Global Macroeconomic Conditional Skewness and the Carry Risk Premium

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Abstract

This paper shows that the time-variation in measures of global growth prospects constructed from the cross-section of individual macroeconomic forecasts can help explain currency markets. I show that conditional expectation and skewness of global economic growth have predictive ability in explaining the quarterly returns to carry trade and that the global skewness measure is particularly important in explaining a large cross-section of currencies. I provide the economic mechanism for the role of cross-sectional skewness in forecasts using a consumption-based asset pricing model with heterogeneous agents.

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1 Introduction

The carry trade is a well known investment strategy that exploits the profitability of borrowing in the low interest rate currencies to invest in the high interest rate currencies. In this paper I document that the time-variation in the distribution of global growth prospects has predictive power for carry trade returns. I study the macroeconomic risks that the carry trade investor faces. Interestingly, I provide evidence that the time-variation in conditional skewness in global growth prospects has significant predictive power, namely that a one standard deviation decline in the skewness measure increases the next-quarter carry trade risk premium by 5.24% per annum. The novel contribution of the paper is that global macroeconomic conditional skewness plays an important role in the variation in the currency risk premium.

I empirically test if the variation in the cross-sectional measures of macroeconomic prospects explains the currency market. I collect analysts' forecasts for the growth rates of real GDP for a list of major countries corresponding to eight of the G10 currencies plus China. The currencies of these countries constitute 85.75% of the total foreign exchange turnover[1]. The individual forecasts are contributed by analysts in different sectors of the economy and are collected primarily by Consensus Economics and Bloomberg. At each point in time and for each country, I construct measures of the cross-sectional mean, dispersion and skewness of the distribution of forecasts across analysts. Then for each quarter, I calculate the cross-sectional average of the means across countries and, similarly, the average of the dispersion and the average of the skewness across countries. This yields time-varying measures of the distribution of, what I shall refer to as, *global* growth prospects. The main empirical strategy proposed in this paper tests if my proposed global measures predict carry trade returns in the time-series.

I find evidence that the time-variation in global conditional expected growth and global conditional skewness can help predict next-quarter carry trade returns. The estimated coefficients are negative, indicating that when global expected growth or global skewness is low or negative, subsequent carry trade returns tend to be high or positive, i.e., yielding a positive risk premium. Notably, global skewness appears to be the most robust predictor among the different moments, especially as I repeat the exercise with strategies based on a larger set of currencies of up to 33

[1] Source: BIS (2016)

developed and emerging markets. I conduct a series of robustness tests, such as forming dynamic and static portfolios, changing the number of currencies in the formation of portfolios, and aggregating country-specific measures, e.g., by taking the first principal component or by computing the GDP-weighted average across countries. I also try jointly regressing on the global skewness measure along with other known explanatory variables.

A key benefit of my approach is that it yields a time-varying proxy for conditional skewness of macroeconomic growth prospects. A skewness measure is related to, but has an interesting distinction from, the notion of disaster. Disasters are one-sided by nature and are often referred to as events that rarely happen. On the contrary, I observe frequent fluctuations of my skewness measure between positive and negative domains, even outside of times of heightened concerns about severe recessions. Moreover, my empirical strategy allows obtaining real-time measures based on a collection of professional forecasters' views each time a survey is reported, thus revealing information about macroeconomic prospects that are otherwise not easy to detect. Furthermore, my results are robust to the exclusion of the Great Recession of 2008-09, confirming that they are not driven by extreme left-tail events.

I build a model in which agents have heterogeneous beliefs, so that it can be mapped directly to my empirical investigation. In this economy, there are two countries, each populated by three agents. In each country, one agent has the correct beliefs about the future growth rate of the economy, while the other two agents have expectations that are either larger ("the optimist") or smaller ("the pessimist") than the true growth rate. Depending on the specific degree of optimism and pessimism of those two agents, the cross-sectional distribution of beliefs within each country can take on any possible extent of skewness.

The presence of an agent with correct beliefs in each country is relevant because these agents will act as the marginal investors that pin down the equilibrium adjustment of the exchange rate. Assuming that financial markets are complete, the exchange rate between the currencies of the two countries is equal to the ratio of marginal utilities of the two agents with correct beliefs by a simple no-arbitrage argument (as in Backus, Foresi, and Telmer (2001)).

Let us consider the situation in which the cross-sectional skewness is negative in one country and equal to zero in the other country. According to the definition that I adopt in my empirical approach, this situation corresponds to one in which the global skewness is negative. It is intuitive to conclude that the risk-free rate should be lower in the first country, in which the pessimist drives up the demand for the risk-free asset by a larger extent. Carry trade would thus involve borrowing in the currency of the first country with negative skewness and investing in the currency of the other country with zero skewness.

A key feature of economies with heterogeneous beliefs is that agents want to consume the most in states of the world that they think are the most likely. This means that the marginal investor consumes less than the pessimist in bad times. This helps explain why shorting the currency of the negatively skewed country is a risky strategy. In bad times, the marginal utility (consumption) of the marginal investor goes up (drops) more in the negatively skewed country. This, by no-arbitrage, results in an appreciation of the currency of this country. Equivalently, the carry trade is risky because it loses money in bad times. A similar argument can be used to show that it gains money in good times.

This example illustrates why the risk premium is higher in times in which the global skewness is more negative. Based on this idea, the model implies that carry trades are risky when the investor faces negatively skewed global prospects.

1.1 Literature Review

The cross-sectional measures of GDP forecasts have been previously considered in the literature primarily to explain domestic equity or bond risk premia. Campbell and Diebold (2009) document that expected business conditions, measured by taking the consensus forecasts, can predict next period stock returns. Bansal and Shaliastovich (2010) find that cross-sectional dispersion of forecasts informs us about confidence risk, which helps explain the equity risk premia. Buraschi and Whelan (2012) show that dispersion in forecasts can predict subsequent bond excess returns with the argument specifically about belief dispersion. Colacito, Ghysels, Meng, and Siwasarit (2016) find that negative cross-sectional skewness precedes recessions and helps predict future stock returns.

I argue in this paper that my measure of macroeconomic conditional skewness is a global risk factor. The implication for the currency market is that it should affect the stochastic discount factors of countries based on the exposure to the risk so that the movement of the foreign exchange rate is also affected. This fits in with the literature following Lustig, Roussanov, and Verdelhan (2011) that currency risk premia can be explained by the exposure to a systematic risk. My model is consistent in that different countries have different exposure to global macroeconomic skewness, which causes the highly exposed countries to have more severely skewed distribution in forecasts.

There is a large literature that interprets the dispersion of forecasts as a measure of disagreement among analysts. Anderson, Ghysels, and Juergens (2005) find that dispersion in analysts' forecasts about expected earnings is a priced factor in the equities market. Buraschi, Trojani, and Vedolin (2014) provide evidence that belief disagreement, also constructed from earnings forecasts, can explain the cross-section of corporate bond and stock returns. In my model, currency risk premia are driven by the cross-sectional skewness in forecasts because the resultant risk-sharing among agents will determine the riskiness in the foreign exchange rate.

We may relate the role of skewness to that of disaster risk. Farhi and Gabaix (2016) and Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2015) find that rare disaster risk can account for a large fraction of the carry trade risk premia. However, notice that a measure of skewness is not restricted to the notion of a rare, extreme event. In fact, my time-series of global macroeconomic conditional skewness tends to be low, well in advance of the onset of the recessions. Moreover, a skewed distribution in growth prospects has the further benefit that it measures both negative and positive directions of asymmetry, which cannot be captured by disaster risk.

The literature provides many competing explanations for currency risk premia, one of which emphasizes the role of commodities. In the model of Ready, Roussanov, and Ward (2014), the high interest rate countries, which correspond to the investment currencies, tend to be the commodity exporters, while the low interest rate countries, which correspond to the funding currencies, tend to be the exporters of the finished goods. The authors show empirical support that the strategy of sorting based on net exports in basic goods, which measure how much one specializes in producing and exporting basic commodities, yields high returns. Chen, Rogoff, and Rossi (2010) and Bakshi and Panayotov (2013) provide empirical evidence on the relationship between exchange rates and commodity prices.

Other explanations for the currency risk premia include the role of global foreign exchange volatility which rises precisely when the high interest rate currencies yield poor returns as shown in Menkhoff, Sarno, Schmeling, and Schrimpf (2012). In the work of Gabaix and Maggiori (2015), since the net debtor country borrows from the financial market that has limited risk-bearing capacity, their currency requires a compensation. Della Corte and Krecetovs (2016) actually provide interesting evidence that the currency risk premia can be explained by current account uncertainty, which is measured by the cross-sectional dispersion of current account forecasts, dominating other macro uncertainty variables like the dispersion in GDP forecasts. My paper looks specifically at the GDP forecasts and instead examines different moments of the distribution.

My paper also sheds some perspectives on the macro-finance literature that bridges international asset prices and consumption dynamics. Colacito and Croce (2013) provide evidence that the highly correlated long-run growth prospects can explain the Backus and Smith (1993) anomaly that the correlation between consumption differentials and exchange rate movements is low. Gourio, Siemer, and Verdelhan (2013) develop a standard real business cycle framework, in which the risk premia vary with the probability of a disaster that leads to a decline in investment. My measures of global risks are not directly from consumption or growth data, but they are derived from analysts' views of future real economic growth prospects.

This paper is organized as follows. Section 2 introduces a model that yields testable predictions. Section 3 provides an explanation on the forecasts data and highlights stylized facts about the proposed global measures of risks. Section 4 presents the main currency predictability results. Lastly, section 5 provides concluding remarks.

2 Model

In this section I focus on a static model with heterogeneous agents to highlight the economic mechanism of how the cross-sectional skewness in forecasts affects the riskiness of a currency trade. I follow up with an extension that builds a dynamic version of the model.

2.1 Setup of the Economy

Consider a two-period, complete market economy with two countries, which I call home and foreign. The home country produces good X, and the foreign country produces good Y. The true data generating processes for the endowment goods X and Y are as follows

$$\log X = \log X_0 + ''_X \qquad\qquad \log Y = \log Y_0 + ''_Y \tag{1}$$

where the endowment shocks $''_X \quad N(\ ; \ ^2)$ and $''_Y \quad N(\ ; \ ^2)$ have a correlation of .

