, the "good" carry trade portfolio does not have negative skewness and the Sharpe ratio is higher than that of the corresponding carry portfolio (Bekaert and Panayotov, 2020).

6.2. *The risk-return relation estimated unconditionally*

Before estimating conditional models, we present unconditional results as a benchmark and motivation for our main approach. Realized volatility at time t is regressed onto the expected return at time $t+1$. Table 2 displays the parameter estimates for the unconditional model, and column (1) indicates that the estimated parameter for carry is negative and marginally statistically significant at the 10% level. This negative value of β implies that additional risk is associated with lower return, irrespective of economic states, although the unconditional relationship is not strong in a statistical sense. In contrast, the estimated carry α is statistically significant at the 5% level. The carry return is associated with a global business cycle, which means that past FX volatility is not sufficient to explain the expected return (Bakshi and Panayotov, 2013; Ready et al., 2017a; Byrne et al., 2019). Economic states which are captured as volatility in our study, are linked to changes in the investment opportunity set (Meron, 1973). When volatility bears a negative risk price in the cross-sectional context, the relationship between volatility and asset returns should be negative (Maio and Santa-Clara, 2012). The risk price on FX volatility is negative in carry trade portfolios, as report by Menkhoff et al. (2012a), and hence β in the carry portfolio is negative.[16] We will provide the further discussion in Section 7.3. Given that β is not important for any other portfolios and R^2s are consistently low, the importance of economic states for risk-return trade-offs, and therefore the volatility beta β is potentially washed out using an unconditional approach. Overall, the unconditional model results do not identify a risk-return trade-off in the foreign exchange market.

6.3. *Volatility estimation results*

In the previous section we identified a weak unconditional relationship between expected return and volatility. Given that this link may be contingent upon economic states, we now

[16] Moreira and Muir (2017) and Suh (2019) report low volatility leads to a higher Sharpe ratio and a higher profit of the carry trade strategy.

investigate this relationship using a conditional approach. First, we examine conditional volatility using the factor model in Equation (12). Table 3 presents parameter estimates for the factor model and column (1) uses only U.S. common factors(F_j). We adopt the general-to-specific approach and only retain statistically significant parameters. The common factors F_1 and F_5 are the main drivers explaining future FX volatility. Following Ludvigson and Ng (2007), we obtain marginal-R^2 to interpret these factors, and F_1 is strongly linked to output variables such as industrial production growth.[17] This is associated with the idea that industrial production captures business cycles (e.g. Lustig et al. 2014). Furthermore, F_5 is associated with money supply and commercial banks' assets. Both level and squared terms of F_1 and F_5 are statistically significant at least at the 5% level in Table 3.

We add lagged FX volatility in column (2) of Table 3, since Guo and Whitelaw (2006), and Moreira and Muir (2017) report that lagged volatility is important to predict stock market volatility. We confirm the same result for FX volatility: including lagged FX volatility increases R^2 to 0.53. The empirical result also suggests that the lagged FX volatility drives out F_5, F_4^2, and F_5^2, while the real output factor F_1 remains statistically significant. U.S. real output is strongly linked to future FX volatility.

Next, global common factors (G_j) are considered in the empirical model. Column (3) in Table 3 implies that the level and squared global factors G_5, G_1^2, and G_5^2 are statistically significant at least at the 5% level. G_1 is strongly correlated with producer price indices and G_5 is the short-term interest rate factor. There is marginal incremental information however by including the global factor, since a R^2 in column (3) is 0.40, which is almost similar to that of column (1).

Finally, we consider whether both global factors and lagged FX volatility explain volatility in column (4) of Table 3. We observe that the US real output factor and the lagged FX volatility are the main drivers of FX volatility. Global factors, in levels and squared, G_5, G_4^2, and G_5^2 have incremental information for the model: as mentioned, G_5 is the interest

[17]See the online Appendix Figure A4.

rate factor and G_4 is related to central banks' reserves. It is reasonable that global reserves and interest rate factors have different information from the U.S. real output factor. In summary, the U.S. factors, the global factors, and the past FX volatility predict future FX volatility.

FX volatility estimated by the factor model tracks realized FX volatility but with some advantages. Figure 1 compares the estimated and the realized FX volatilities. Interestingly, the realized volatility has more frequent spikes than the estimated volatility, which is consistent with the notion that realized volatility contains relatively more noise than signal. The converse is the case with model estimated volatility since it summarizes a large amount of information. We will use the fitted value of the final model in Table 3 column (4) for the next risk-return trade-off analysis. Although the R^2 of column (2) is slightly higher than that of column (4), while employing the latter model is more reasonable since it includes both U.S. and global information.

6.4. *The risk-return relation estimated by factor model*

Given we have estimated future FX volatility, we now investigate risk-return relations using a factor model. Utilizing the estimated volatility, allows us to take investors' expectations into account. Furthermore, if risk-return trade-offs in foreign exchange rate markets are associated with business cycles, it is reasonable to employ global macroeconomic information. To extract information from a large numbers of macroeconomic indicators, we adopt an empirical factor model (e.g. Ludvigson and Ng, 2007). We repeat the same estimation reported in Table 2, while we replace realized with estimated FX volatility based upon the discussion in the previous section. Note that FX volatility conditional upon the macroeconomic information, while the parameters β and α are time-invariant.

Table 4 presents the risk-return relation between estimated FX volatility and expected FX returns. We find strong negative relations for carry portfolios, and the risk-return parameters for carry and global imbalances (IMB) are statistically significant. The coefficient of determination also increase by around 7%, which highlights the importance of the common component across macroeconomic measures as in Jurado (2015), since the R^2s are greater than those of Table 2. In summary, we observe that there is no systematic trade-off between conditional volatility and expected returns.

6.5. *Time-varying risk-return relation*

The negative relation between conditional volatility and the expected return on carry and global imbalance portfolios may be due to a lack of time variation of the parameters. Although we extract investors' information by adopting the empirical factor model, it may not be sufficient to reflect changes in economic states. Indeed, the relationship between conditional volatility and expected returns varies over time in the U.S. and European stock markets (e.g. Rossi and Timmermann, 2010; Ghysels et al., 2014; Aslanidis et al., 2016). This study employs the time-varying conditional factor model proposed by Ang and Kristensen (2012), which does not impose any specifications on conditioning variables and parameters, and allows continuous changes in model parameters.

Now, we move on to our main findings and Figure 2 presents time-varying risk-return parameters with 90% confidence intervals. We adopt the same model in Table 4 and the risk-return parameter of carry trade is negative whereas the magnitude varies over time. It is close to zero around the years 2000 and 2012, while there are troughs around 1997 and 2006.[18] This means that when the carry trade provides a higher return, the parameter tends to be negative. Interestingly, both the risk-return parameters of value and momentum portfolios exhibit wider fluctuations and flip signs. This could be a helpful explanation as to why we do not observe significant relations between conditional volatility and expected returns in Table 4. The parameter values of the momentum portfolios reach 0.2 and those of the value portfolios attain 0.4, which are smaller than results reported by the stock market literature, but they are still meaningful because some studies do not

[18] We also estimate the time-varying relations with realized FX volatility in Online Appendix. The impact becomes weaker than that of the estimated FX volatility model.

find estimated signs consistent with theory (e.g. Glosten et al., 1993). In contrast, the risk-return parameters of good carry, AFD, IMB, and ΔFXC portfolios illustrate more stable changes since their bandwidths derived by Ang and Kristensen's (2012) method are larger than those of the other portfolios.

Our empirical results furthermore suggest that positive average returns of the momentum and the value strategies are explained by the standard risk-return framework. These parameters increase in particular during the global financial crisis, which suggests that investors require higher returns for investing in currency during a crisis. Guiso et al. (2018) investigate investors' surveys which were conducted in 2007 and 2009. Investors were asked questions related to thier subjective risk beliefs and its certainty equivalent value. Guiso et al. (2018) observe that investors' risk aversion increased in 2009 and most investors chose more conservative risk-return combinations at that time.

Our main findings are also related to the currency momentum literature. Menkhoff et al. (2012b) indicate that it is difficult to explain average positive returns of the currency momentum strategies based upon standard financial factors. Our empirical findings reveal that the time variation of the risk-return parameters plays an important role. Overall, we find that the signs of parameters on the momentum and the value portfolios are consistent with the volatility risk premium story.

7. Further analysis and discussion

The results obtained in the previous section demonstrate the importance of introducing time variation. In this section, we provide further analysis of our findings. First, we use a rolling regression approach that is widely employed to obtain time-varying coefficients. Second, we formally test whether time-varying risk-return relations are associated with business cycles. Finally, we discuss the relationship between our results and the related studies.

7.1. *Rolling regression approach*

Section 6 presented formal statistical evidence of time-varying relations between conditional volatility. Given we use a data intensive non-parametric approach, we may, however, have insufficient data to successfully to draw confidence intervals. We also employ a more conservative rolling regression approach therefore to examine time variations (e.g. Lustig et al., 2011). We choose a rolling window size as an optimal bandwidth employed in the previous section.

Figure 3 demonstrates the time-varying relations obtained by the rolling regressions. Our main findings remain the same and the risk–return parameters on the momentum and the value portfolios flip signs. More importantly, both parameters increase in the financial crisis and these confidence intervals are above zero. Derived optimal bandwidths of good carry, AFD, and ΔFXC portfolios are large, and the estimation periods are short. In addition, we find that the zero axis is within error bands more frequently for the rolling regression, since the nonparametric regression fits local data and has a more flexible functional form.[19]

7.2. *Characterizing changes in risk-return trade-offs*

Having found that the risk-return trade-off varies over time, we explore whether these changes are driven by business cycles. We regress a change in the risk-return parameter $\beta_{i,t}$ in Equation (13) for each result onto changes in U.S. and global industrial production growths and those in changes in U.S. and global short-term rate. We employ the global industrial production growth and the global short-term rate as first principal components of G10 countries excluding U.S. data. Then, following Lustig et al. (2014) and Bekaert and Panayotov (2020), we extract a residual by regressing the U.S. variable onto the global variable.

[19]For an econometric critique of rolling windows in conditional asset pricing models see Gagliardini et al. (2016).

The change in $\beta_{i,t}$ of the momentum portfolio is driven by U.S. industrial production growth and the global short-term rate. Weak business conditions are proxied by low industrial production growth and a high interest rate (Ang and Kristensen, 2012; Lustig et al., 2014). Results in Table 5 indicate that the momentum portfolio is consistent with the risk story. U.S. industrial production growth, ΔIP_{us}, and the global short-term rate, Δi_{world}, are statistically significant at the 1% level. Also the estimated coefficient in Table 5 on ΔIP_{us} has a negative sign and Δi_{world} has a positive sign. This is consistent with the momentum risk-return relationship being counter-cyclical: risk requires greater compensation in a downturn, than would otherwise be the case. For the value portfolio, the counter-cyclical risk-return relationship is less clear than that of the momentum portfolio in the entire period, while it has the clear relationship during the global financial crisis as shown by Figure 2. Finally, the result of the ΔFXC portfolio is similar to that of the momentum portfolio, while the change in $\beta_{i,t}$ for the ΔFXC portfolio is slow, we should be cautious to conclude that the risk-return trade-off hold for the ΔFXC portfolio.

