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Abstract

There is a well-established literature that documents the failure of the uncovered interest parity (UIP) condition. While a host of factors have been examined as possible reasons behind this result, the role of uncertainty is not fully understood. In this paper, we examine the extent to which economic uncertainty affects the UIP condition in a sample of fourteen economies over the period 2003:1-2018:12. Using threshold panel regression models and exchange rate survey data, we find evidence that the UIP condition holds during low-uncertainty periods but does not during high-uncertainty periods. This finding is robust to the inclusion of other controls, different proxies of uncertainty, changes in the deposit maturity, and estimation method.

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Keywords: exchange rates; uncertainty; panel threshold models.

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1 Introduction

Over the past four decades, the validity of the uncovered interest parity (UIP) condition has been extensively examined, but with mostly unfavorable results. The UIP condition establishes that the expected returns in domestic currency of an asset denominated in both domestic currency and foreign currency must be equal.[1] Empirically, this condition has been examined by regressing the (expected) change in the bilateral exchange rate on the short-term deposit interest rate differential-the so-called Fama regression.[2,3] In this regression, the slope coefficient implied by the UIP condition is equal to one. Most empirical studies, however, report that the estimated slope coefficient is either negative or smaller than one (Froot and Thaler, 1990; Burnside et al., 2006, among others). This result implies that the expected returns across currencies do not equalize, as economies with a higher interest rate display a more appreciated exchange rate than that implied by the UIP condition. This finding has been labeled the UIP puzzle.[4]

Several factors have been identified as possible reasons for this puzzle. First, most empirical studies have examined the joint hypothesis of UIP and rational expectations (Chinn and Meredith, 2004; Bussière et al., 2018). It is only under this joint null hypothesis that the slope coefficient must be equal to one. A fundamental assumption behind the Fama regression is that the covered interest parity (CIP) condition holds. According to this condition, the return of a domestic asset and the return of a foreign asset expressed in domestic currency using the forward exchange rate must be equal.

A vast literature documents that CIP generally holds in the data until the Global Financial Crisis (GFC).[5] Since then, some studies have reported deviations from the CIP (Du et al., 2017; Cerutti et al., 2019). These deviations seem to reflect a combination of structural factors, such as post-crisis changes in financial regulation; and transitory

[1]Domestic and foreign assets must be comparable in terms of their maturity, default risk, taxes, etc.

[2]The exchange rate is the spot rate of the domestic currency in units of the foreign currency (typically the dollar) -thus an increase in the exchange rate means that the domestic currency has depreciated. The expected change in the spot exchange rate refers to the h-period change. The interest rate differential refers to the difference between the domestic currency deposit rate and foreign currency deposit rate, both with maturity of h-periods.

[3]Fama (1984) established a relationship between the expected exchange rate change and the difference between the forward value of the exchange rate and its spot rate. Several simplifying assumptions are then needed to transform this relationship into the UIP regression equation -including the holding of the covered interest rate parity, rational expectations, etc.

[4]Several studies have shown that this puzzle is more prevalent when using short-term (monthly, quarterly) data. When using long-term (5-years, 10-years) data, the estimated slope coefficients are positive and closer to one (Chinn and Meredith, 2004; Chinn and Quayyum, 2013).

[5]During this period there were small and transient departure episodes from CIP -see, for instance, Akram et al. (2008)- often associated with financial uncertainty and market turbulence. Despite these episodes it was safe to assume that CIP held before the GFC.

factors, such as divergent monetary policies across countries and the 2016 reform of the US prime money market fund (Cerutti et al., 2019). The implications of these CIP deviations on the UIP slope coefficient are, nevertheless, not well understood. Other studies have examined whether exchange rate expectations are rational -that is, whether exchange rate forecasts are unbiased. There is ample evidence to suggest the failure of the unbiasedness hypothesis (Meese and Rogoff, 1983; Froot and Thaler, 1990; Flood and Rose, 2002, among others) -since prediction errors are often negatively related to the interest differential so that estimated slopes are negative.[6]

Second, some studies have noted that the Fama regression equation may be omitting one or more important explanatory variables. If economic agents are risk-averse, then the Fama regression equation needs to include a time-varying risk premia term. The exclusion of such a variable in the Fama regression is likely to bias the slope coefficient downward. Part of the literature suggests that in the case of standard consumer preferences, with a risk aversion coefficient based on empirical studies, risk premiums might not vary sufficiently to generate a negative slope coefficient; thus, the relevance of this variable is downplayed (Engel, 1996).