Each country is populated by three agents, denoted AG_i for the home country and AG_i^* for the foreign country. Each agent forms a subjective probability density function about the endowment shocks. I assume that all agents correctly form the underlying distributional shape, the variance and the covariance of the shocks but that agents can have biased expectations about the mean of the shocks, which I will interchangeably refer to as the forecast or the prediction. For each country, there will be an optimist and a pessimist as well as an unbiased forecaster whose prediction coincides with the correct mean. Furthermore, for simplicity I assume that all agents correctly forecast the mean of the other country's endowment shock. Mathematically, each home agent AG_i forms a joint probability distribution $\ _i(''_X; ''_Y) \quad N((\ _i; \ )';$

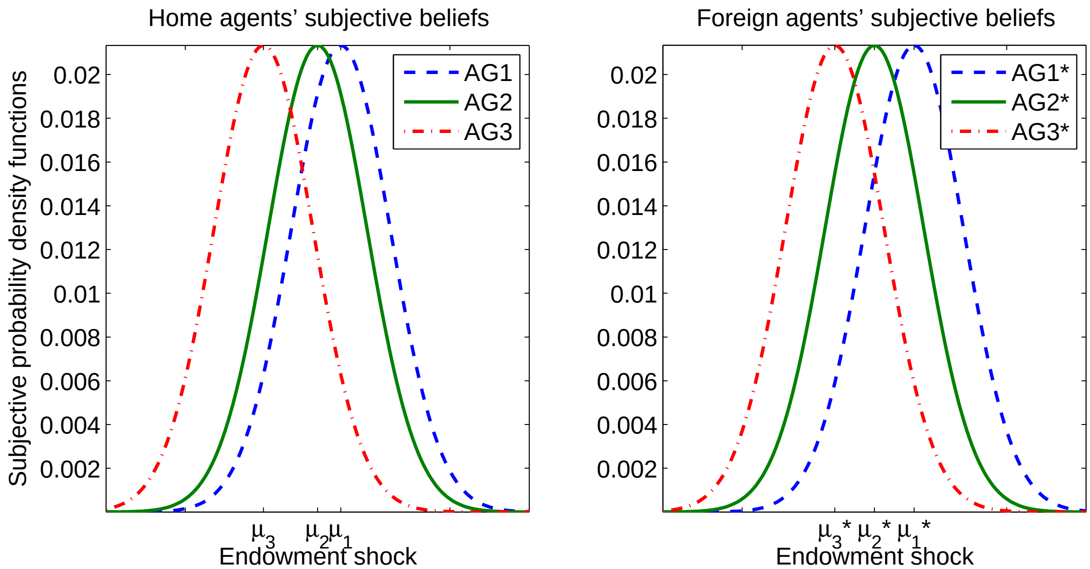

Figure 1: Example of home and foreign forecasts having different extent of cross-sectional skewness in forecasts of means. Each line corresponds to each agent's subjective probability density functions (pdf) about the endowment shock of his respective country. $_i$ or $^*_i$ corresponds to the subjective mean forecast made by an agent. Above is an illustration on a 2-dimensional graph, but in my model endowment shocks $(''_X; ''_Y)$ have an additional dimension.

2.2 Equilibrium and Solution of the Model

The social planner optimizes the weighted average of the expected utility of each agent. Since the model has only two periods, the planner forms the optimal allocation by choosing next period consumption for each agent C_i and C_i^*

$$\Pi = \mathbb{E}_1\left[\frac{C_1^{1-\gamma}}{1-}\right] + \mathbb{E}_2\left[\frac{C_2^{1-\gamma}}{1-}\right] + \mathbb{E}_3\left[\frac{C_3^{1-\gamma}}{1-}\right] + \mathbb{E}_{1*}\left[\frac{C_1^{*1-\gamma}}{1-}\right] + \mathbb{E}_{2*}\left[\frac{C_2^{*1-\gamma}}{1-}\right] + \mathbb{E}_{3*}\left[\frac{C_3^{*1-\gamma}}{1-}\right] \tag{2}$$

where each expectation $\mathbb{E}_i$ or $\mathbb{E}_{i*}$ is taken over the subjective distribution $_i$ or $^*_i$ formed by the home or foreign agent i. As a result of complete home bias, the social planner satisfies the following budget constraints

$$X = X_1 + X_2 + X_3 \qquad \text{and} \qquad Y = Y_1 + Y_2 + Y_3 \tag{3}$$

where X_i is the home agent AG_i's optimal consumption of the home goods X next period, and Y_i is the foreign agent AG_i^*'s consumption of the foreign goods Y next period. I will use $X_{i;0}$ and $Y_{i;0}$

to denote the equivalent current period consumption, which is assumed equal across all agents in this economy.

Upon solving the above optimization problem we can write down the allocations next period

$$C_i = \frac{\ _i^{1=}}{\sum_{i=1}^{3} \ _i^{1=}} \quad X \tag{4}$$

$$C_i^* = \frac{(\ _i^*)^{1=}}{\sum_{i=1}^{3} (\ _i^*)^{1=}} \quad Y \tag{5}$$

for $\forall i \in \{1; 2; 3\}$. Notice how the allocation at each state depends on the subjective distributions of all agents in the same country. An agent will consume optimally based on how his perceived probability of a state differs from that of the other agents. On an intuitive level, each agent will want to consume more in the states that he thinks are likely to occur.

2.3 Asset Pricing

Home and foreign interest rates can be computed via the objective marginal utility of any home agent M

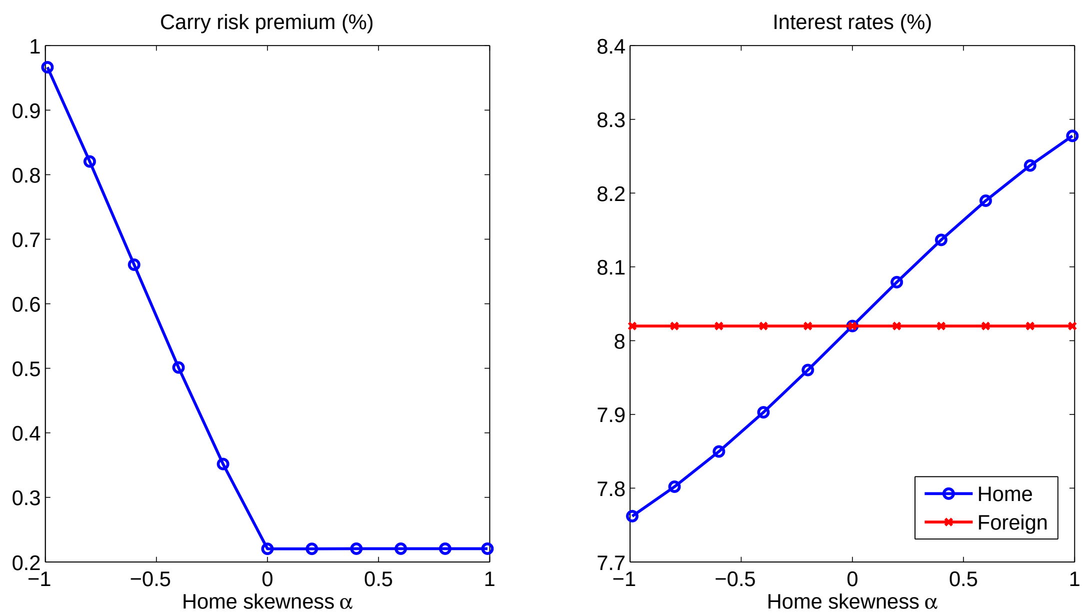

Figure 2: The comparative statics of changing the skewness α in home forecasts, while fixing the skewness α^* in foreign forecasts to 0. The left and right panels show the resulting carry risk premium and the interest rates for each country, respectively.

countries is

$$\Delta s = \log M^* - \log M \tag{8}$$

where I will refer to an appreciation of the foreign currency as the rise in Δs.

2.4 Skewness in Forecasts and Currency Risk Premium

From a currency investor's perspective, the excess return on investing in the foreign currency and shorting the home currency can be written as $cxr = i^* - i + \Delta s$. Since the carry trade is taking a long position in the currency of the higher interest rate country while shorting the other currency, the carry risk premium in levels can be written as

$$\text{carry risk premium} = \begin{cases} \log \mathbb{E}[\exp\{i^* - i + \Delta s\}] & \text{if } i^* > i \\ \log \mathbb{E}[\exp\{-(i^* - i) - \Delta s\}] & \text{if } i^* < i \end{cases}$$

Let us consider the comparative statics of varying the extent of skewness in forecasts. The panels in

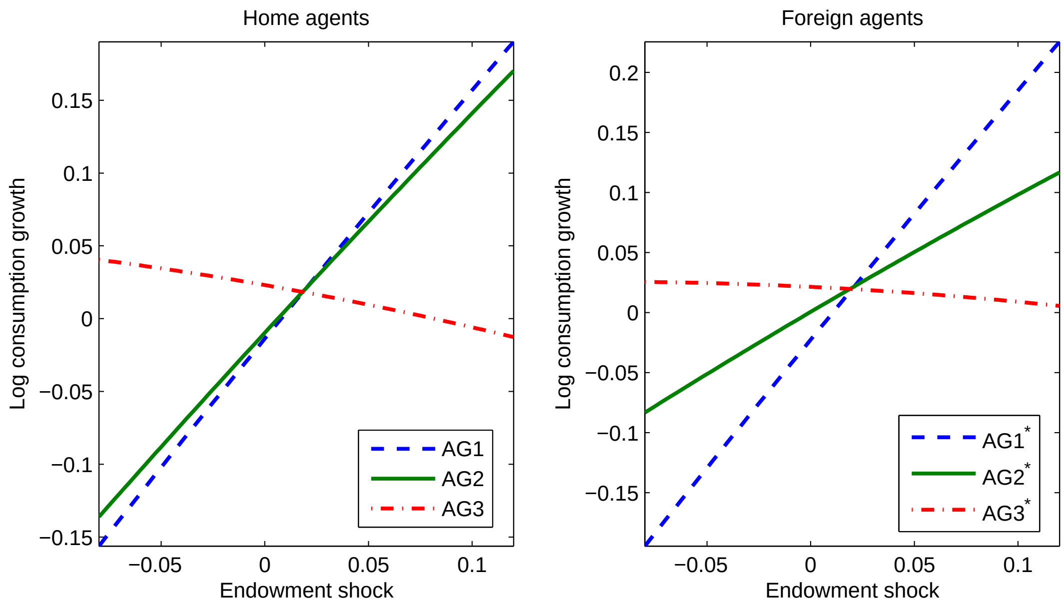

Figure 3: Each agent's optimal consumption allocations in terms of log consumption growth for the case of $\ = 0.8$ and $\ ^* = 0$. For illustration on a 2-dimensional graph, I display only the diagonal slice of the $(\varepsilon_X, \varepsilon_Y)$ domain in which ε_X and ε_Y are equal in value.

to consume more in the states that he thinks are the most likely. Since the bad state of the world is the state in which the pessimist is more correct, the pessimist enjoys a larger share of the pie, leaving less for AG_2 to consume.

What does the consumption of AG_2^* and AG_2 imply for asset pricing? Recall that these agents are those with the unbiased predictions about the underlying distribution of endowment shocks. This makes their consumption directly applicable for computing the (objective) marginal utility of consumption in each country

$$M = \left(\frac{C_2}{C_{2,0}}\right)^{-} \qquad \text{and} \qquad M^* = \left(\frac{C_2^*}{C_{2,0}^*}\right)^{-} \tag{9}$$

Based on the discussion in the previous paragraph, let us consider what happens upon a bad endowment shock. Relative to AG_2^*, in the home country AG_2 consumes much less because he is entitled to provide large insurance to the pessimist. The marginal utility of any home agent, therefore, goes up much more relative to a foreign agent's marginal utility. That makes the growth in the foreign exchange rate $\Delta s = \log(M^*) - \log(M)$ depreciate, which would be a loss to the carry investor because the currency that he holds next period is valued less in terms of the home currency. Upon a good shock, Δs would appreciate, delivering a positive return to the carry investor. Importantly, notice that the above carry trade is risky strategy to implement because the investor loses in the bad state of the world. The no-arbitrage argument suggests that prices would adjust so that there should be a high risk premium for implementing this risky strategy.