7.3. *Discussion of counter-cyclicality*

Having uncovered countercyclical-risk-return relationship in the momentum and value portfolios, we consider why these two portfolios displays this clear pattern. We focus upon currency portfolios which are rebalanced at a monthly frequency. This monthly rebalancing operation is associated with institutional and/or individual investors who have substantial financial knowledge. For instance, Calvet et al. (2009) find that Swedish households with greater knowledge tend to rebalance their financial portfolios more actively. Cohn et al. (2015) conduct an experiment with financial professionals and observe that they become more risk-averse in financial downturns. In theory, Chien et al. (2012) consider why most investors do not rebalance their portfolios frequently, and therefore a small number of the professional investors account for aggregate risk shocks. This mechanism causes a counter-cyclical risk price which is consistent with our momentum and value results. The momentum and value strategies are widely employed in currency markets by professional investors, as reported by Pojarliev and Levich (2010). This may explain why the other nonstandard strategies, such as "good" carry and IMB portfolios, do not provide a clear time-varying risk-return relationship.

The carry portfolio is also widely used by professional investors, but does not display the same behaviour as the momentum and value portfolios. There are several studies which indicate that the global financial crisis impacted carry returns, and hence there are specific reasons why the carry portfolio does not display the time-varying pattern of momentum and value portfolios. Bussiere et al. (2019) investigate deviations from uncovered interest rate parity condition, which underpins carry returns. They find that investor's expectational errors are negatively correlated with interest rate differentials before the global financial crisis in 2008, while the correlation signs change after the crisis. They conclude that the systematic change in investor expectations is the main reason that carry dissipated after the crisis.[20] Ready et al. (2017b) propose a two-country general equilibrium model with commodity exporting and importing countries. In their model, interest rates and real exchange rate are jointly determined. They illustrate a commodity exporting country demands less precautionary saving, leading to higher interest rates and the positive carry return. They regard the global financial crisis as a large productivity shock in the commodity importing countries, causing declines in the commodity price and the carry return.

8. Conclusion

To summarise this study, we theoretically motivate and empirically explore risk-return relations between conditional volatility and expected returns on currency portfolios. This allows us to uncover time-varying risk-return relationships in the foreign exchange market.

[20] Lilley et al. (2019) observe that the change in capital flows after the global financial crisis and highlight the importance of the U.S. dollar as a safe haven currency.

Currency carry portfolios have similar characteristics to stock markets, as pointed out by Dobrynskaya (2014) and Lettau et al. (2014), while currency momentum and value portfolios are regarded as having more specific characteristics. Furthermore, we explore several new currency portfolios such as dollar carry trade (Lustig et al. 2014), global imbalances (Della Corte et al. 2016b), good carry trade (Bekaert and Panayotov, 2020), and foreign exchange rate correlations (Mueller et al. 2017).

We introduce a time-varying relation in our analysis of the FX market, since a conditional relationship between excess return and systematic risk is frequently considered to be a key characteristic in the stock market (Whitelaw, 2000). We find that the risk-return trade-offs on the momentum, and value portfolios vary over time. During the financial crisis, there was an increase in the estimated model parameters on the momentum and the value portfolios, indicating they required a higher risk premium. In particular, the time variation of the momentum portfolio is linked to the business cycle. Our empirical factors, which span a large amount of macro fundamentals, better reflects investors' expectations. This empirical factor model provides sharper results than the other approach employing realized volatility. The empirical factor uses information that is both more expansive and more detailed to more clearly reflect underlying economic states and allow us, therefore, to successfully identify the time-varying relationship between volatility risk and currency returns.

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Table 1. Descriptive Statistics

	Mean	Std.dev	Skew	Kurt	Max	Min	SR
carry	3.17	8.96	-0.41	4.81	10.84	-10.57	0.35
mom	1.92	9.47	0.44	4.97	12.52	-6.90	0.20
value	3.59	9.17	0.06	4.68	11.19	-10.34	0.39
good	4.16	8.13	0.56	5.52	12.77	-7.33	0.51
AFD	4.42	8.31	0.04	3.80	10.32	-7.29	0.53
IMB	1.46	9.52	-0.93	9.87	10.49	-18.26	0.15
ΔFXC	2.65	8.36	-0.25	4.53	7.09	10.65	0.32

Notes: This table reports annualized mean, annualized standard deviations, skewness, kurtosis, maximum, minimum, and the Sharpe ratio of excess returns of currency portfolios. We employ seven currency portfolios: carry, momentum, value, "good" carry (good, Bekaert and Panayotov, 2020), Average Forward Discount (AFD, Lustig et al., 2014), global imbalances (IMB, Della Corte et al., 2016b), and global correlation risk (ΔFXC, Mueller et al., 2017). "Good" carry portfolio includes three currency pairs. The sample period is January 1984 and September 2016.

Table 2. Expected Return and Volatility Risk

	(1)	(2)	(3)	(4)
	carry	mom	value	good
α	1.00**	0.42	0.19	0.83
	(0.43)	(0.55)	(0.48)	(0.38)
β	-0.07*	-0.03	0.01	-0.05
	(0.05)	(0.05)	(0.04)	(0.04)
adj-R^2(%)	0.6	-0.1	-0.2	-0.2
	(5)	(6)	(7)	
	AFD	IMB	ΔFXC	
α	0.79	0.62	0.40	
	(0.48)	(0.94)	(0.51)	
β	-0.04	-0.05	-0.02	
	(0.05)	(0.10)	(0.05)	
adj-R^2(%)	0.1	0.1	-0.2	

Notes: This table presents time series regressions of excess returns of the currency portfolio on a constant and lagged global FX volatility. We run the following time-invariant regression model: $ret_{i,t+1} = \alpha_i, + \beta_i \sigma_{FX,t} + \epsilon_{i,t+1}$. We employ seven currency portfolios: carry, momentum, value, "good" carry (good, Bekaert and Panayotov, 2020), Average Forward Discount (AFD, Lustig et al., 2014), global imbalances (IMB, Della Corte et al., 2016b), and global correlation risk (ΔFXC, Mueller et al., 2017). The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). The adjusted R^2 is also reported. *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is between January 1984 and September 2016.

Table 3. Results of Volatility Estimation Using the Factor Model

	(1)	(2)	(3)	(4)
constant	9.48***	4.72***	9.61***	4.41***
	(0.22)	(0.44)	(0.25)	(0.43)
F_1	1.00***	0.71***	1.11***	0.96***
	(0.21)	(0.20)	(0.26)	(0.26)
F_2			0.35**	
			(0.16)	
F_5	0.31**			
	(0.15)			
F_1^2	0.40***	0.21**		
	(0.06)	(0.09)		
F_2^2			-0.25*	
			(0.14)	
F_3^2			-0.19* *	
			(0.09)	
F_4^2	0.51***		0.53***	
	(0.15)		(0.13)	
F_5^2	0.18***			
	(0.06)			
G_5			0.28**	0.37**
			(0.14)	(0.18)
G_1^2			0.43***	
			(0.07)	
G_4^2				-0.09**
				(0.05)
G_5^2			0.08***	0.09**
			(0.02)	(0.04)
σ_{t-1}^2		0.52***		0.57***
		(0.04)		(0.04)
adj-R^2	0.39	0.53	0.40	0.51

Notes: This table presents of time series regressions of future global FX volatility on common factors. The common factors are obtained as in Ludvigson and Ng (2007), and F_j indicates U.S. and G_j indicates global factors. We also include square terms of the U.S. and the global factors. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). The adjusted R^2 is also reported. *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is between January 1984 and September 2016.

Table 4. Expected Return and Volatility Risk:Factor Model

	(1)	(2)	(3)	(4)
	carry	mom	value	good
α	3.48***	-0.17	-0.20	0.89
	(0.70)	(1.11)	(0.98)	(0.39)
β	-0.31***	0.03	0.05	-0.05
	(0.07)	(0.11)	(0.10)	(0.06)
adj-R^2(%)	7.6	-0.2	-0.1	-0.0
	(5)	(6)	(7)	
	AFD	IMB	ΔFXC	
α	0.56	3.38**	1.28	
	(0.79)	(1.66)	(0.95)	
β	-0.02	-0.31*	-0.10	
	(0.08)	(0.17)	(0.09)	
adj-R^2(%)	-0.2	6.9	0.7	

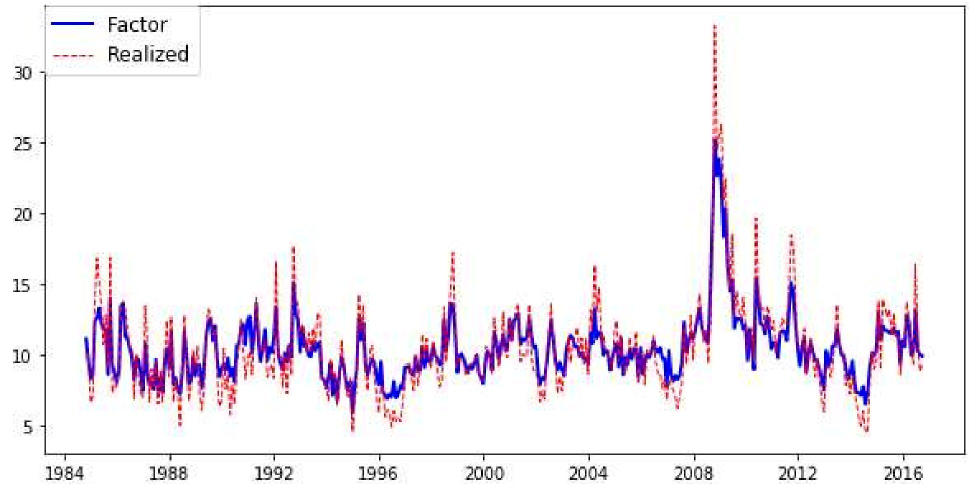
Notes: This table presents time series regressions of excess returns of the currency portfolio on a constant and predicted global FX volatility, $\hat{\sigma}_{FX,t}$, which is obtained by the factor model. We run the following time-invariant regression model: $ret_{i,t+1} = \alpha_{i,} + \beta_i \hat{\sigma}_{FX,t} + \epsilon_{i,t+1}$. We employ seven currency portfolios: carry, momentum, value, "good" carry (good, Bekaert and Panayotov, 2020), Average Forward Discount (AFD, Lustig et al., 2014), global imbalances (IMB, Della Corte et al., 2016b), and global correlation risk (ΔFXC, Mueller et al., 2017). Good carry portfolio includes three currency pairs. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). The adjusted R^2 is also reported. *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is between January 1984 and September 2016.