More recent studies, however, have shown that by using non-standard preferences (Verdelhan, 2010; Lustig et al., 2011) or introducing disaster risk (Farhi and Gabaix, 2016) it is possible to arrive at a time-varying risk premia term that has the potential to explain the UIP puzzle. Other variables that could affect the time-varying risk premia term are capital controls, exchange rate regime, inflation rate, and terms of trade (Farhi and Werning, 2014). Nevertheless, these same studies are unable to match other essential characteristics of the data-such as the evolution of the real exchange rate (Engel, 2016).

Third, other studies have explored the presence of non-linearities in the Fama regression equation. The presence of non-linearities was initially justified as the result of transaction costs (Hollifield and Uppal, 1997) or limits on speculation (Sarno et al., 2006). The Fama equation is now modified by a smooth transition function that establishes how the deviations from UIP converge toward zero. The transition function is determined by the Sharpe ratio (Sarno et al., 2006), the forward premium (Baillie and Kilic, 2006), or other variables related to foreign exchange traders' opportunity costs. It is assumed that when these opportunity costs are high enough, traders carry out exchange transactions that make UIP possible. The introduction of disaster risk into the UIP condition could also be captured using non-linear regression models (Ismailov and Rossi, 2018). Finally, members of the regime-switching model family have been used to examine deviations from CIP -for instance, threshold autoregressive models have been used by Balke and Wohar (1998),

[6]This possibility has been modelled by Gourinchas and Tornell (2004).

and Peel and Taylor (2002).

This paper examines how macroeconomic uncertainty could affect the Fama regression equation. Uncertainty can affect this equation given its influence on aggregate saving and investment, financial and credit market conditions, and currency risk. Macroeconomic uncertainty can affect investment and saving, as greater uncertainty increases the real option value of postponing non-reversible investment (Bloom et al., 2018) as well as increasing precautionary saving. Uncertainty can also affect financial market liquidity as portfolio rebalances and funds move internationally. There is evidence that periods of heightened macroeconomic uncertainty are associated with lower asset trade volumes (Rehse et al., 2018) as well as higher bid-ask spreads. Moreover, higher uncertainty affects credit market conditions. Uncertainty hurts credit growth, and the severity of this effect depends on bank capitalization and liquidity conditions (Bordo et al., 2016). Lastly, increased uncertainty is associated with higher excess returns in currency carry trade operations (Husted et al., 2018; Berg and Mark, 2018). All these factors suggest that macroeconomic uncertainty is an important omitted variable that could affect the Fama regression equation in non-linear ways.

We postulate that macroeconomic uncertainty affects the Fama equation by splitting the sample following a threshold panel regression model. The adoption of this model reflects the fact that the regression coefficients in the Fama regression are not stable (Bussière et al., 2018) and that uncertainty is a threshold variable that endogenously splits the sample into two or more regimes. This is a parsimonious way of introducing uncertainty into the UIP analysis, which allows for differences in the slope and intercept parameters across regimes (Hansen, 2000).

Our econometric analysis utilizes survey-based exchange rate expectations and news-based measures of macroeconomic uncertainty. Survey expectations data has enjoyed an important resurgence in macroeconomics, in part reflecting difficulties with the rational expectation models. Previous work in open macroeconomics has documented that using survey-based exchange rate expectations serves to mitigate deviations from UIP (i.e., the slope coefficient is positive, closer to one, and statistically different from zero) for several economies (Chinn and Frankel, 2019). We use consensus forecast survey data on exchange rate expectations whose adequacy for the empirical work is documented in Stavrakeva and Tang (2015). The news-based measures of economic uncertainty have gained prominence in macroeconomics research in recent years, and we use the economic policy uncertainty index (Baker et al., 2016) because of its country coverage and its countercyclicality with crucial macroeconomic variables. Our database includes information for 14 economies over the period 2003:1-2018:12, and our baseline is the 3-month Fama regression.