To be precise, there are both home endowment shocks and foreign endowment shocks, which adds a dimension of the state of the world. The idea, however, is analogous to the previous argument in that based on possible realization of the foreign exchange rate, the riskiness of the strategy would drive the size of the risk premium by no-arbitrage.

In summary, the above demonstrates that as home skewness in forecasts ( ) becomes more negative, the carry trade becomes riskier, which in equilibrium would bear a higher risk premium. On the contrary when home skewness becomes more positive, the carry trade becomes less risky, and the resulting currency component cancels out with the difference in interest rates, leaving the carry risk premium unchanged.

Now let us discuss the time-series implication of our static model. Imagine that skewness in both home and foreign countries varies over time. If each country's skewness measure is not independent of each other, then from a modeling perspective we can think of a "global" skewness measure that drives the variation in each country's skewness. Moreover, if one country's skewness covaries more with the global measure, then that country's skewness is considered to be more exposed to the global measure. The case in which the skewness of both countries is exactly identical is less interesting because the two countries will be identical, in which case there will be no difference in interest rates.

Our comparative statics of varying home skewness while holding foreign skewness * fixed is precisely to illustrate this notion of difference in exposure. I only varied to explain an extreme case in which the home skewness is highly exposed to a "global" skewness factor, while the foreign skewness is not exposed at all. Based on the conclusion of the static model, in this case a negative shock to global skewness would make the currency trade a risky strategy, thus pushing up the carry risk premium.

Later in the empirical section, I provide evidence that the consumption differentials between the two sets of countries (home versus foreign in the model) can be explained by global conditional skewness. The pattern will be consistent with the argument that indeed the low interest

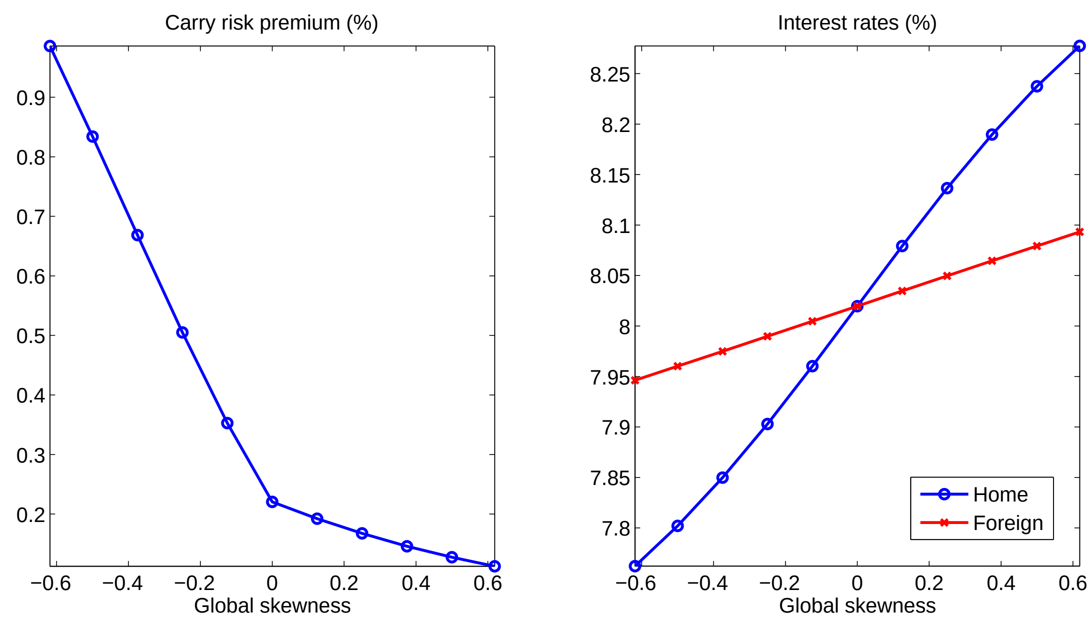

Figure 4: The comparative statics of jointly changing the skewness in home forecasts   and skewness in foreign forecasts *, yet the latter to a smaller extent. Specifically the figures show the case of $^* = 0.25$. Global skewness is the average of   and *. The left and right panels show the resulting carry risk premium and the interest rates for each country, respectively.

rate countries have skewness that is more exposed to global skewness than the high interest rate countries.

One may raise a concern that in my static exercise the carry risk premium is flat on the positive domain of . Recall that the above example is a particular case in which the foreign skewness * is fixed at zero. I have considered other comparative statics, such as varying the foreign skewness * by some fraction of a marginal increase in the home skewness . One example can be found in Figure 4, in which case $^* = 0.25$, specifically. This is a way to understand the time-series implication in which the home skewness is more exposed to the aforementioned "global" skewness than foreign skewness. The global skewness here is defined as the average of   and *, following the empirical setup described in the following section. As long as there is this difference in exposure, the sorting of the interest rates is preserved, *and* the carry risk premium becomes monotonically negatively related to skewness even on the positive domain of . Without pinning down exactly the extent of comovement, I argue that it is more important to look at the overall relationship between the risk premium and global skewness, as opposed to the specific non-linearity in the relationship.

The final comment to be made regarding the exposure to global skewness in the time-series implication is that in my paper I am entirely excluding the discussion on idiosyncratic skewness in an individual country. I am supposing any skewness in a country's forecasts is entirely driven by the global skewness factor. Although idiosyncratic skewness by itself is an interesting avenue of research, my empirical work faces data limitation in that, for some countries in my sample, skewness is not tightly measured enough to tease out information about the idiosyncratic component. Hence, in my theory and empirical sections, I focus entirely on the systematic component based on the argument that for a large enough cross-section of currencies, only the systematic risk should be priced.

2.5 Extension

The static model described so far is stylized for the purpose of highlighting the intuition of the model. In this section, I discuss an extension to a dynamic model with time-variation in agents' beliefs. By doing so, I generate an economy in which global skewness varies over time and thus drives the variation in the carry risk premium.

I similarly model an economy with two countries, each of which is occupied by an optimist, an agent with the correct beliefs and a pessimist. Importantly, I allow time-variation in the beliefs of the optimists and the pessimists $\{\mu_{1,t}, \mu_{3,t}, \mu^*_{1,t}, \mu^*_{3,t}\}$, while the beliefs of the unbiased agents $\mu_{2,t}$ and $\mu^*_{2,t}$ are kept equal to the true average growth rate μ. Specifically I let the variation in the beliefs to be driven by the time-variation in skewness in forecasts

$$\gamma_t = \frac{\mu_{1,t} + \mu_{3,t} - 2\mu_{2,t}}{\mu_{1,t} - \mu_{3,t}} \tag{10}$$

which was defined similarly in the static model. I model the time-series of skewness such that

$$a_t = \rho_a a_{t-1} + \sigma_a \varepsilon_{a,t} \tag{11}$$

where $\varepsilon_{a,t} \sim N(0,1)$ with the mapping $\gamma_t = a_t / \sqrt{1 + a_t^2}$ to resolve the issue that γ_t must be bounded between -1 and 1. The calibration can be found in the Appendix in Table A2. Lastly, I assume that foreign skewness in forecasts γ^*_t is equal to 1/3 of γ_t to model an economy in which the two countries have different extent of exposure to global skewness. Although one can implement a more general time-series model of beliefs, I impose the above structure to keep it stylized so that I can highlight the role of time-varying skewness in forecasts, minimally deviating from the static model.

I adapt a model with heterogeneous beliefs laid out in Anderson, Ghysels, and Juergens (2005). The social planner maximizes

$$\Pi = \sum_{i=1}^{3} \lambda_{i,0} \sum_{t=0}^{T} \mathbb{E}_{i,0}\left[\frac{C_{i,t}^{1-\gamma}}{1-\gamma}\right] + \sum_{i=1}^{3} \lambda^{*}_{i,0} \sum_{t=0}^{T} \mathbb{E}_{i*,0}\left[\frac{C_{i,t}^{*1-\gamma}}{1-\gamma}\right] \tag{12}$$

with initial Pareto weights $\lambda_{i,0}$ and $\lambda^{*}_{i,0}$. The planner optimally allocates consumption $\{C_{i,t}, C^{*}_{i,t}\}$ with perfect home bias.

The solution can be written as

$$C_{i,t} = \frac{\lambda^{1/\gamma}_{i,t}}{\lambda^{1/\gamma}_{1,t} + \lambda^{1/\gamma}_{2,t} + \lambda^{1/\gamma}_{3,t}} X_t \quad \text{and} \quad C^{*}_{i,t} = \frac{\lambda^{*1/\gamma}_{i,t}}{\lambda^{*1/\gamma}_{1,t} + \lambda^{*1/\gamma}_{2,t} + \lambda^{*1/\gamma}_{3,t}} Y_t \tag{13}$$

in terms of the Pareto weights $\lambda_{i,t}$ which is recursively defined as

$$\lambda_{i,t} = \frac{\lambda_{i,t-1}\xi_{i,t}}{\sum_{i=1}^{3}\lambda_{i,t-1}\xi_{i,t} + \sum_{i=1}^{3}\lambda^{*}_{i,t-1}\xi^{*}_{i,t}} \quad \text{and} \quad \lambda^{*}_{i,t} = \frac{\lambda^{*}_{i,t-1}\xi^{*}_{i,t}}{\sum_{i=1}^{3}\lambda_{i,t-1}\xi_{i,t} + \sum_{i=1}^{3}\lambda^{*}_{i,t-1}\xi^{*}_{i,t}} \tag{14}$$

Instead of simulating the model for a very long number of periods, I fix the number of periods to $T = 40$ and start over and repeat 100 times. The purpose of this is that I do not want to consider periods in which one of the agents ends up being infinitesimally small ($\lambda_{i,t} \to 0$) which can happen after many periods.

Based on the simulated data, I regress the subsequent carry trade returns onto the current level of global skewness, defined as $\kappa_t + \kappa^{*}_t$. Table 1 shows that the loading on global skewness is negative and statistically different from zero with sizable t-statistics. Moreover, the loading is of comparable magnitude as the unconditional average of excess returns on the carry.

The above predictive regression suggests a negative time-series relationship between the carry risk premium and global skewness. The result is in line with the earlier discussion on the static model, and moreover it provides implications that are directly testable in the data.

intercept	0:0067*** (0.0014)
global skewness	0:0084*** (0.0016)
AdjR2	0.0081

Table 1: Regression of the subsequent carry trade returns on global skewness $_t + {}^*_t$ based on simulation. The regressor is standardized. Statistical significance is calculated based on Newey-West standard errors.