Table 5. Explaining Changes in Risk-return Trade-offs

	(1) carry	(2) mom	(3) value	(4) good
constant	-0.14	-0.02	-0.02	0.00
	(0.21)	(0.22)	(0.21)	(0.02)
Δi_{us}	0.02	0.59	1.31*	-0.05
	(0.61)	(0.64)	(0.68)	(0.05)
Δi_{world}	0.12	0.31***	-0.27**	0.01
	(0.13)	(0.12)	(0.11)	(0.01)
ΔIP_{us}	0.37*	-0.41***	0.47**	0.01
	(0.19)	(0.14)	(0.19)	(0.02)
ΔIP_{world}	0.04***	-0.05	-0.02	-0.01
	(0.08)	(0.05)	(0.06)	(0.01)
adj-R^2(%)	1.2	2.7	6.5	0.2
	(5) AFD	(6) IMB	(7) ΔFXC	
constant	0.00	-0.18	-0.08**	
	(0.02)	(0.34)	(0.04)	
Δi_{us}	-0.05	0.89	0.11	
	(0.04)	(1.07)	(0.10)	
Δi_{world}	0.01***	0.25	0.08**	
	(0.01)	(0.16)	(0.03)	
ΔIP_{us}	0.01***	0.50	-0.07**	
	(0.01)	(0.30)	(0.03)	
ΔIP_{world}	-0.01***	-0.01	-0.01	
	(0.01)	(0.12)	(0.02)	
adj-R^2(%)	1.8	1.9	7.5	

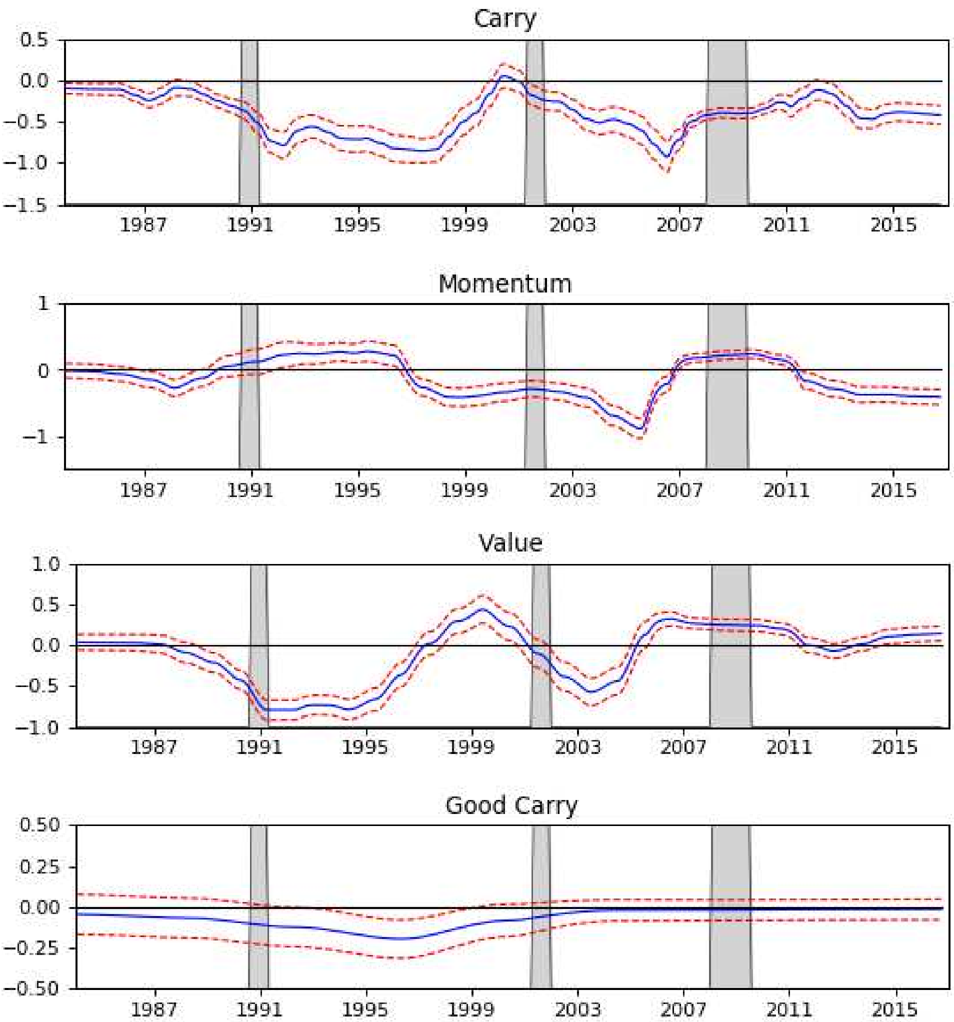
Notes: This table presents the results of the time-varying $\beta_{i,t}$ on U.S. and global short rates, and U.S. and global industrial production as: $\beta_{i,t} = a_i + b_1\Delta i_{us,t} + b_2\Delta i_{world,t} + b_3\Delta IP_{us,t} + b_4\Delta IP_{world,t} + e_{i,t}$. i_{world} and IP_{world} are residuals by regressing the U.S. variables onto the global variables which obtained by first principal components. We employ seven currency portfolios: carry, momentum, value, "good" carry (good, Bekaert and Panayotov, 2020), Average Forward Discount (AFD, Lustig et al., 2014), global imbalances (IMB, Della Corte et al., 2016b), and global correlation risk (ΔFXC, Mueller et al., 2017). Good carry portfolio includes three currency pairs. The standard errors are reported in parentheses and obtained by the Newey and West (1987) procedure with optimal lag selection according to Andrews (1991). The adjusted R^2 is also reported. *,**, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The sample period is between January 1984 and September 2016.

Figure 1. Realized and factor volatility



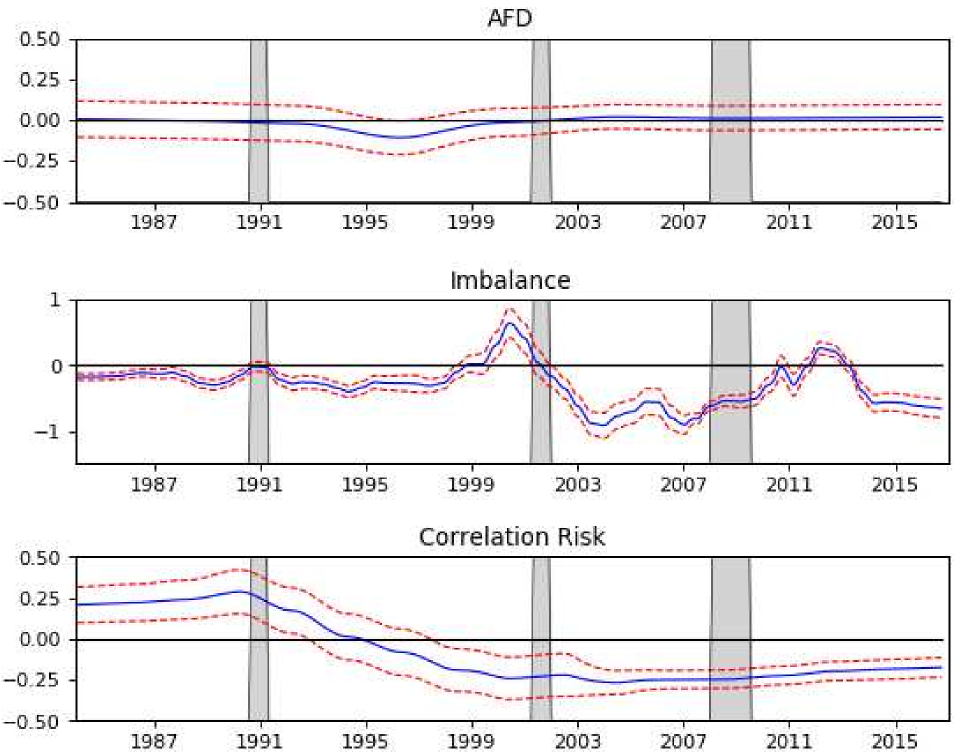
Notes: This figure presents realized and factor model volatility. The realized global FX volatility is calculted as: $\sigma_{FX,t} = \frac{1}{T_t}\sum_{d=1}^{T_t}\sigma_{FX,d}$ where $\sigma_{FX,d}$ is the daily global FX volatility and T_t is the total number of trading days in month t. The factor model volatility is estimated as: $\sigma_{FX,t+1} = \phi f_t + e_{t+1}$ where f_t is the common factors extracted from U.S. and global macroeconomic indicators. The sample period is between January 1984 and September 2016.

Figure 2. Time-varying trade-off between volatility and expected return: Kernel estimation