This paper thus incorporates elements of the different factors identified as possible explanations of the UIP puzzle. First, by utilizing survey-based exchange rate expectations, it mitigates potential issues with the *ex-post* Fama regression literature. Second, by using a threshold panel regression model, it examines the possibility that uncertainty is an important omitted variable associated with time-varying risk premia that alters the Fama regression equation in non-linear ways.

We find that macroeconomic uncertainty is a threshold variable that splits the sample into two regimes -which we will call “low-uncertainty” and “high-uncertainty”. In the low-uncertainty regime, the slope coefficient of the Fama regression is not statistically different from one, which means that the UIP condition holds. In contrast, in the high-uncertainty regime, the slope coefficient is negative and statistically different from one, so the UIP condition does not hold. This means that carry trade is profitable; however, carry trade activity is likely to be limited by the liquidity and credit squeeze that often characterizes this regime. These results are robust to the inclusion of other controls and changes in term maturity, proxies of macroeconomic uncertainty, and estimation methods.

Our findings are related to those reported in Ismailov and Rossi (2018), the only other study we are aware of that examines the effects of uncertainty on UIP for five industrialized economies over the period 1993:11-2015:1. Their findings, based on single-country Fama regressions and new exchange-rate uncertainty index, also suggest that the UIP holds or that deviations from UIP are smaller in less uncertain environments. They distinguish between low uncertain and high uncertain environments, which they identify using *ad hoc* statistical rules applied to the exchange rate uncertainty index before conducting the regression analysis. Our work complements theirs, in that we use a more comprehensive dataset and a superior regression framework. We also rely on more widely used uncertainty measures and survey-based exchange rate expectations.[7] Moreover, we do not a priori impose the existence of two uncertainty regimes, as the number of these regimes is determined by the data. Lastly, we test whether the slope coefficient estimates of the Fama regressions in each regime are statistically different from one.

The remainder of this paper is organized as follows. In Section 2, we discuss the methodology and dataset we use in this study. In Section 3, we examine the Fama regression model using a panel threshold framework where macroeconomic uncertainty is the threshold variable. In Section 4, we discuss certain robustness exercises. Finally, in Section 5, we conclude with a summary of our findings.

[7] Ismailov and Rossi (2018) use an exchange rate uncertainty measure that is constructed by comparing the realized forecast error of the exchange rate with the unconditional forecast error distribution of the same variable. Their uncertainty measure, however, depends on the Fama regression model used to forecast exchange rates; for this reason they focus on an *ex-post* rather than *ex-ante* estimation.

2 Methodology and data

In this section, we briefly discuss our methodology and database. We postulate that macroeconomic uncertainty affects the Fama regression by separating the sample into two or more regimes. In particular, we embed the Fama equation within a panel threshold regression model, whereby macroeconomic uncertainty is the threshold variable that splits the sample. The dataset comprises monthly information for 14 countries over the period 2003:1-2018:12. The data comes from several sources, including Bloomberg, Datastream, Economic Policy Uncertainty, and Consensus Forecast.

2.1 The Fama equation

The uncovered interest parity condition states that the returns in local currency of an asset denominated in both local and foreign currency must be equal. Thus, the following should hold,

$$(1 + i_{h,t}) = (1 + i^*_{h,t})\frac{E_t S_{t+h}}{S_t}, \tag{1}$$

where $i_{h,t}$ and $i^*_{h,t}$ are the domestic and foreign interest rates for a fixed asset that matures in h periods. S_t is the spot exchange rate (domestic currency/foreign currency), E_t is the expectation conditional on information in period t and S_{t+h} is the spot exchange rate in $t+h$. Taking the logarithms to both sides of equation (1) and ignoring Jensen's inequality, we obtain the following linear equation, which is known as the Fama regression equation

$$E_t s_{t+h} - s_t = i_{h,t} - i^*_{h,t}, \tag{2}$$

where s_{t+h} is the spot exchange rate in logs in $t+h$.