3 Global Measures of Risk: Data Sources and Stylized Facts

Constructing a measure of conditional skewness on macroeconomic growth prospects is challenging. The standard Pearson measure of skewness requires high frequency of data points for an appropriate time window given our interest in a conditional measure of skewness. For our purpose, measuring the time-varying skewness of macroeconomic variables then becomes far from obvious because most macroeconomic indicators are available only at quarterly frequency. Instead, I use the third moment from the cross-sectional distribution of individual forecaster's macroeconomic forecasts. I construct global measures of risks by: (i) computing cross-sectional moments of each country and then (ii) aggregating across countries to obtain global expected growth, global uncertainty and global skewness. In terms of aggregation, I take the simple average across countries, i.e. I take the average of each country's expected growth across countries, and so forth. I also supply alternative specifications of aggregation as robustness tests, using the 1st principal component or taking the weighted average based on GDP weights.

The two primary data sources that provide individual forecasts for various countries are Consensus Forecasts and Bloomberg. Consensus Forecasts is a monthly periodical that has been surveying reputable institutions of their forecasts of future macroeconomic variables for the major countries of the world. The publication provides individual forecasts of real GDP growth rates broken down by each forecaster. Bloomberg is another popular data source that makes available individual forecasts, but since only post-2008 data were available to me I augment Bloomberg data to the data from Consensus Forecasts. In addition, I also include a few country-specific forecasts datasets, one of which is New Zealand and is kindly provided by the Reserve Bank of New Zealand. New Zealand's forecasts data are available through Bloomberg but the data from Consensus Forecasts was not available to me. Since the dataset from the Reserve Bank of New Zealand does not make available the name of the institution, I do not augment Bloomberg forecasts data. For Sweden and Switzerland, whose forecasts data are available by Consensus Forecasts and Bloomberg, the number of analysts who cover these countries are not sufficient for the early part of the sample, so I also augment national sources. The respective forecasts data have been generously provided by the National Institute of Economic Research (NIER) in Sweden and the KOF Swiss Economic Institute. Lastly, I include China starting from the first quarter of 2008, for which I only have Bloomberg's individual forecasts data. To alleviate the concern that China's economic growth plays a large role in global markets, I augment the cross-sectional first moment of real GDP growth forecasts in China all the way back to the beginning of 2000 using an alternative forecasts survey called Blue Chip Economic Indicators. Note that other measures, such as uncertainty and skewness, are not available for China for the period from 2000 to 2007 because of the lack of data on forecasts broken down by individual forecaster. I end up with the following list of countries: United States, United Kingdom, Japan, New Zealand, Germany, France, Sweden, Canada, Italy, Spain, Switzerland, and China. I choose the sample period from the first quarter of 1995 up to the first quarter of 2015 at quarterly frequency with the exception of Switzerland which starts in the second quarter of 1998 and China as just described. Table 2 shows the sample period for each country and the descriptive statistics on the number of forecasters.

		Num. of forecasters		
Country	Start date	25^{th}%	median	75^{th}%
US	1995.q1	29	33	63
UK	1995.q1	28	36	40
Japan	1995.q1	20	23	28
New Zealand	1995.q1	44	49	59
Germany	1995.q1	30	32	43
France	1995.q1	19	22	26
Sweden	1995.q1	16	18	25
Canada	1995.q1	16	17	25
Italy	1995.q1	15	19	22
Spain	1995.q1	14	17	26
Switzerland	2000.q1	19	32	46
China	2008.q1	17	23	54

Table 2: Start date of forecasts data and summary statistics of the number of forecasters. Since the number of forecasters for each country is changing through time, I report the quantiles.

Individual analysts respond to the survey by providing their own forecasts of real GDP growth rates, for example, for the current and next calendar years. I linearly interpolate the 1-year horizon growth rate from the current quarter up to 1 year ahead, based on the number of quarters remaining until the end of the year. For each country at every point in time, I construct the quartile-based cross-sectional moments of individual forecasts: (i) expected growth is measured by the median; (ii) uncertainty is measured as the 75th percentile minus 25th percentile; and (iii) skewness is measured as (75th perc. + 25th perc. - 2   median) (75th perc. - 25th perc.). The quartile-based measures of moments are simple ways to make them robust to a few outliers. This becomes particularly important for the third moment because the usual approach of calculating sample skewness is highly sensitive to large deviations. The quartile-based measure, on the other hand, is not affected by one very large deviation but still captures the extent of skewness of the distributional shape.

One may raise the question that the proposed measure of skewness is not exactly a representative agent's belief of the distributional shape of the growth rate. Although I have demonstrated the exact economic mechanism of the role of cross-sectional skewness in forecasts, I provide the following intuition on why the measure can relate to macroeconomic skewness. My argument is that one may view the survey as a collective group view of the forecasters and is informative about the prospects of the variable being forecasted. Similar to how the median forecast can serve as the expectation of growth rate, the extent of how dispersed the predictions are can serve as the proxy for variance. Moreover, if one notes a pronounced asymmetry in the distribution of predictions in that a fraction of respondents are making very low (or very high) predictions, then one may infer that there are some beliefs that the growth rate can tank significantly (or boost significantly), while there still prevails non-extreme beliefs about growth. Analogously, a negatively (or positively) skewed distribution of macroeconomic prospects indicates there are some chances of left-tail (or right-tail) events while the remaining mass of the distribution is at the non-extreme part of the domain. Hence, our cross-sectional skewness of forecasts can arguably be interpreted as a measure of skewness risk about the macroeconomic prospects.

The first three plots in Figures 5 show the time series of my global measures. My global expected growth measure appears procyclical and drops significantly especially during the recent financial crisis. The global uncertainty measure on the other hand increases significantly during the crisis and notably remains elevated for a while after the end of that NBER-designated recession.

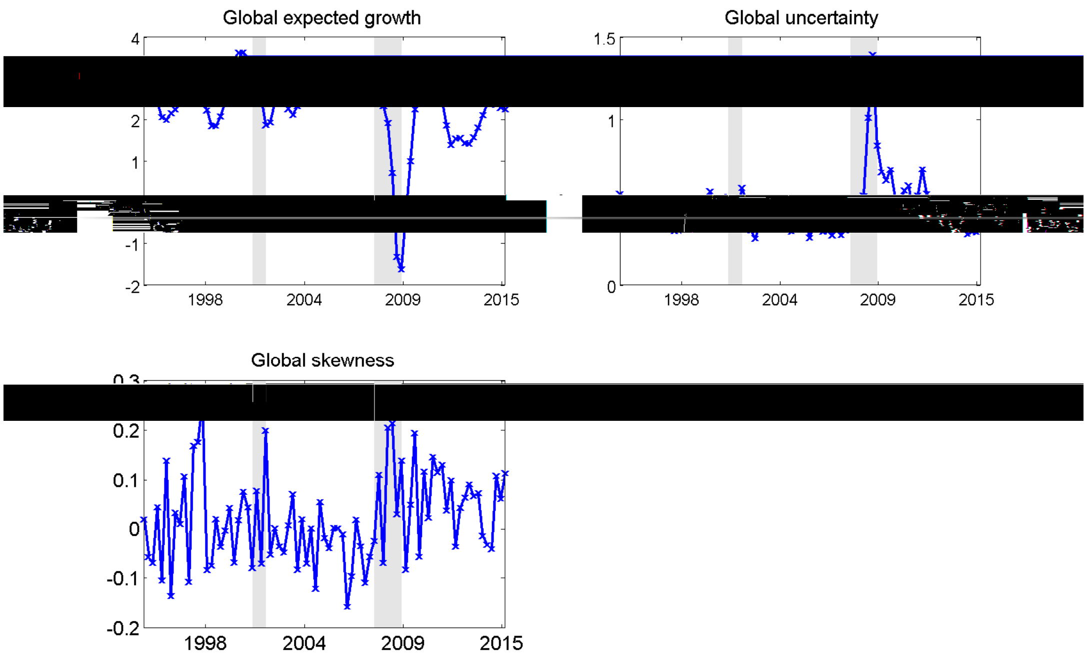

Figure 5: Global measures of risks. Shown are the three cross-sectional measures of global growth prospects

Global skewness, which will serve as the measure of interest in our empirical analysis, displays an interesting pattern a number of quarters before the recessions. What we can observe is that global skewness tends to be low and negative a number of quarters before the onset of each recession. Intuitively, this means that a fraction of forecasters makes significantly pessimistic predictions relative to the non-pessimistic crowd at periods before a recession begins. When a bad event actually realizes, most of the survey respondents revise their predictions downward, so that the skewness of the distribution is no longer low. It is precisely this dynamic that I believe captures important time-series information about global macroeconomic risks.

Data on personal consumption and population are mostly from national sources and have been downloaded through Datastream. These include: Federal Statistical Office of Germany, State Secretariat for Economic Affairs of Switzerland, Cabinet Office of Japan, Australian Bureau of Statistics, Statistics New Zealand and Statistics Norway. World Bank and IMF International Financial Statistics have been also used for population data.

Foreign exchange data are obtained primarily from Thomson Reuters through Datastream. I obtain foreign exchange spot rates and 3-month forward rates on 33 currencies from Thomson Reuters: United Kingdom, Japan, New Zealand, Australia, Sweden, Switzerland, Norway, Canada, South Africa, Singapore, Denmark, Euro, Austria, Belgium, Finland, France, Germany, Greece, Italy, Netherlands, Portugal, Spain, Ireland, South Korea, Czech Republic, Hungary, India, Malaysia, Mexico, Philippines, Poland, Taiwan, and Thailand. However, the data I have from Thomson Reuters only go back to the end of 1996, so for the period of 1995 through the third quarter of 1996 I use the 3-month interest rates and the spot rates for the major and Euro-joining currencies: United Kingdom, Japan, New Zealand, Australia, Sweden, Switzerland, Norway, Canada, South Africa, Singapore, Denmark, Austria, Belgium, Finland, France, Germany, Greece, Italy, Netherlands, Portugal, Spain, and Ireland. The sample period differs for different currencies either because of foreign exchange regimes, unreliable volatile periods, or data unavailability. The details for the foreign exchange data that we use can be found in Table A3 in the Appendix.

4 Empirical Results

The empirical highlight of this paper is to show that my global measures of risks can predict carry trade returns. At the end I provide evidence from consumption growth differentials that there is indeed heterogeneity in how countries are exposed to the global skewness measure, which provides justification for the argument in the model.

4.1 Predictive Regressions of Currency Returns

A common approach to understand the currency market is to study the returns to the carry trade. In practice this trading strategy involves taking long positions in currencies with high forward discount and taking short positions in those with low forward discount. This is roughly equivalent to forming long-short portfolios based on the aforementioned interest rate differentials, given that the covered interest rate parity approximately holds.