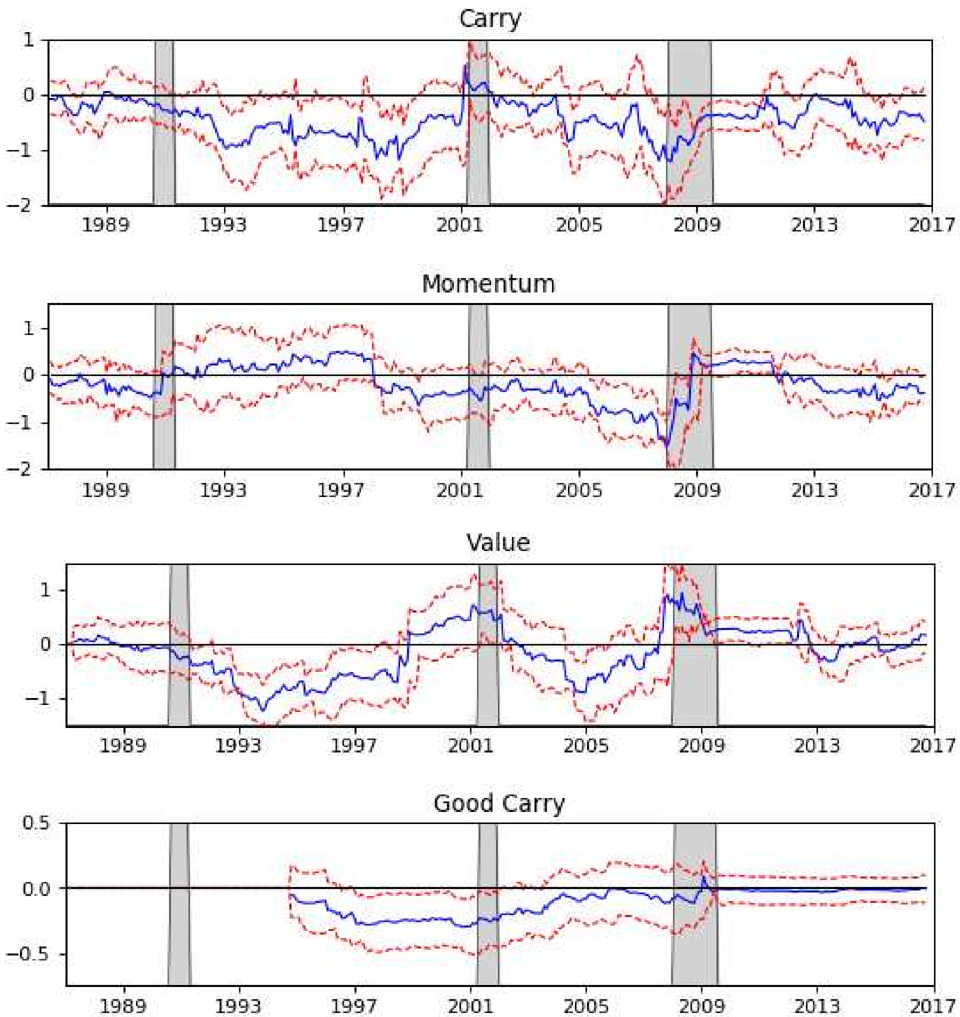
Notes: See the next page

Figure 2. continued



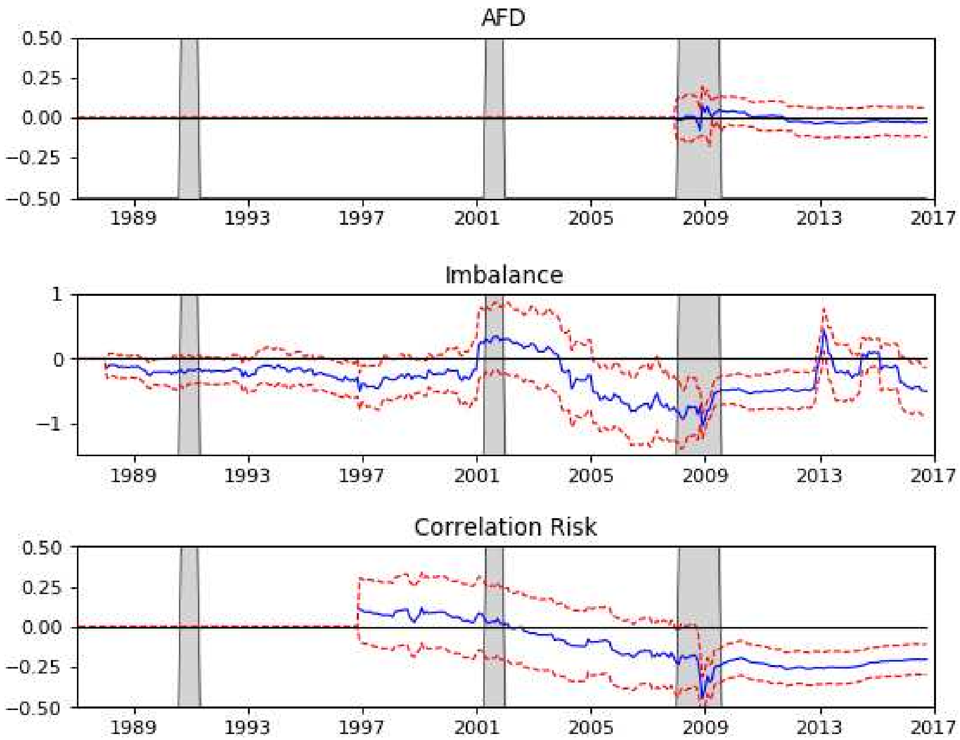
Notes:This figure provides plots of the estimated parameters with 90% confidence intervals. Ang and Kristensen (2012) estimation method is employed and predicted global FX volatility is obtained by the factor model. The confidence intervals are estimated based upon the standard errors derived by Ang and Kristensen (2012). We employ seven currency portfolios: carry, momentum, value, good carry (Bekaert and Panayotov, 2020), Average Forward Discount (AFD, Lustig et al., 2014), global imbalances (IMB, Della Corte et al., 2016b), and global correlation risk (ΔFXC, Mueller et al., 2017). Good carry portfolio includes three currency pairs. The shaded regions are NBER recessions.

Figure 3. Time-varying trade-off between volatility and expected return: Rolling regression



Notes: See the next page.

Figure 3. continued



Notes:This figure provides plots of the estimated parameters with 90% confidence intervals. A rolling regression approach is employed and predicted global FX volatility is obtained by the factor model The rolling window size corresponds to the size of bandwidth used by the kernel estimation. We employ seven currency portfolios: carry, momentum, value, good carry (Bekaert and Panayotov, 2020), Average Forward Discount (AFD, Lustig et al., 2014), global imbalances (IMB, Della Corte et al., 2016b), and global correlation risk (ΔFXC, Mueller et al.,2017). The shaded regions are NBER recessions.

The Conditional Volatility Premium on Currency Portfolios

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Online Supplement, Not for Publication

This material provides additional results which are not reported in the main text. These include Figure A1 Conditional trade-off between realized volatility and return, Figure A2 Rolling regression trade-off between realized volatility and return, Figure A3 Conditional trade-off between volatility and larger number of currencies and Figure A4-A9 marginal R^2 from empirical factor model. Table A1 is bandwidth estimation. Table A2-A4 provides data definition.

Figure A1. Time-varying trade-off between volatility and expected return: Realized volatility

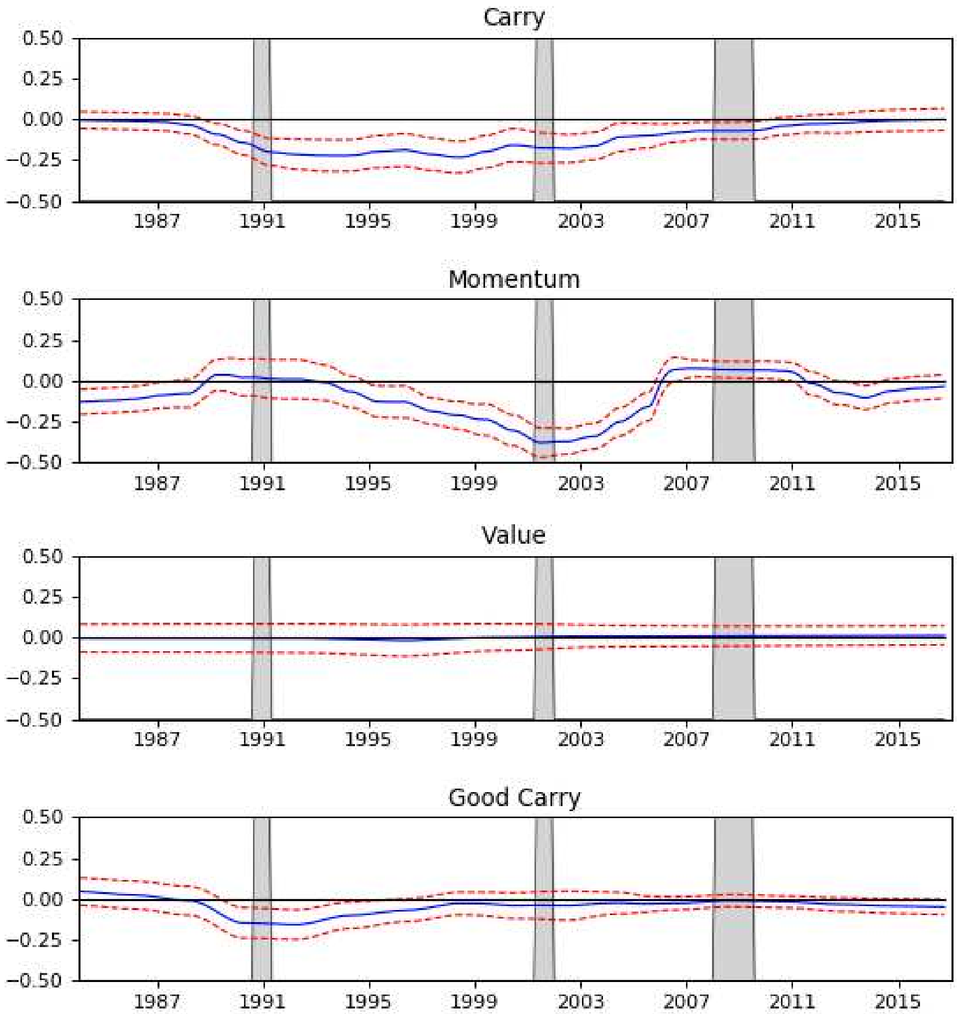

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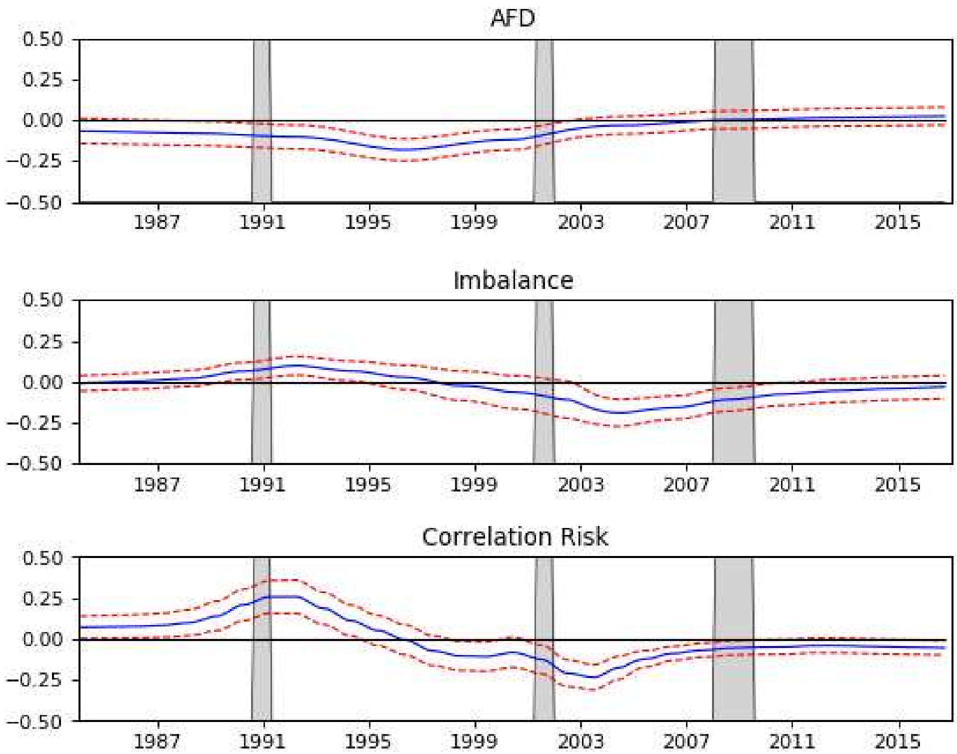
Figure A1. continued



Notes:This figure provides plots of the estimated parameters with 90% confidence intervals. Ang and Kristensen (2012) estimation method is employed and predicted global FX volatility is realized volatility. The confidence intervals are estimated based upon the standard errors derived by Ang and Kristensen (2012). We employ seven currency portfolios: carry, momentum, value, good carry (Bekaert and Panayotov, 2020), Average Forward Discount (AFD, Lustig et al., 2014), global imbalances (IMB, Della Corte et al., 2016b), and global correlation risk (ΔFXC, Mueller et al., 2017). The shaded regions are NBER recessions.