Based on the ordering of the forward discount, which is defined as the difference between the log forward rate f_t^i and the log spot rate s_t^i, I separate currencies into usually five buckets from the highest to the lowest. For exercises that restrict the investable set of currencies to, a smaller number of currencies, say the G10, then I separate them into three buckets instead. The dynamic strategy means that I take long positions in the currencies in the high bucket and short positions in the currencies in the low bucket, while re-balancing the portfolio every quarter based on the sorting of currencies. For the static strategy, I instead form a static portfolio based on the time series average of the forward discount for each currency. As an example with the most actively traded currencies in the world, the static strategy would involve taking long positions on the Australian dollar, New Zealand dollar, and Norwegian Krone, while taking short positions on the Deutsche Mark (soon replaced by the Euro), Swiss Franc, and Japanese Yen. The predictive regression exercise is to regress the next-quarter carry trade returns onto one or more of our global measures of risks X_t:

$$xr_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1} \tag{15}$$

where xr_{t+1} indicates the return on the carry trade strategy from time t to the next quarter $t+1$, which consists of a long position in the high bucket and a short position in the low bucket. The currency excess return on a single foreign exchange rate i is defined as $xr^i_{t+1} = s^i_{t+1} - f^i_t$, and the portfolio return on a particular bucket is the average of the individual excess return xr^i_{t+1} for the currencies in the bucket. For the period before 1996.Q4, in which I use bonds data, the excess returns on the currency i are defined as $xr^i_{t+1} = i^i_t - i^{US}_t + \Delta s_{t+1}$ and the forward discount is defined as $fd^i_t = i^i_t - i^{US}_t$.

Table 3 presents the main regression results of my exercise. For ease of interpretation I standardize all global measures so that each has a mean of 0 and a standard deviation of 1. Panels A and B show the results for the static carry, and panels C and D show for the dynamic carry. Panels A and C present the results for portfolios formed using the G10 currencies, one of which is the Euro which replaced the Deutsche Mark in 1999. Panels B and D correspond to portfolios formed using all 33 currencies, in which the set of currencies being considered is changing through time (See Table A3 in Appendix). One can observe that the static carry trade returns based on the major currencies loads significantly on the global expected growth and global skewness with a negative sign and loads positively on global uncertainty, given the regression is done separately. If all three regressors are used altogether, then global expected growth and global skewness remain significant predictors of the carry trade returns. Moving onto the second panel, we can see that global uncertainty is no longer a significant predictor of the returns. Global skewness remains a

Panel A	carry trade: G10 currencies				
intercept	0:0042	0:0042	0:0042	0:0042	0:0042
	(0.0049)	(0.0050)	(0.0046)	(0.0044)	(0.0044)
x_t^g	0:0097***			0:0124***	0:0078**
	(0.0026)			(0.0022)	(0.0035)
v_t^g		0:0094***			0:0067
		(0.0032)			(0.0048)
sk_t^g			0:0084**	0:0113***	0:0119***
			(0.0037)	(0.0035)	(0.0035)
AdjR2	0:0356	0:0320	0:0231	0:0859	0:0858
Panel B	carry trade: all currencies				
intercept	0:0052	0:0052	0:0052	0:0052	0:0052
	(0.0043)	(0.0044)	(0.0035)	(0.0035)	(0.0036)
x_t^g	0:0037			0:0082**	0:0038
	(0.0040)			(0.0040)	(0.0040)
v_t^g		0:0045			0:0064
		(0.0043)			(0.0055)
sk_t^g			0:0167***	0:0186***	0:0191***
			(0.0046)	(0.0053)	(0.0058)
AdjR2	0:0056	0:0027	0:1271	0:1481	0:1477
Panel D	carry trade: G10 currencies				
intercept	0:0085	0:0085	0:0085*	0:0085*	0:0085*
	(0.0054)	(0.0054)	(0.0049)	(0.0049)	(0.0050)
x_t^g	0:0066***			0:0092***	0:0062
	(0.0025)			(0.0022)	(0.0043)
v_t^g		0:0060*			0:0044
		(0.0033)			(0.0055)
sk_t^g			0:0086**	0:0108***	0:0111***
			(0.0039)	(0.0038)	(0.0040)
AdjR2	0:0099	0:0062	0:0260	0:0553	0:0481
Panel D	carry trade: all currencies				
intercept	0:0138***	0:0138***	0:0138***	0:0138***	0:0138***
	(0.0041)	(0.0041)	(0.0037)	(0.0037)	(0.0037)
x_t^g	0:0002			0:0029	0:0021
	(0.0030)			(0.0032)	(0.0038)
v_t^g		0:0006			0:0011
		(0.0039)			(0.0056)
sk_t^g			0:0124***	0:0131***	0:0131**
			(0.0043)	(0.0048)	(0.0051)
AdjR2	0:0126	0:0125	0:0749	0:0676	0:0559

Table 3: Regression next-quarter carry trade portfolio returns onto global measures. The top panel is based on static carry trades, and the bottom panel is based on dynamic carry trades. The regressors $x_t^g; v_t^g; sk_t^g$ correspond to global expected growth, global uncertainty, and global skewness, respectively, and all are standardized. Statistical significance is calculated based on Newey-West standard errors.

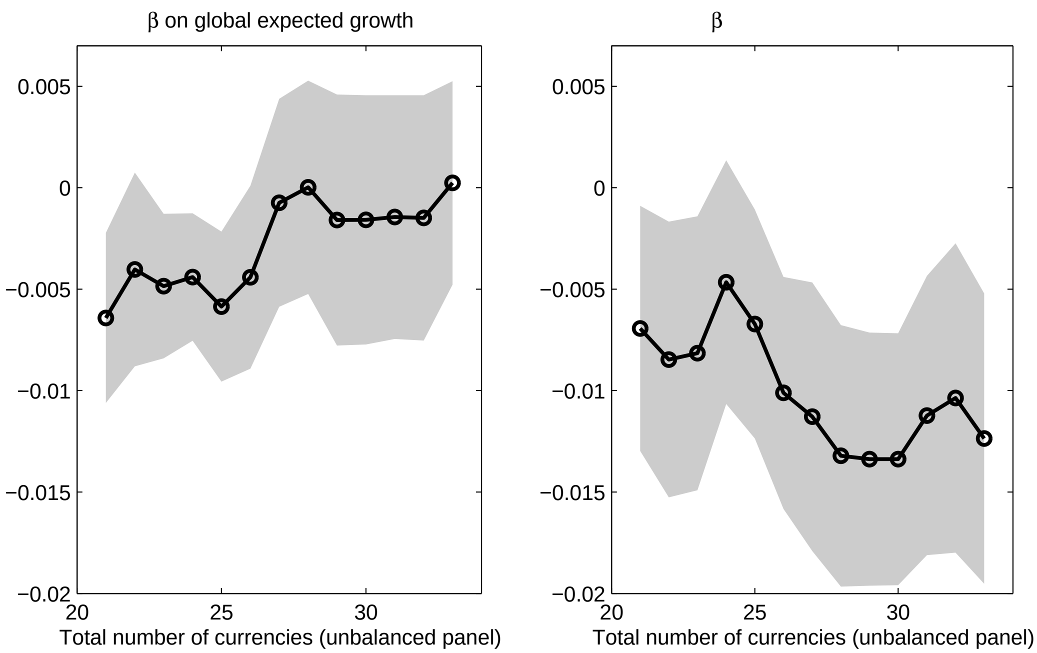

Figure 6: Estimated loadings for the dynamic carry trade and their 90% confidence intervals for different sets of currencies. We have an unbalanced panel of currencies, so the number of currencies changes over time.

reliably significant predictor of carry trade returns, while the loadings on global expected growth is not particularly significant. Likewise, the bottom panels C and D on the dynamic carry trade shows that the signs are consistent with those in the top panels A and B.

The economic magnitude of global conditional skewness is large. For the case of the dynamic carry trade based on a large set of currencies regressed on all three global measures, the loading on global skewness is -0.0131. Since my global measure is standardized, the coefficient suggests that a one standard deviation decline in global skewness indicates a rise in 5.24% risk premium per annum. Many of the other regressions suggest a per annum effect of at least 4%. Therefore, global conditional skewness risk appears to contribute to the time-variation in the carry risk premium with large economic significance.

One notable pattern is that global skewness seems to be a more robust predictor in explaining the carry trade based on a large list of currencies. Figure 6 presents a visualization of how the estimates change as we include more and more currencies in constructing portfolios. The two panels present the estimated loadings as well as the 90% confidence intervals plotted against the number of currencies that we use in forming portfolios. The left panel shows the beta estimates for global expected growth, and the right figure shows them for global skewness. We can see that as we utilize a larger number of currencies in constructing portfolios, we obtain more reliable negative estimates for global skewness. That means that the predictive ability of global skewness becomes stronger in describing a larger set of currencies in the world, which includes not just the major currencies but also a number of emerging market currencies. On the contrary, global expected growth loadings become less negative as we consider a larger number of currencies. Hence we can argue that global expected growth has less predictive power in explaining the risk premia for a wider universe outside of the G10 currencies.

The negative loadings on global conditional expected growth and global conditional skewness inform us about the time-varying compensation for risk in the currency risk premium. When global conditional expected growth is low, the currency risk premium on the carry trade portfolio is high, meaning that there is a large risk premium arising from pessimistic prospects on global expected growth. Similarly, when global conditional skewness is low, or negative, the carry trade offers a high risk premium due to the perception of a negatively skewed distribution of global prospects, i.e., a high chance of a very significant downturn in the global economy. Conditional on such cases, the carry trade portfolio is considered risky, thus offering a high expected return.

What is notable is that the predictive power of global conditional skewness remains significant when the recent crisis period is excluded. I define the recent crisis period consistent with the corresponding NBER recession, i.e., the fourth quarter of 2007 through the second quarter of 2009.

uncertainty is perceived to be high, the carry trade portfolio tends to yield high expected excess returns, meaning that there is a large risk premium when global uncertainty is ex ante high. This is consistent with the argument that when agents expect high economic uncertainty, they require high compensation for investing those risky currencies. As noted before, however, the statistical significance of the loading on the second moment is not very pronounced. If all three regressors are included on the right hand side of the regression, the coefficient on global uncertainty is never statistically different from zero. Although global economic uncertainty does have explanatory power in currency returns, it is usually subsumed by the other moments. Note that global conditional skewness contains the information about the direction of the risks, in that a negative skewness is very different from a positive value. Hence, we may argue that skewness contains information about whether the impending uncertainty is good or bad. Since skewness effectively informs the sign of the uncertainty, the role that the second moment can play is relatively diminished in explaining returns. Given the relatively weaker explanatory power of global uncertainty, for subsequent analyses I exclude the results for it.

I have also repeated the work with alternative procedures of constructing global measures. Recall that I have taken the simple average across countries in aggregating country-specific values to single global measures. Instead I have tried taking the first principal component for countries, for which the entire history is available. This leaves 10 countries for analysis, ignoring Switzerland and China. The results are presented in Table A5. I have alternatively tried an aggregation method of taking the average weighted by each country's GDP share. The results are in Table A6. These robustness exercises generally convey a consistent message that global expected growth and global skewness seem to have predictive ability in explaining carry trade returns.