Figure A2. Time-varying trade-off between volatility and expected return: Realized volatility

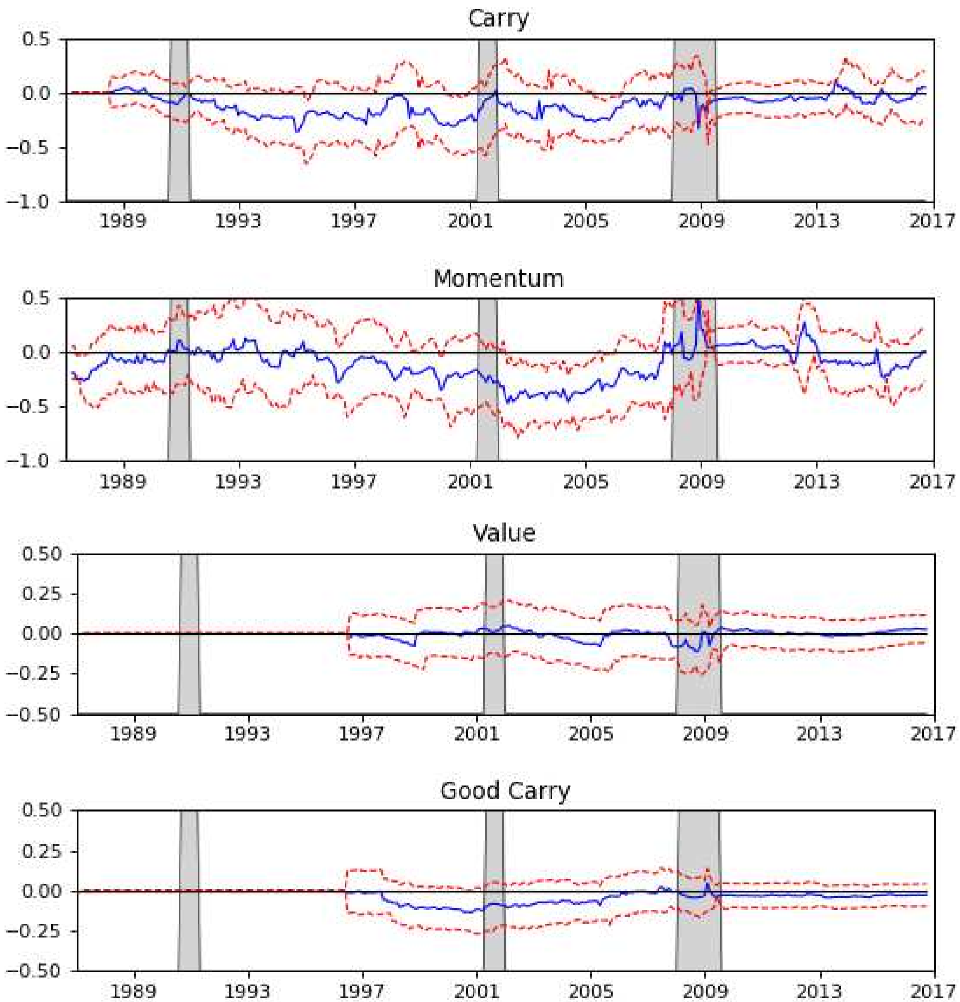


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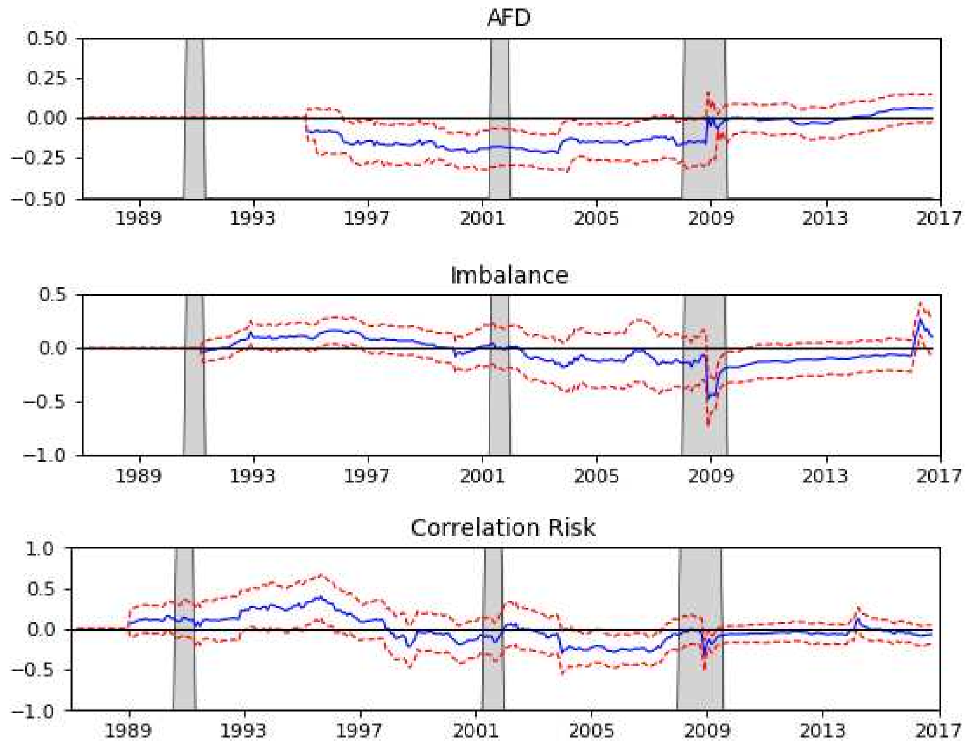
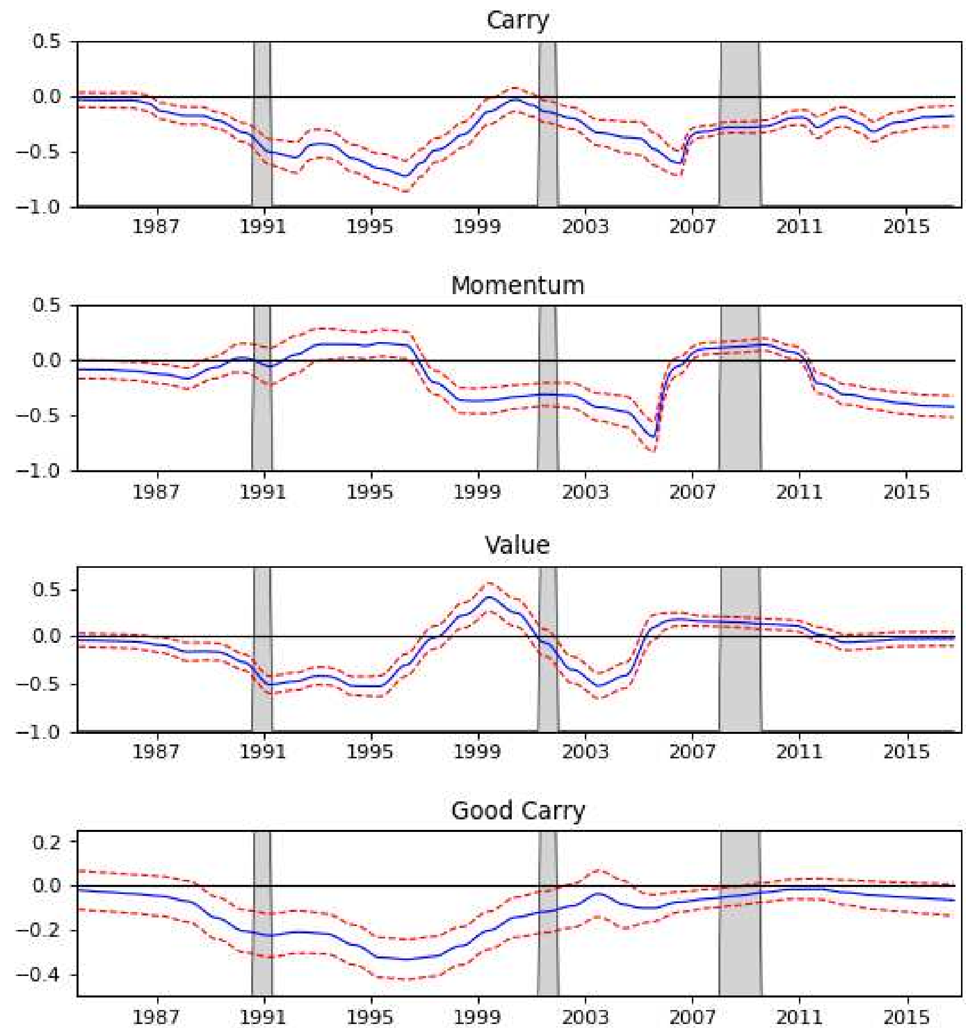
Figure A2. continued



Notes:This figure provides plots of the estimated parameters with 90% confidence intervals. A rolling regression approach is employed and predicted global FX volatility is realized volatility. The rolling window size corresponds to the size of bandwidth used by the kernel estimation. We employ seven currency portfolios: carry, momentum, value, good carry (Bekaert and Panayotov, 2020), Average Forward Discount (AFD, Lustig et al., 2014), global imbalances (IMB, Della Corte et al., 2016b), and global correlation risk (ΔFXC, Mueller et al., 2017). The shaded regions are NBER recessions.

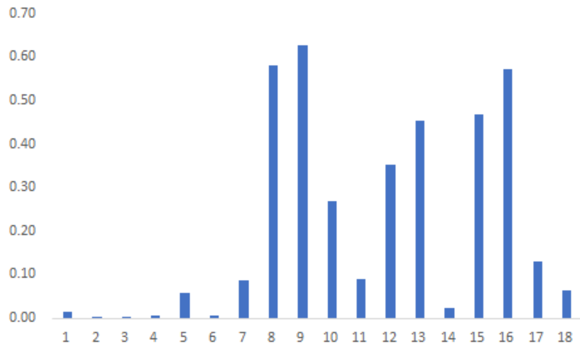
Figure A3. Time-varying trade-off between volatility and expected return: Six currencies



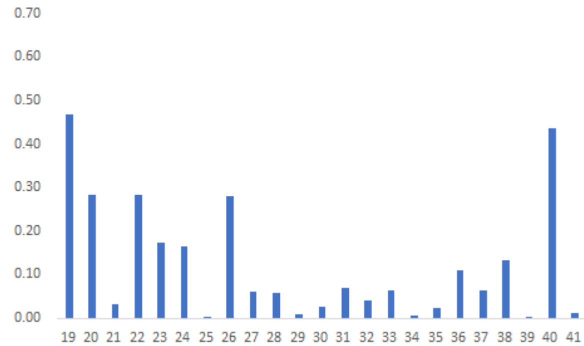
Notes: Notes:This figure provides plots of the estimated parameters with 90% confidence intervals. Three currencies go long and three currencies go short. Ang and Kristensen (2012) estimation method is employed and predicted global FX volatility is obtained by the factor model. The confidence intervals are estimated based upon the standard errors derived by Ang and Kristensen (2012). We employ seven currency portfolios: carry, momentum, value, good carry (Bekaert and Panayotov, 2020),