I further show predictive regressions using alternative measures of skewness in Table A7. I denote the component of global conditional skewness that is not explained by global expected growth as $sk_t^{g,\perp}$. In other words, I regress global skewness onto global expected growth x_t^g and take the residuals that are not explained by x_t^g. The first and third columns show that this measure still significantly predicts carry trade returns. The second and fourth columns use the alternative measure that is constructed as $\sqrt[3]{sk_t^g} \quad \sqrt{v_t^g}$. It measures the third moment raised to the power of one third and captures the direction of the uncertainty. I find evidence that this measure is also a significant predictor of the carry trade returns, which is consistent with the equity return results shown in Colacito, Ghysels, Meng, and Siwasarit (2016).

We may take a closer look at the carry trade regressions by examining the individual portfolios. Recall that carry trade is a high minus low strategy, i.e., it takes a long position in the high portfolio and takes a short position in the low portfolio. What we can instead study is to look at the returns on the high and low portfolios as well as the intermediate portfolios. We can take the time series of the returns on each portfolio, regress them onto our global measures of risks and compare the loadings across the portfolios.

Table 4 presents the results of regressing the individual portfolio returns onto global conditional skewness. The first column repeats the loadings on global skewness for reference, while the latter columns correspond to the high bucket portfolio, the middle, and the low, respectively. One can observe that the beta coefficients are negative and statistically significant for the high and medium portfolio, while the loading for the low portfolio is close to zero. A similar pattern holds in the case of the dynamic trading strategy.

Observing the results for the static portfolios based on a large list of currencies, we can observe an apparent pattern in the individual portfolio loadings. We can see that there is roughly a monotonic pattern in the loadings in that the high portfolio has the most negative loading, and the magnitude of the loading becomes smaller as we look at the subsequent portfolios. The pattern is similar with the dynamic portfolios, if we think of p4 through p2 as roughly similar portfolios. We can conclude that the the returns on the higher forward-discount portfolios load more negatively on global skewness, thus explaining the high minus low carry strategy that I showed earlier.

The results for regressing on global expected growth are presented in Table 5. Although we can find a similar monotonic pattern if the set of currencies was limited to the G10 currencies, this is not necessarily the case if we include many other currencies. The loadings on the 'high' bucket are not significantly negative and are not necessarily larger in magnitude than the others. Therefore, I argue that global conditional skewness seems to be the stronger predictor that produces a monotonic pattern when comparing across the portfolios formed on the forward discount.

In summary, the empirical results show that my measures of global expected growth and global skewness have predictive ability in explaining the carry trade returns. In particular, the explanatory power of global skewness becomes more robust as I include a larger number of currencies.

Panel A	Static carry: G10 currencies			
	carry	p3	p2	p1
intercept	0:0042	0:0020	0:0051	0:0118**
	(0.0046)	(0.0068)	(0.0045)	(0.0054)
sk_t^g	0:0084**	0:0093**	0:0098***	0:0005
	(0.0037)	(0.0038)	(0.0033)	(0.0044)
AdjR2	0:0231	0:0202	0:0513	0:0126

Panel B	Static carry: all currencies					
	carry	p5	p4	p3	p2	p1
intercept	0:0052	0:0002	0:0018	0:0037	0:0075	0:0110***
	(0.0035)	(0.0047)	(0.0053)	(0.0039)	(0.0048)	(0.0039)
sk_t^g	0:0167***	0:0155***	0:0093***	0:0033	0:0046	0:0026
	(0.0046)	(0.0050)	(0.0030)	(0.0056)	(0.0040)	(0.0029)
AdjR2	0:1271	0:0851	0:0433	0:0049	0:0027	0:0068

Panel C	Dynamic carry: G10 currencies			
	carry	p3	p2	p1
intercept	0:0085*	0:0008	0:0065	0:0133**
	(0.0049)	(0.0064)	(0.0048)	(0.0055)
sk_t^g	0:0086**	0:0096**	0:0094**	0:0004
	(0.0039)	(0.0037)	(0.0038)	(0.0042)
AdjR2	0:0260	0:0244	0:0371	0:0126

Panel D	Dynamic carry: all currencies					
	carry	p5	p4	p3	p2	p1
intercept	0:0138***	0:0045	0:0021	0:0055	0:0073	0:0150***
	(0.0037)	(0.0049)	(0.0044)	(0.0048)	(0.0047)	(0.0044)
sk_t^g	0:0124***	0:0133***	0:0045	0:0082**	0:0066	0:0004
	(0.0043)	(0.0045)	(0.0042)	(0.0038)	(0.0041)	(0.0028)
AdjR2	0:0749	0:0772	0:0014	0:0333	0:0132	0:0125

Table 4: Predictive regressions of the carry returns on global expected growth and the regressions on returns of individual buckets of currencies. Panels A and B are based on static carry trades, and panels B and C are based on dynamic carry trades. p1 indicates the portfolio of currencies with the lowest forward discount. p3 (or p5) indicates the portfolio with the largest forward discount, given the G10 currencies (or entire set of currencies). Statistical significance is calculated based on Newey-West standard errors.

Panel A	Static carry: G10 currencies			
	carry	p3	p2	p1
intercept	0:0042	0:0020	0:0051	0:0118**
	(0.0049)	(0.0069)	(0.0048)	(0.0053)
x_t^g	0:0097***	0:0130**	0:0072*	0:0042
	(0.0026)	(0.0054)	(0.0036)	
AdjR2	0:0356	0:0514	0:0218	0:0041

Panel B	Static carry: all currencies					
	carry	p5	p4	p3	p2	p1
intercept	0:0052	0:0002	0:0018	0:0037	0:0075	0:0110***
	(0.0043)	(0.0053)	(0.0054)	(0.0041)	(0.0047)	(0.0038)
x_t^g	0:0037	0:0071	0:0091**	0:0039	0:0071**	0:0043
	(0.0040)	(0.0054)	(0.0043)	(0.0035)	(0.0032)	(0.0026)
AdjR2	0:0056	0:0081	0:0410	0:0019	0:0236	0:0033

Panel C	Dynamic carry: G10 currencies			
	carry	p3	p2	p1
intercept	0:0085	0:0008	0:0065	0:0133**
	(0.0054)	(0.0066)	(0.0052)	(0.0053)
x_t^g	0:0066***	0:0125**	0:0050	0:0069*
	(0.0025)	(0.0052)	(0.0038)	(0.0037)
AdjR2	0:0099	0:0502	0:0013	0:0129

Panel D	Dynamic carry: all currencies					
	carry	p5	p4	p3	p2	p1
intercept	0:0138***	0:0045	0:0024	0:0055	0:0077	0:0150***
	(0.0041)	(0.0053)	(0.0044)	(0.0051)	(0.0048)	(0.0041)
x_t^g	0:0002	0:0063	0:0075**	0:0059	0:0057	0:0074**
	(0.0030)	(0.0048)	(0.0034)	(0.0035)	(0.0038)	(0.0030)
AdjR2	0:0126	0:0075	0:0238	0:0109	0:0085	0:0297

Table 5: Predictive regressions of the carry returns on global expected growth and the regressions on returns of individual buckets of currencies. Panels A and B are based on static carry trades, and panels B and C are based on dynamic carry trades. p1 indicates the portfolio of currencies with the lowest forward discount. p3 (or p5) indicates the portfolio with the largest forward discount, given the G10 currencies (or entire set of currencies). Statistical significance is calculated based on Newey-West standard errors.

4.2 Robustness

In order to provide evidence that global skewness is indeed a robust predictor, I consider a few variables known to have explanatory power for the foreign exchange market. The first variable I consider is the innovations to liquidity $\Delta\text{liquidity}_t$, where liquidity is proxied by the negative of the TED spread (LIBOR minus the 3-month Treasury Bill rate), retrieved from the FRED. The literature has documented that changes in liquidity can help predict subsequent carry trade returns as shown in Brunnermeier, Nagel, and Pedersen (2009) and Bakshi and Panayotov (2013).

Table 6 shows the results when next-quarter carry trade returns are regressed jointly on global skewness and the liquidity innovation. The predictive ability of the carry trade returns remains robust, when the liquidity channel is controlled for.

I also consider two other explanatory variables that are contemporaneous instead of lagged. I consider the innovations in foreign exchange volatility Δfxvol_{t+1}, in which foreign exchange volatility is defined as

$$\text{fxvol}_t = \frac{1}{9}\sum_{i=1}^{9}\sqrt{\sum_{\in \text{quarter } t}(\Delta s^{\text{daily}})^2} \tag{16}$$

for $i \in \{\text{G10 currencies}\}$. This variable is in line with Menkhoff, Sarno, Schmeling, and Schrimpf (2012) who find that the long-end of the carry trades tends to deliver low returns during periods of unexpected high global FX volatility. Following their argument, unexpected volatility proxy should be a contemporaneous variable instead of a predictor, namely that the timing of unexpected volatility Δfxvol_{t+1} is consistent with the timing of the carry trade returns cxr_{t+1}.

Another explanatory variable of interest is the growth rate of a commodity index called the Commodity Research Bureau BLS Spot Index, retrieved from Datastream. Despite the proposed relationship between commodity prices and foreign exchange rates, there is mixed evidence of whether commodity prices can predict future foreign exchange rates (Chen, Rogoff, and Rossi (2010)). I instead consider the contemporaneous innovation $\Delta\text{commod}_{t+1}$.

Table 6 shows that the predictive ability of global skewness remains robust with the inclusion of either explanatory variable. Notice that these contemporaneous variables increase the R^2 by a large extent. In addition, correlations among the covariates likely change the coefficient estimates.

Nonetheless, global skewness appears to be a statistically significant predictor of future carry trade returns.