Figure A4. Marginal R^2 for F_1

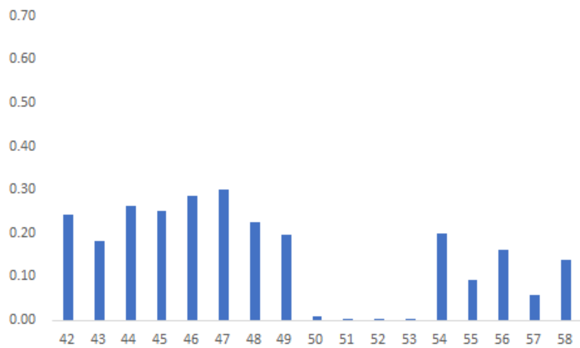
Money, production, income, and consumption



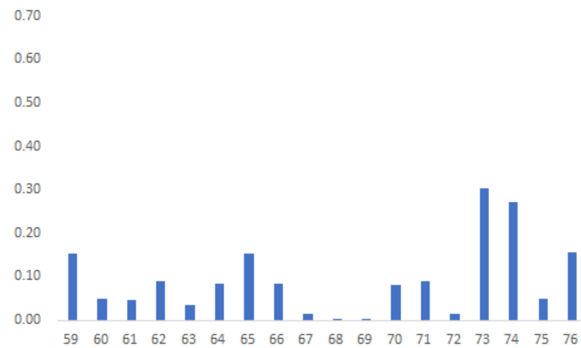
Employment, hours, and prices



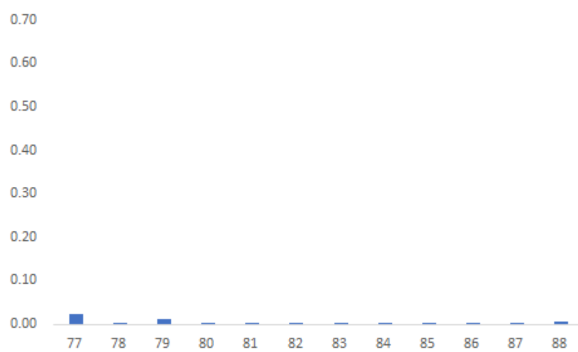
Interest rate, exchange rate, and expenditure



Housing

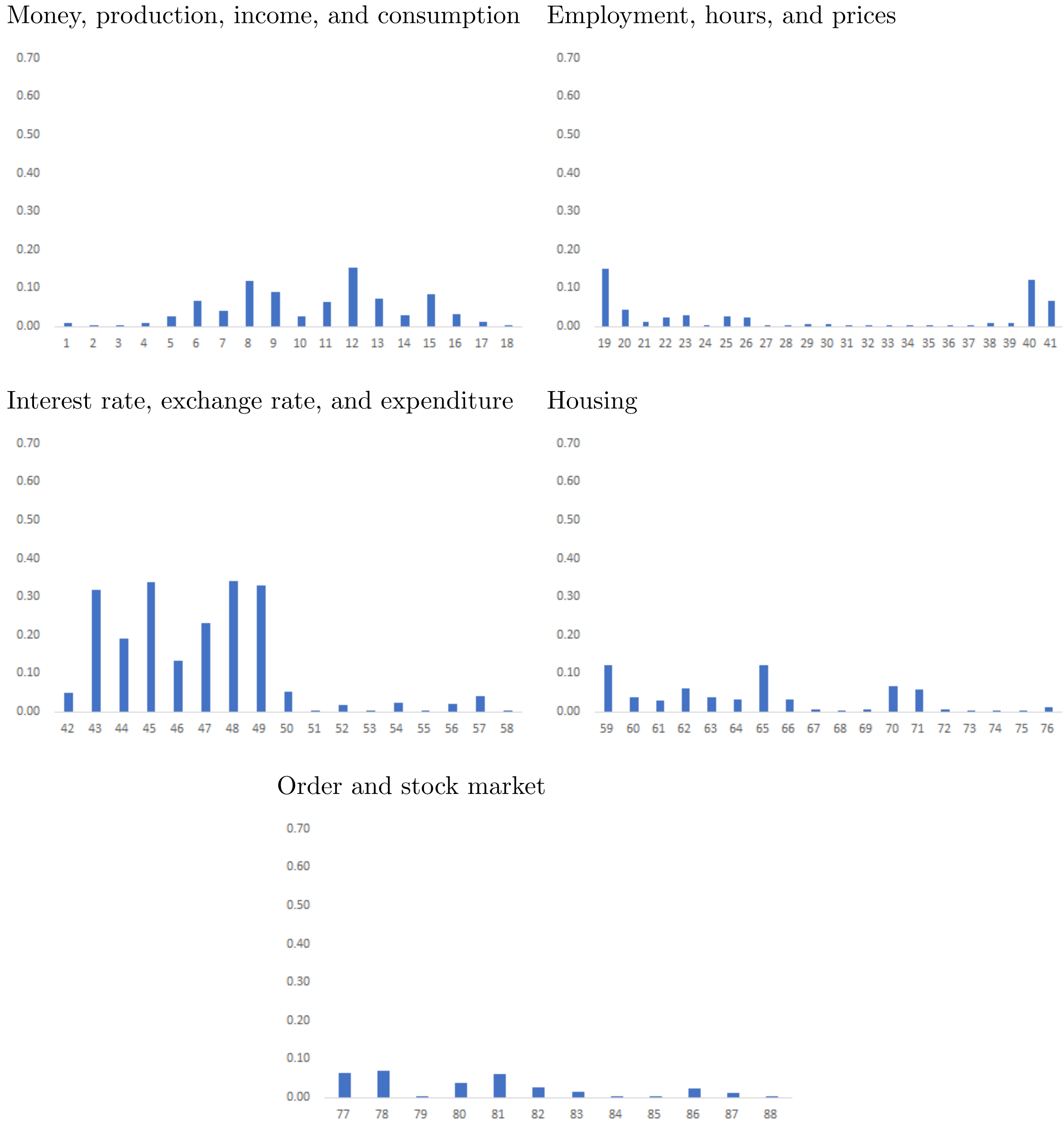


Order and stock market



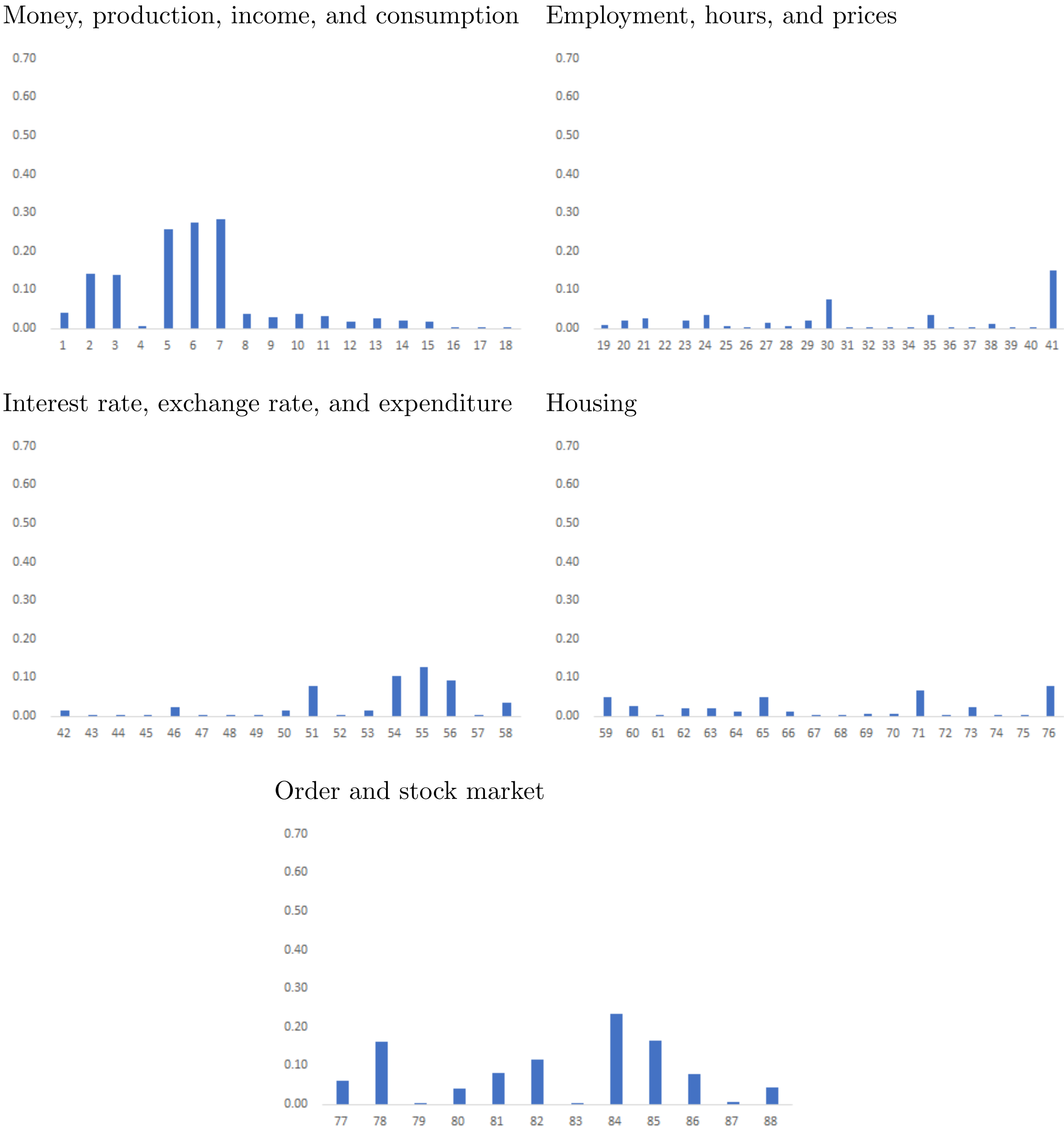
Notes: This figure present the R-square from regressing the U.S. macroeconomic series number given on the x-axis onto the estimated factor named in the heading. See the Table A2 for a description of the numbered series.

Figure A5. Marginal R^2 for F_4



Notes: This figure present the R-square from regressing the U.S. macroeconomic series number given on the x-axis onto the estimated factor named in the heading. See the Table A2 for a description of the numbered series.

Figure A6. Marginal R^2 for F_5

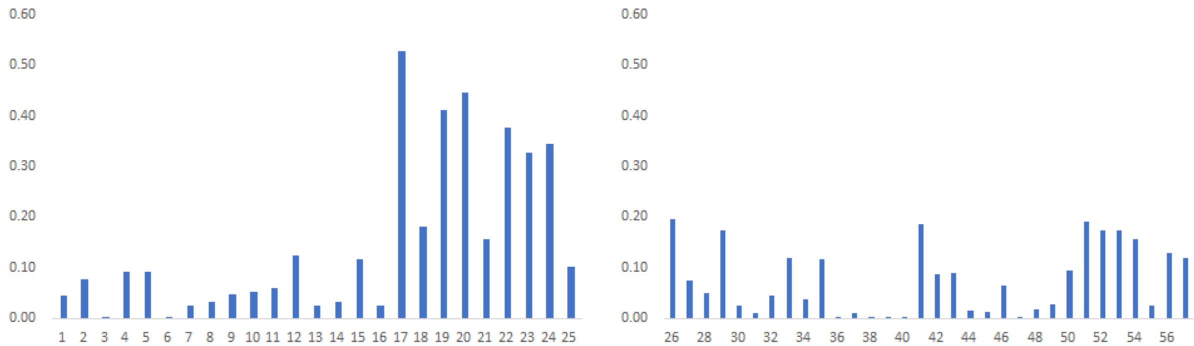


Notes: This figure present the R-square from regressing the U.S. macroeconomic series number given on the x-axis onto the estimated factor named in the heading. See the Table A2 for a description of the numbered series.

Figure A7. Marginal R^2 for G_1

Production, employment, and PPI

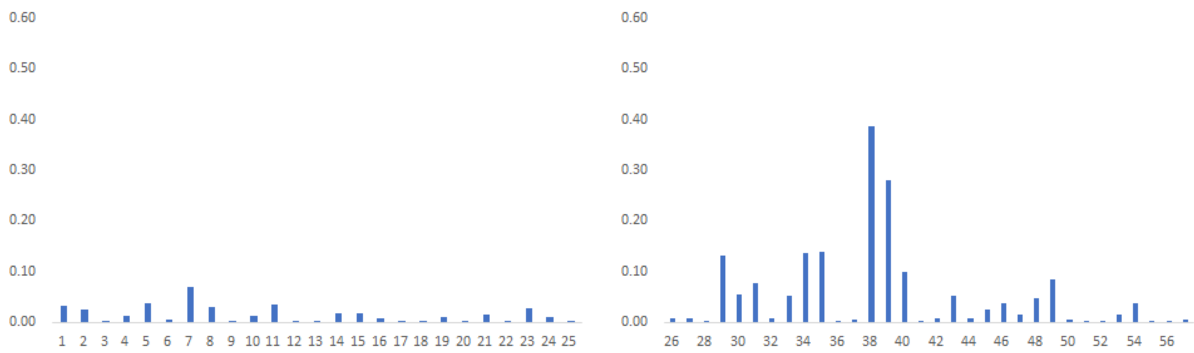
CPI, interest rate, reserves, and stock market



Notes: This figure present the R-square from regressing the global macroeconomic series number given on the x-axis onto the estimated factor named in the heading. See the Table A3 for a description of the numbered series.

Figure A7. Marginal R^2 for G_4

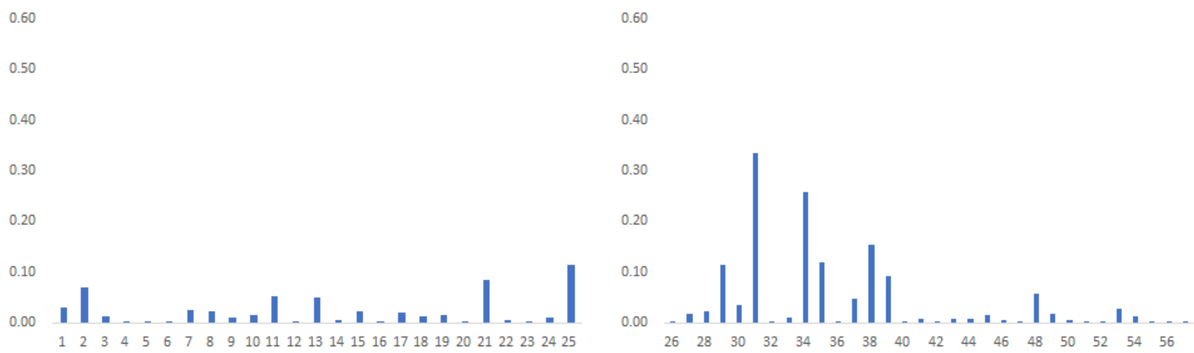
Production, employment, and PPI | CPI, interest rate, reserves, and stock market



Notes: This figure present the R-square from regressing the global macroeconomic series number given on the x-axis onto the estimated factor named in the heading. See the Table A3 for a description of the numbered series.

Figure A8. Marginal R^2 for G_5

Production, employment, and PPI | CPI, interest rate, reserves, and stock market



Notes: This figure present the R-square from regressing the global macroeconomic series number given on the x-axis onto the estimated factor named in the heading. See the Table A3 for a description of the numbered series.

Table A1 Estimates of Bandwidths

	carry	mom	value	good	AFD	IMB	ΔFXC
Realized Volatility	107.1	75.94	299.35	289.7	260.7	172.5	119.5
Factor Model	53.7	66.3	78.3	257.2	115.0	47.7	154.2

Notes: This table reports estimates of bandwidths and the values are reported as monthly equivalent units. We employ the method proposed by Ang and Kristensen (2012). We employ seven currency portfolios: carry, momentum, value, good carry (Bekaert and Panayotov, 2020), Average Forward Discount (AFD,Lustig et al., 2014), global imbalances (IMB, Della Corte et al., 2016b), and global correlation risk (ΔFXC, Mueller et al.,2017).

Table A2: Definition of Data:U.S.

Number	Transform	Description
Money		
1	lnDF	M1 Money Stock, Billions of Dollars, Monthly, SA
2	lnDF	M2 Money Stock, Billions of Dollars, Monthly, SA
3	lnDF	M3 Money Stock, Billions of Dollars, Monthly, SA
4	lnDF	Total Reserves excluding Gold for United States, Dollars, Monthly, Not SA
5	lnDF	Commercial and Industrial Loans, All Commercial Banks, Billions of U.S. Dollars, Monthly, SA
6	lnDF	Total Assets, All Commercial Banks, Billions of U.S. Dollars, Monthly, SA
7	lnDF	Loans and Leases in Bank Credit, All Commercial Banks, Billions of U.S. Dollars, Monthly, SA
Production		
8	lnDF	Industrial Production Index, Index 2012=100, Monthly, SA
9	lnDF	Industrial Production: Manufacturing (NAICS), Index 2012=100, Monthly, SA
10	lnDF	Industrial Production: Durable Consumer Goods, Index 2012=100, Monthly, SA
11	lnDF	Industrial Production: Nondurable Consumer Goods, Index 2012=100, Monthly, SA
12	lnDF	Industrial Production: Business Equipment, Index 2012=100, Monthly, SA
13	lnDF	Industrial Production: Materials, Index 2012=100, Monthly, SA
14	lnDF	Industrial Production: Energy Materials: Energy, total, Index 2012=100, Monthly, SA
15	lnDF	Industrial Production: Business supplies, Index 2012=100, Monthly, SA
16	lnDF	Industrial Production: Construction supplies, Index 2012=100, Monthly, SA
Income and Consumption		
17	lnDF	Personal Income, Billions of Dollars, Monthly, SA Annual Rate
18	lnDF	Disposable Personal Income, Billions of Dollars, Monthly, SA Annual Rate
Employment and Hours		
19	lnDF	All Employees: Total Nonfarm Payrolls, Thousands of Persons, Monthly, SA
20	lnDF	Civilian Employment Level, Thousands of Persons, Monthly, SA
21	lnDF	Civilian Labor Force, Thousands of Persons, Monthly, SA
22	DF	Civilian Unemployment Rate, Percent, Monthly, SA
23	DF	Average Weekly Hours of Production and Nonsupervisory Employees: Total private, Hours, Monthly, SA
24	DF	Average Weekly Overtime Hours of Production and Nonsupervisory Employees: Manufacturing, Hours, Monthly, SA
25	DF	Average (Mean) Duration of Unemployment, Weeks, Monthly, SA
26	DF	Unemployment Rate: 20 years and over, Percent, Monthly, SA
Prices		
27	lnDF	Consumer Price Index for All Urban Consumers: All Items, Index 1982-1984=100, Monthly, SA
28	lnDF	Consumer Price Index: Total All Items: Wage Earners for the United States,

Continued: Definition of Data:U.S.

Number	Transform	Description
		Index 2010=1, Monthly, Not SA
29	lnDF	Consumer Price Index for All Urban Consumers: All Items Less Food and Energy, Index 1982-1984=100, Monthly, SA
30	lnDF	Consumer Price Index for All Urban Consumers: Energy, Index 1982-1984=100, Monthly, SA
31	lnDF	Consumer Price Index for All Urban Consumers: All items in New York-Northern New Jersey-Long Island, Monthly, Not SA
32	lnDF	Producer Price Index by Commodity for Final Demand: Finished Goods, Index 1982=100, Monthly, SA
33	lnDF	Producer Price Index by Commodity for Final Demand: Finished Goods Less Foods and Energy, Index 1982=100, Monthly, SA
34	lnDF	Producer Price Index by Commodity for Final Demand: Finished Consumer Foods, Crude, Index 1982=100, Monthly, SA
35	lnDF	Producer Price Index by Commodity for Final Demand: Finished Consumer Foods, Processed, Index 1982=100, Monthly, SA
36	lnDF	Producer Price Index by Commodity for Intermediate Demand by Commodity Type: Processed Goods for Intermediate Demand, Index 1982=100, Monthly, SA
37	lnDF	Producer Price Index by Commodity for Intermediate Demand by Commodity Type: Unprocessed Goods for Intermediate Demand, Index 1982=100, Monthly, SA
38	lnDF	Producer Price Index by Commodity for Intermediate Demand by Commodity Type: Materials for Durable Manufacturing, Index 1982=100, Monthly, SA
39	DF	Average Hourly Earnings of Production and Nonsupervisory Employees: Total Private, Dollars per Hour, Monthly, SA
40	lnDF	Indexes of Aggregate Weekly Payrolls of Production and Nonsupervisory Employees: Total Private, Index 2002=100, Monthly, SA
41	DF	Consumer Opinion Surveys: Confidence Indicators: Composite Indicators: OECD Indicator for the United States, Normalised (Normal=100), Monthly, SA
Interest Rate		
42	DF	Effective Federal Funds Rate, Percent, Monthly, Not SA
43	DF	10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not SA
44	DF	3-Month Treasury Bill: Secondary Market Rate, Percent, Monthly, Not SA
45	DF	3-Year Treasury Constant Maturity Rate, Percent, Monthly, Not SA
46	DF	3-Month or 90-day Rates and Yields: Certificates of Deposit for the United States, Percent, Monthly, Not SA
47	DF	6-Month Treasury Bill: Secondary Market Rate, Percent, Monthly, Not SA
48	DF	5-Year Treasury Constant Maturity Rate, Percent, Monthly, Not SA
49	DF	7-Year Treasury Constant Maturity Rate, Percent, Monthly, Not SA
Exchange Rate		
50	lnDF	Japan / U.S. Foreign Exchange Rate, Japanese Yen to One U.S. Dollar, Monthly, Not SA
51	lnDF	Canada / U.S. Foreign Exchange Rate, Canadian Dollars to One U.S. Dollar, Monthly, Not SA
52	lnDF	U.S. / U.K. Foreign Exchange Rate, U.S. Dollars to One British Pound, Monthly, Not SA
Expenditure		
53	DF	Prices for Personal Consumption Expenditures: Chained Price Index: PCE excluding food and energy, Percent Change from Preceding Period, Monthly, SA
54	lnDF	Personal Consumption Expenditures, Billions of Dollars, Monthly, SA Annual Rate
55	lnDF	Personal Consumption Expenditures: Durable Goods, Billions of Dollars, Monthly, SA Annual Rate
56	lnDF	Personal consumption expenditures excluding food and energy, Billions of Dollars, Monthly, SA Annual Rate
57	lnDF	Personal Consumption Expenditures: Services, Billions of Dollars, Monthly, SA Annual Rate
58	lnDF	Personal Consumption Expenditures: Nondurable Goods, Billions of Dollars, Monthly, Seasonally Adjusted Annual Rate
Housing		
59	lnDF	Housing Starts: Total: New Privately Owned Housing Units Started, Thousands of Units, Monthly, SA Annual Rate
60	lnDF	Housing Starts in Midwest Census Region, Thousands of Units, Monthly, SA Annual Rate
61	lnDF	Housing Starts in Northeast Census Region, Thousands of Units, Monthly, SA Annual Rate
62	lnDF	Housing Starts in South Census Region, Thousands of Units, Monthly, SA Annual Rate
63	lnDF	Housing Starts in West Census Region, Thousands of Units, Monthly, SA Annual Rate

Continued: Definition of Data:U.S.