A similar exercise for the carry based on the G10 currencies is reported in the Appendix (Table A8). The predictive power.yo5o87,2(glo87,)-294(sk)28(ew8(ergredictinew8(eraew8(erc)-1d)-214carolew8(er)-298

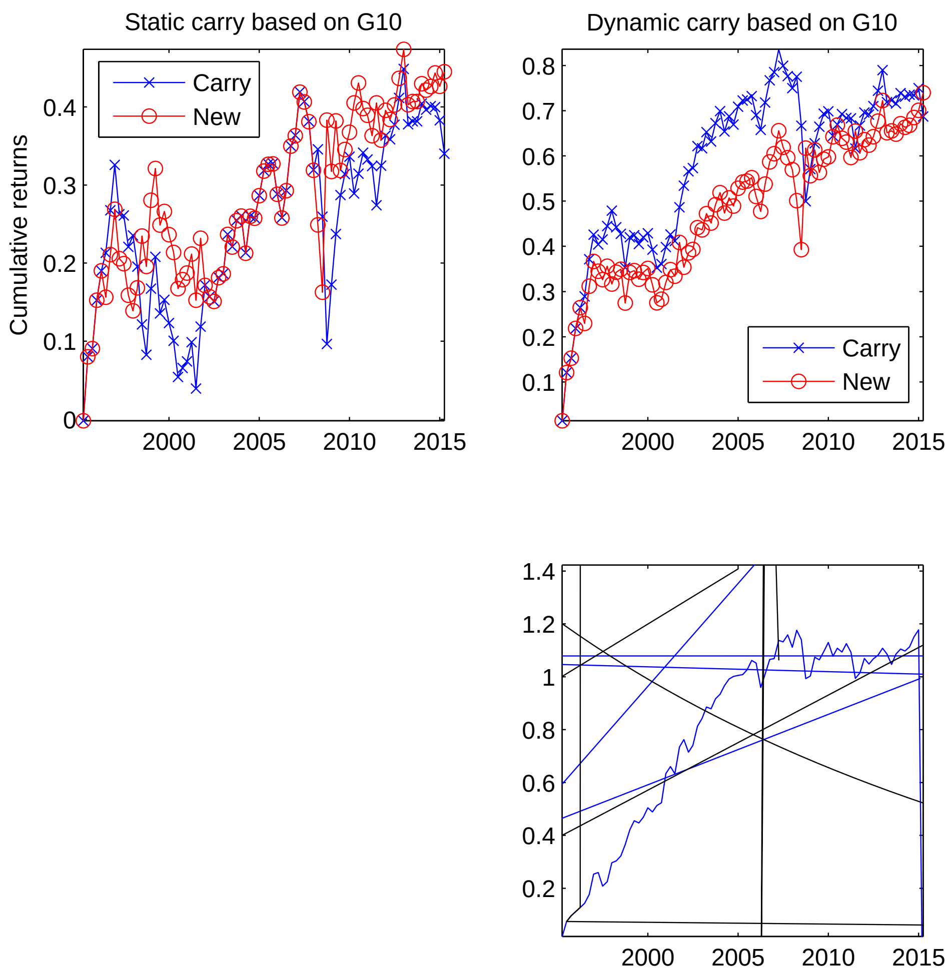

Figure 7: Comparison of cumulative returns to the ordinary carry and the new strategy. The new strategy involves implementing the carry, except when $\frac{sk_t^g}{\sqrt{\mathbb{V}[sk_t^g]}} > \bar{s}$, in which case we swap the long-short positions. Above are based on the threshold $\bar{s} =$

	Panel A: G10				Panel B: All currencies			
	Static		Dynamic		Static		Dynamic	
	Carry	New	Carry	New	Carry	New	Carry	New
Mean	0:0042	0:0055	0:0138	0:0176	0:0052	0:0157	0:0138	0:0176
Std.dev	0:0446	0:0477	0:0421	0:0439	0:0449	0:0459	0:0421	0:0439
Sharpe Ratio	0:0942	0:1152	0:3292	0:4006	0:1153	0:3418	0:3292	0:4006

Table 7: Comparison of the summary statistics of the ordinary carry returns and the new strategy returns. The new strategy involves implementing the carry, , except when $sk_t^g > \bar{s}$, in which case we swap the long-short positions. Above are based on the threshold $\bar{s} = \sqrt{\mathbb{V}[sk_t^g]}$. All values are quarterly and shown in decimals.

Figure 7 shows the comparison between the cumulative returns on the carry trade and the cumulative returns on the new strategy for a particular specification. One can visually see that the new strategy tends to deliver a more stable time-series of cumulative returns. Table 7 provides summary statistics of the comparison between the ordinary carry and the new strategy. We can see that the new strategy that conditions on the information on global skewness yields more attractive Sharpe ratios.

4.4 Consumption Growth Differential

Finally, I provide the following empirical evidence that connects our predictability pattern with the consumption implication of the model. Consider our static portfolio of taking long positions in Norwegian Krone, New Zealand Dollar and Australian Dollar and taking short positions in Swiss Franc, Japanese Yen and Deutsche Mark. Recall that based on our assumption of time-additive CRRA preference the stochastic discount factor can be written in terms of the consumption growth of the unbiased agent as: $\log(M) = \log \quad \Delta c$. Hence, any shock to a global risk factor must be reflected in the consumption growth of that agent. To relate to our portfolio, we can examine the consumption growth differential between two sets of of countries as in

$$\Delta c_{t+1}^{L} \quad \Delta c_{t+1}^{H} \tag{17}$$

$$(\Delta c_{t+1}^{\text{Switz.}} + \Delta c_{t+1}^{\text{Japan}} + \Delta c_{t+1}^{\text{Germany}}) \quad (\Delta c_{t+1}^{\text{Norway}} + \Delta c_{t+1}^{\text{New Zealand}} + \Delta c_{t+1}^{\text{Australia}}) \tag{18}$$

where the L- and H-countries denote the low-interest rate and high-interest rate countries, respectively. In order to justify that there is indeed heterogeneity in the exposure to global conditional skewness as it was in the model, I can regress my consumption growth differential onto the global conditional skewness measure.

intercept	0:0101*** (0.0021)	0:0238*** (0.0068)
sk_t^g	0:0048*** (0.0018)	0:0038** (0.0016)
div.yield		0:5845** (0.2675)
AdjR2	0.0507	0.0899

Table 8: Regression of the consumption growth differential of a portfolio of countries $\Delta c_{t+1}^L \quad \Delta c_{t+1}^H$ onto global conditional skewness sk_t^g. The L-countries include Switzerland, Japan and Germany, and the H-countries include Norway, New Zealand and Australia. The control variable div. yield is the dividend yield of Germany. Statistical significance in calculated based on Newey-West standard errors.

As shown in Table 8, the positive and statistically significant relationship suggests that when global conditional skewness declines, the consumption of the L-countries tends to be lower relative to that of the H-countries. In the case of global conditional skewness rising, the consumption growth of the L-countries tends to be higher than that of the H-countries. This documents that there is indeed heterogeneity in the exposure of a country's skewness to global skewness. Moreover, the pattern is consistent with the argument that the countries that usually belong to the short-leg of the carry trade (the L-countries) tend to be more exposed to global skewness compared to the countries that belong to the long-leg of the carry trade (the H-countries). Hence, the carry trade strategy of investing in the H-currencies and shorting the L-currencies is just like investing in the "foreign" currency and shorting the "home" currency in the model when global skewness drops negative. Moreover, as the model suggests, there will be a high risk premium for implementing this strategy arising from negative global skewness risk.

Hence, this empirical finding connects the predictability results to my earlier model, in which countries have differing exposures to the global skewness factor. These countries will then have different extent of (time-varying) skewness, which will generate the riskiness and the risk premium in the currency market as the model implies.

5 Conclusion

In this paper I construct global measures of macroeconomic risks, constructed from the cross-section of GDP forecasts, and find that they have predictive ability in explaining carry trade returns. I motivate the discussion by building a consumption-based asset pricing model with heterogeneous agents to highlight the role of the cross-sectional skewness in forecasts, which is the novel contribution of this paper. I empirically find that the measures of global expected growth and global skewness negatively predict carry trade returns, and especially global skewness appears to be a robust risk factor that can price a large set of currencies. Hence, I provide novel evidence that the carry risk premium is partially driven by the variation in global macroeconomic skewness risk.

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Appendix

0.02	0.0187	0.3	0.98	3

Table A1: Calibration of the model. and denote the mean and volatility of endowment shocks "$_i$ for good i 2 $fX; Y g$, and denotes correlation between them. denotes the subjective discount factor, and denotes the risk aversion parameter. Individual agents make subjective mean predictions $_i$ or $^*_i$ about the shock to the endowment good in their respective country. In the text I refer to (or *) as a metric that summarizes skewness in forecasts: $= (_1 + _3 \; 2 \; _2)=(_1 \; _3)$. The baseline, no-skewness case of $= 0$ corresponds to $(_1; _2; _3) = (0{:}0215; 0{:}02; 0{:}0185)$. The comparative statics of changing is done by adjusting $_1$ and $_3$ that hold the cross-sectional variance fixed to that of the baseline case.

					$_a$	$_a$
0.02	0.0187	0.3	0.98	3	0.5	1

Table A2: Calibration of the dynamic model. and denote the mean and volatility of endowment shocks $''_i$ for good $i\ 2\ fX; Yg$, and denotes correlation between them. denotes the subjective discount factor, and denotes the risk aversion parameter. The last two columns show the calibration of the time-series dynamics of skewness $a_t = \ _a a_{t-1} + \ _a ''_{a;t}$ with the mapping $_t = a_t = \mathrm{p}\overline{1 + a_t^2}$ to ensure that the variable of interest $_t$ is bounded between -1 and 1.

Individual agents make subjective mean predictions $_{i;t}$ or $^*_{i;t}$ about the shock to the endowment good in their respective country. I define $_t$ as a metric that summarizes skewness in forecasts: $_t = (\ _{1;t} + \ _{3;t} \quad 2 \ _{2;t}) = (\ _{1;t} \quad _{3;t})$. When skewness in forecasts $_t$ is equal to zero, the beliefs are calibrated as $(\ _{1;t}; \ _{2;t}; \ _{3;t}) = (0{:}03; 0{:}02; 0{:}01)$. Then changing $_t$ is done by adjusting $_{1;t}$ and $_{3;t}$ while holding the cross-sectional variance fixed to that of the zero-skewness case.

Country	Source	Sample	Notes
UK	Thomson Reuters	1995.Q1-2015.Q2	
Japan	Thomson Reuters	1995.Q1-2015.Q2	
New Zealand	Thomson Reuters	1995.Q1-2015.Q2	
Australia	Thomson Reuters	1995.Q1-2015.Q2	
Sweden	Thomson Reuters	1995.Q1-2015.Q2	
Switzerland	Thomson Reuters	1995.Q1-2015.Q2	
Norway	Thomson Reuters	1995.Q1-2015.Q2	
Canada	Thomson Reuters	1995.Q1-2015.Q2	
South Africa	Thomson Reuters	1995.Q1-2015.Q2	
Singapore	Thomson Reuters	1995.Q1-2015.Q2	
Denmark	Thomson Reuters	1995.Q1-1999.Q1	Danish krone almost pegged to Euro
Euro	Thomson Reuters	1999.Q1-2015.Q2	
Germany	WM/Reuters	1996.Q4-1999.Q1	Augment 1995.Q1-1996.Q3 use spot & 3-month rates for calc.
Greece	WM/Reuters	1996.Q4-1999.Q1	Augment 1995.Q1-1996.Q3 use spot & 3-month rates for calc.
Austria	WM/Reuters	1996.Q4-1997.Q4	Augment 1995.Q1-1996.Q3 use spot & 3-month rates for calc.; 1998- almost pegged to Deutsche Mark
Belgium	WM/Reuters	1996.Q4-1997.Q4	Augment 1995.Q1-1996.Q3 use spot & 3-month rates for calc.; 1998- almost pegged to Deutsche Mark
Finland	WM/Reuters	1996.Q4-1997.Q4	Augment 1995.Q1-1996.Q3 use spot & 3-month rates for calc.; 1998- almost pegged to Deutsche Mark
France	WM/Reuters	1996.Q4-1997.Q4	Augment 1995.Q1-1996.Q3 use spot & 3-month rates for calc.; 1998- almost pegged to Deutsche Mark
Italy	WM/Reuters	1996.Q4-1997.Q4	Augment 1995.Q1-1996.Q3 use spot & 3-month rates for calc.; 1998- almost pegged to Deutsche Mark
Netherlands	WM/Reuters	1996.Q4-1997.Q4	Augment 1995.Q1-1996.Q3 use spot & 3-month rates for calc.; 1998- almost pegged to Deutsche Mark
Portugal	WM/Reuters	1996.Q4-1997.Q4	Augment 1995.Q1-1996.Q3 use spot & 3-month rates for calc.; 1998- almost pegged to Deutsche Mark
Spain	WM/Reuters	1996.Q4-1997.Q4	Augment 1995.Q1-1996.Q3 use spot & 3-month rates for calc.; 1998- almost pegged to Deutsche Mark
Ireland	WM/Reuters	1996.Q4-1997.Q4	Augment 1995.Q1-1996.Q3 use spot & 3-month rates for calc.; 1998- almost pegged to Deutsche Mark
South Korea	WM/Reuters	2002.Q2-2015.Q2	
Czech Republic	WM/Reuters	1996.Q4-2015.Q2	
Hungary	WM/Reuters	1997.Q4-2015.Q2	
India	WM/Reuters	1997.Q4-2015.Q2	
Malaysia	WM/Reuters	1999.Q4-2015.Q2	Start 1999.Q4 because values are too volatile during the Asian crisis
Mexico	WM/Reuters	1996.Q4-2015.Q2	
Philippines	WM/Reuters	1996.Q4-2015.Q2	
Poland	WM/Reuters	1996.Q4-2015.Q2	
Taiwan	WM/Reuters	1996.Q4-2015.Q2	
Thailand	WM/Reuters	1996.Q4-2015.Q2	