Number	Transform	Description
64	lnDF	New Private Housing Units Authorized by Building Permits, Thousands of Units, Monthly, SA Annual Rate
65	lnDF	Housing Starts: Total: New Privately Owned Housing Units Started, Thousands of Units, Monthly, SA Annual Rate
66	lnDF	New Private Housing Units Authorized by Building Permits, Thousands of Units, Monthly, SA Annual Rate
67	lnDF	New Privately-Owned Housing Units Completed: 1-Unit Structures, Thousands of Units, Monthly, SA Annual Rate
68	lnDF	New Privately-Owned Housing Units Completed: 2-4 Unit Structures, Thousands of Units, Monthly, SA Annual Rate
69	lnDF	New Privately-Owned Housing Units Completed: 5-Unit Structures or More, Thousands of Units, Monthly, SA Annual Rate
70	lnDF	Privately Owned Housing Starts: 1-Unit Structures, Thousands of Units, Monthly, SA Annual Rate
71	lnDF	Privately Owned Housing Starts: 5-Unit Structures or More, Thousands of Units, Monthly, Seasonally Adjusted Annual Rate
72	lnDF	Housing Starts: 2-4 Units, Thousands of Units, Monthly, SA Annual Rate
73	lnDF	New Privately-Owned Housing Units Under Construction: Total, Thousands of Units, Monthly, SA
74	lnDF	New Privately-Owned Housing Units Under Construction: 1-Unit Structures, Thousands of Units, Monthly, SA
75	lnDF	New Privately-Owned Housing Units Under Construction: 2-4 Unit Structures, Thousands of Units, Monthly, SA
76	lnDF	New Privately-Owned Housing Units Under Construction: 5-Unit Structures or More, Thousands of Units, Monthly, SA
Order		
77	DF	Current New Orders; Diffusion Index for FRB - Philadelphia District, Index, Monthly, SA
78	DF	Future New Orders; Diffusion Index for FRB - Philadelphia District, Index, Monthly, SA
79	DF	Current New Orders; Percent Reporting No Change for FRB - Philadelphia District, Percent, Monthly, SA
80	DF	Current New Orders; Percent Reporting Increases for FRB - Philadelphia District, Percent, Monthly, SA
81	DF	Future New Orders; Percent Reporting Increases for FRB - Philadelphia District, Percent, Monthly, Not SA
82	DF	Future New Orders; Percent Reporting Decreases for FRB - Philadelphia District, Percent, Monthly, SA
83	DF	Future New Orders; Percent Reporting No Change for FRB - Philadelphia District, Percent, Monthly, SA
Stock Market		
84	lnDF	Total Share Prices for All Shares for the United States, Index 2010=1, Monthly, Not SA
85	level	Fama and French Market Factor
86	level	Size Factor
87	level	Value Factor
88	level	Momentum Factor

Notes: This Table shows each series, the transformation applied to the series, and a brief data description. In the transformation column, level denotes level of the series, ln denotes logarithm, and lnFD and lnFD2 denote the first and second difference of the logarithm. The data source is Federal Reserve Bank St.Louis. The data period is from December 1983 to September 2016.

Table A3: Definition of Data: Global

Number	Transform	Description
Production		
1	lnDF	Production of Total Industry in Australia, Index 2010=100, Quarterly, SA
2	lnDF	Production of Total Industry in Canada, Index 2010=100, Monthly, SA
3	lnDF	Production of Total Industry in Denmark, Index 2010=100, Monthly, SA
4	lnDF	Production of Total Industry in Germany, Index 2010=100, Monthly, SA
5	lnDF	Production of Total Industry in Japan, Index 2010=100, Monthly, SA
6	lnDF	Production of Total Industry in Norway, Index 2010=100, Monthly, SA
7	lnDF	Production of Total Industry in New Zealand, Index 2010=100, Quarterly, SA

Continued: Definition of Data: Global

Number	Transform	Description
8	lnDF	Industrial Production Index in the United Kingdom, Index 2012=100, Monthly, SA
9	lnDF	Production of Total Industry in Sweden, Index 2010=100, Monthly, SA
Employment		
10	lnDF	Harmonized Unemployment Rate: Total: All Persons for Australia, Percent, Monthly, SA
11	lnDF	Unemployment Rate: Aged 15 and Over: All Persons for Canada, Percent, Monthly, SA
12	lnDF	Harmonized Unemployment Rate: Total: All Persons for Sweden, Percent, Monthly, SA
13	lnDF	Harmonized Unemployment Rate: Total: All Persons for Sweden, Percent, Monthly, SA
14	lnDF	Unemployment Rate: Aged 15-64: All Persons for Japan, Percent, Monthly, SA
15	lnDF	Registered Unemployment Rate for the United Kingdom, Percent, Monthly, SA
16	DF	Harmonized Unemployment Rate: Total: All Persons for Sweden, Percent, Monthly, SA
Prices		
17	lnDF	Producer Prices Index: Economic Activities: Total Manufacturing for Australia, Index 2010=1, Quarterly, Not SA
18	lnDF	Producer Prices Index: Economic Activities: Total Manufacturing for Canada, Index 2010=1, Monthly, Not SA
19	lnDF	Domestic Producer Prices Index: Manufacturing for Denmark, Index 2010=100, Quarterly, Not SA
20	lnDF	Domestic Producer Prices Index: Manufacturing for Germany, Index 2010=100, Monthly, Not SA
21	lnDF	Producer Prices Index: Total Consumer Goods for Japan, Index 2010=1, Monthly, Not SA
22	lnDF	Domestic Producer Prices Index: Manufacturing for Norway, Index 2010=100, Quarterly, Not SA
23	lnDF	Domestic Producer Prices Index: Manufacturing for New Zealand, Index 2010=100, Quarterly, Not SA
24	lnDF	Wholesale (Producer) Price Index in the United Kingdom, Index 2010=100, Quarterly, Not SA
25	lnDF	Producer Prices Index: Economic Activities: Total Manufacturing for Sweden, Index 2010=1, Monthly, Not SA
26	DF	Consumer Price Index of All Items in Australia, Index 2010=100, Quarterly, Not SA
27	lnDF	Consumer Price Index: Total, All Items for Canada, Index 2010=1, Monthly, Not SA
28	lnDF	Consumer Price Index: All Items for Denmark, Index 2010=100, Monthly, Not SA
29	lnDF2	Consumer Price Index of All Items in Germany, Index 2010=100, Monthly, Not SA
30	lnDF2	Consumer Price Index of All Items in Japan, Index 2010=100, Monthly, Not SA
31	lnDF	Consumer Price Index: All Items for Norway, Index 2010=100, Monthly, Not SA
32	lnDF2	Consumer Price Index: All Items for New Zealand, Index 2010=100, Quarterly, Not SA
33	lnDF2	Consumer Price Index of All Items in the United Kingdom, Index 2010=100, Monthly, Not SA
34	lnDF2	Consumer Price Index: All Items for Sweden, Index 2010=100, Monthly, Not SA
Interest Rate		
35	lnDF	3-Month or 90-day Rates and Yields: Bank Bills for Australia, Percent, Monthly, Not SA
36	lnDF	3-Month or 90-day Rates and Yields: Interbank Rates for Canada, Percent, Monthly, Not SA
37	DF	3-Month or 90-day Rates and Yields: Interbank Rates for Sweden, Percent, Monthly, Not SA
38	DF	3-Month or 90-day Rates and Yields: Interbank Rates for Germany, Percent, Monthly, Not SA
39	DF	Immediate Rates: Less than 24 Hours: Central Bank Rates for Japan, Percent, Monthly, Not SA
40	DF	3-Month or 90-day Rates and Yields: Interbank Rates for Norway, Percent, Monthly, Not SA
41	DF	3-Month or 90-day Rates and Yields: Bank Bills for New Zealand, Percent, Monthly, Not SA
42	DF	3-Month or 90-day Rates and Yields: Treasury Securities for the United Kingdom, Percent, Monthly, Not SA
43	DF	3-Month or 90-day Rates and Yields: Interbank Rates for Sweden, Percent, Monthly, Not SA
44	DF	3-Month or 90-day Rates and Yields: Eurodollar Deposits for Switzerland, Percent, Monthly, Not SA
Reserves		
45	lnDF	Total Reserves excluding Gold for Australia, Dollars, Monthly, Not SA
46	lnDF	Total Reserves excluding Gold for Canada, Dollars, Monthly, Not SA
47	lnDF	Total Reserves excluding Gold for Germany, Dollars, Monthly, Not SA
48	lnDF	Total Reserves excluding Gold for Japan, Dollars, Monthly, Not SA
49	lnDF	Total Reserves excluding Gold for United Kingdom, Dollars, Monthly, Not SA
Stock Markets		
50	lnDF	Total Share Prices for All Shares for Australia, Index 2010=1, Monthly, Not SA
51	lnDF	Total Share Prices for All Shares for Canada, Index 2010=1, Monthly, Not SA
52	lnDF	Total Share Prices for All Shares for Denmark, Index 2010=1, Monthly, Not SA
53	lnDF	Total Share Prices for All Shares for Germany, Index 2010=1, Monthly, Not SA
54	lnDF	Total Share Prices for All Shares for Japan, Index 2010=1, Monthly, Not SA
55	lnDF	Total Share Prices for All Shares for New Zealand, Index 2010=1, Monthly, Not SA

Continued: Definition of Data: Global

Number	Transform	Description
56	lnDF	Total Share Prices for All Shares for the United Kingdom, Index 2010=1, Monthly, Not SA
57	lnDF	Total Share Prices for All Shares for Sweden, Index 2010=1, Monthly, Not SA

Notes: This Table shows each series, the transformation applied to the series, and a brief data description. In the transformation column, level denotes level of the series, ln denotes logarithm, and lnFD and lnFD2 denote the first and second difference of the logarithm. The data source is Federal Reserve Bank St.Louis. The data period is from December 1983 to September 2016.