Table A3: Details about foreign exchange rate data

Panel A

	carry trade returns: G10 currencies					carry trade returns: all currencies				
intercept	0:0059	0:0059	0:0059	0:0059	0:0059	0:0073*	0:0073**	0:0073**	0:0073**	0:0073**
	(0.0043)	(0.0043)	(0.0039)	(0.0038)	(0.0038)	(0.0037)	(0.0036)	(0.0030)	(0.0030)	(0.0030)
x_t^g	0:0046			0:0061***	0:0058**	0:0007			0:0015	0:0021
	(0.0028)			(0.0023)	(0.0029)	(0.0031)			(0.0029)	(0.0034)
v_t^g		0:0017			0:0007		0:0028			0:0015
		(0.0037)			(0.0040)		(0.0042)			(0.0044)
sk_t^g			0:0098***	0:0107***	0:0107***			0:0155***	0:0158***	0:0156***
			(0.0033)	(0.0032)	(0.0033)			(0.0045)	(0.0046)	(0.0046)
AdjR2	0:0005	0:0120	0:0524	0:0645	0:0515	0:0135	0:0085	0:1554	0:1452	0:1343

Panel B

	carry trade returns: G10 currencies					carry trade returns: all currencies		
intercept	0:0108**	0:0108**	0:0108**	0:0108**	0:0108**	0:0164***	0:0164***	0:0164***

1452,47((0. Tf 3.03 0 Td [(0108)]o.222 299.40

[(14 Tf -559 Td [( )]TJ(28 10.9091 Tf8[((0.0033))-3477(]0 d 009662978 w 0 0 m 643.083 0 l S Q BT /F8 10.9091 Tf 659.306 313.352 Td 33.98 T190.610 0 m 0 18.5

Panel A

	carry trade returns: G10 currencies					carry trade returns: all currencies				
intercept	0:0042	0:0042	0:0042	0:0042	0:0042	0:0052	0:0052	0:0052	0:0052	0:0052
	(0.0050)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0042)	(0.0043)	(0.0042)	(0.0043)	(0.0043)
x_t^g	0:0088***			0:0087***	0:0065	0:0020			0:0019	0:0010
	(0.0029)			(0.0026)	(0.0048)	(0.0043)			(0.0036)	(0.0042)
v_t^g		0:0083**			0:0036		0:0029			0:0015
		(0.0041)			(0.0052)		(0.0050)			(0.0056)
sk_t^g			0:0082*	0:0081**	0:0078**			0:0106**	0:0105**	0:0104**
			(0.0042)	(0.0039)	(0.0037)			(0.0042)	(0.0042)	(0.0041)
AdjR2	0:0271	0:0221	0:0216	0:0483	0:0400	0:0105	0:0084	0:0435	0:0331	0:0212

Panel B

	carry trade returns: G10 currencies					carry trade returns: all currencies				
intercept	0:0085	0:0085	0:0085	0:0085	0:0085	0:0138***	0:0138***	0:0138***	0:0138***	0:0138***
	(0.0054)	(0.0053)	(0.0053)	(0.0054)	(0.0054)	(0.0039)	(0.0040)	(0.0042)	(0.0040)	(0.0040)
x_t^g	0:0043			0:0042	0:0023	0:0024			0:0026	0:0022
	(0.0033)			(0.0032)	(0.0056)	(0.0036)			(0.0031)	(0.0038)
v_t^g		0:0049			0:0031		0:0013			0:0006
		(0.0040)			(0.0061)		(0.0041)			(0.0050)
sk_t^g			0:0048	0:0047*	0:0045			0:0083*	0:0083*	0:0083*
			(0.0029)	(0.0028)	(0.0027)			(0.0044)	(0.0044)	(0.0044)
AdjR2	0:0030	0:0002	0:0007	0:0041	0:0140	0:0092	0:0117	0:0265	0:0178	0:0052

Table A5: Regression next-quarter carry trade portfolio returns onto global measures, each of which is aggregated by taking the 1st principal component. The top panel is based on static carry trades, and the bottom panel is based on dynamic carry trades. The regressors $x_t^g; v_t^g; sk_t^g$ correspond to global expected growth, global uncertainty, and global skewness, respectively. Statistical significance is calculated based on Newey-West standard errors.

Panel A

	carry trade returns: G10 currencies					carry trade returns: all currencies				
intercept	0:0042 (0.0050)	0:0042 (0.0050)	0:0042 (0.0047)	0:0042 (0.0044)	0:0042 (0.0045)	0:0052 (0.0043)	0:0052 (0.0043)	0:0052 (0.0040)	0:0052 (0.0040)	0:0052 (0.0040)
x_t^g	0:0105** (0.0041)			0:0134*** (0.0042)	0:0113** (0.0044)	0:0059 (0.0044)			0:0091* (0.0054)	0:0090 (0.0056)
v_t^g		0:0083** (0.0035)			0:0038 (0.0043)		0:0032 (0.0045)			0:0001 (0.0044)
sk_t^g			0:0061 (0.0049)	0:0100* (0.0056)	0:0101* (0.0057)			0:0081* (0.0047)	0:0107* (0.0060)	0:0107* (0.0061)
AdjR2	0:0431	0:0222	0:0063	0:0783	0:0715	0:0050	0:0077	0:0203	0:0460	0:0336

Panel B

	carry trade returns: G10 currencies					carry trade returns: all currencies				
intercept	0:0085 (0.0052)	0:0085 (0.0054)	0:0085* (0.0051)	0:0085* (0.0046)	0:0085* (0.0046)	0:0138*** (0.0041)	0:0138*** (0.0040)	0:0138*** (0.0041)	0:0138*** (0.0040)	0:0138*** (0.0038)
x_t^g	0:0110*** (0.0034)			0:0144*** (0.0034)	0:0147*** (0.0046)	0:0049* (0.0029)			0:0069* (0.0036)	0:0098** (0.0040)
v_t^g		0:0055 (0.0036)			0:0006 (0.0047)		0:0011 (0.0040)			0:0053 (0.0042)
sk_t^g			0:0073* (0.0038)	0:0116*** (0.0043)	0:0116*** (0.0043)			0:0048 (0.0051)	0:0068 (0.0058)	0:0067 (0.0055)
AdjR2	0:0505	0:0031	0:0155	0:1030	0:0914	0:0013	0:0120	0:0004	0:0131	0:0117

Table A6: Regression next-quarter carry trade portfolio returns onto global measures, each which is aggregated by averaging with GDP weights. The top panel is based on static carry trades, and the bottom panel is based on dynamic carry trades. The regressors $x_t^g; v_t^g; sk_t^g$ correspond to global expected growth, global uncertainty, and global skewness, respectively. Statistical significance is calculated based on Newey-West standard errors

Panel A

	carry trade returns: G10 currencies		carry trade returns: all currencies	
intercept	0:0042 (0.0044)	0:0042 (0.0048)	0:0052 (0.0035)	0:0052 (0.0037)
x_t^g	0:0097*** (0.0023)		0:0037 (0.0035)	
$sk_t^{g;+}$	0:0110*** (0.0034)		0:0181*** (0.0051)	
$sk_t^{1=3} \quad v_t^{1=2}$		0:0048 (0.0046)		0:0142*** (0.0046)
AdjR2	0:0859	0:0011	0:1481	0:0883

Panel B

	carry trade returns: G10 currencies		carry trade returns: all currencies	
intercept	0:0085* (0.0049)	0:0085* (0.0051)	0:0138*** (0.0037)	0:0138*** (0.0035)
x_t^g	0:0066*** (0.0023)		0:0002 (0.0027)	
$sk_t^{g;+}$	0:0105*** (0.0037)		0:0127*** (0.0047)	
$sk_t^{1=3} \quad v_t^{1=2}$		0:0067 (0.0045)		0:0126*** (0.0036)
AdjR2	0:0553	0:0111	0:0676	0:0776

Table A7: Regression next-quarter carry trade portfolio returns onto alternative global measures. The top panel is based on static carry trades, and the bottom panel is based on dynamic carry trades. The regressor $sk_t^{g;+}$ corresponds the component of global skewness that is orthogonal (not explained by) global expected growth.

	Panel A: dynamic			Panel B: static		
intercept	0:0081*	0:0077*	0:0069	0:0039	0:0033	0:0027
	(0.0045)	(0.0045)	(0.0050)	(0.0042)	(0.0039)	(0.0043)
sk_t^g	0:0097***	0:0059	0:0048	0:0093***	0:0052	0:0046
	(0.0035)	(0.0044)	(0.0045)	(0.0034)	(0.0040)	(0.0045)
Δliqudity$_t$	4:0171***			3:5206**		
	(1.1048)			(1.5190)		
Δfxvol$_{t+1}$		1:3194*			1:5548**	
		(0.7062)			(0.6111)	
Δcommod$_{t+1}$			0:3081**			0:3028***
			(0.1208)			(0.1061)
AdjR2	0:1716	0:2242	0:1952	0:1291	0:2962	0:1818

Table A8: Regressions of carry trade returns onto global skewness and other explanatory variables. Above carry trades are formed based on G10 currencies. The left three columns are based on the dynamic carry, and the right three columns are based on the static carry. Δliquidity$_t$ is a lagged innovations to liquidity, defined as the minus of TED spread. Δfxvol$_{t+1}$ is a contemporaneous innovations to the foreign exchange volatility constructed from the G10 currencies. Δcommod$_{t+1}$ is a contemporaneous growth rate of the CRB BLS Spot Index.