To estimate the Fama regression equation, we need a proxy for exchange rate expectations. In the empirical literature, two such proxies have been used. The most common one is the *ex-post* exchange rate expectation. Proceeding this way, the null is a joint hypothesis of UIP and rational expectations. However, as noted earlier, there is ample evidence to suggest that rational expectations do not hold. This has prompted several researchers to use survey-based exchange rate expectations. For instance, Bussière et al. (2018), and Chinn and Frankel (2019) find that when using survey-based data, the deviations from UIP are much smaller than those resulting from *ex-post* expectations. In this paper, we utilize the survey-based exchange rate expectations obtained from the Consensus Forecast. There is evidence that this survey data does not follow mechanical rules associated with either the forward exchange rate or interest rate differentials (Stavrakeva and Tang, 2015).

The *ex-ante* Fama regression equation for a given country is now given by (Bussière et al., 2018)

$$\widehat{s}_{t+h} - s_t = \alpha + \beta(i_{h,t} - i^*_{h,t}) + e_{t+h}, \tag{3}$$

where $\widehat{s}_{t+h}$ is the survey-based exchange rate expectation and e_{t+h} is an error term. When the survey-based exchange rate expectations are not biased, i.e., they have mean zero, then e_{t+h} also has mean zero. From now on, we will assume that this is the case. When the intercept α is equal to zero, and the slope β is equal to 1, then the UIP hypothesis holds in the data. In more realistic settings, however, the intercept might be different from zero; for instance, when there are differentiated and time-invariant taxes to the domestic and foreign currency deposits, constant risk aversion, among other scenarios.

The *ex-ante* Fama panel regression equation is

$$\widehat{s}_{it+h} - s_{it} = \mu_i + \alpha + \beta(i_{h,it} - i^*_{h,it}) + e_{it+h}, \tag{4}$$

where the sub-index i refers to country i, $1 \leq i \leq n$, and μ_i is an unobserved country-specific effect which is assumed to be fixed. Equation (4) is a Fama panel regression model that allows us to capture common parameters and to control for country-unobservable characteristics persistent over time.

We focus on panel regression models for three main reasons. First, panel data regression models allow for more accurate inference of model parameters, since they usually contain more degrees of freedom and more sample variability than time-series data, thus improving the efficiency of econometric estimates (Hsiao, 2007) and the model of predictive performance (Mark, 2012).[8] Second, panel data regression models allow country-specific omitted variables to be controlled for. Those are variables that we cannot observe or measure, or which are available at a low frequency. Examples of such variable include financial market structures and differential taxation, among others. Third, macroeconomic models are inherently dynamic. With the panel regression model, we can rely on inter-individual differences to reduce the correlation between a given variable and its lags (Hsiao, 2007). Note that the Fama regression equation is not itself dynamic, as it does not include the dependent variable as a regressor.

2.2 The threshold Fama panel regression model

We initially postulate that macroeconomic uncertainty affects the *ex-ante* Fama panel regression by splitting the sample into two regimes. Thus, the resulting *ex-ante* threshold

[8] One important potential drawback of using panel data is the need to impose the same slope parameter for all countries, when these countries are very heterogenous.

Fama panel regression model is given by

$$\widehat{s}_{it+h} - s_{it} = \mu_i + (\alpha_1 + \beta_1(i_{h,it} - i^*_{h,it}))1(q_{it} \leq \gamma) + (\alpha_2 + \beta_2(i_{h,it} - i^*_{h,it}))1(q_{it} > \gamma) + e_{it+h}, \quad (5)$$

where q_{it} stands for macroeconomic uncertainty in country i and period t (threshold variable), γ is the threshold parameter which needs to be estimated along with the other parameters in the regression equation, and 1(.) is the indicator function, which takes on the value of 1 if the inequality inside the bracket is true, and 0 otherwise. In this model the marginal effect of interest rate differentials is given by

$$\frac{\partial(\widehat{s}_{it+h} - s_{it})}{\partial(i_{h,it} - i^*_{h,it})} = \begin{cases} \beta_1 & \text{if} \quad q_{it} < \gamma \\ \beta_2 & \text{if} \quad q_{it} \geq \gamma, \end{cases} \quad (6)$$

where β_1 could be different from β_2; that is, the slopes could differ across regimes.

The empirical analysis of these models involves three steps: estimation, inference, and testing. The estimation and inference theory for these models is developed in Hansen (2000). In particular, the latter develops a method to construct confidence intervals for the threshold parameter, γ, in a simple closed-form expression. Hansen (1999) extends these methods to a balanced panel data context. After estimating model (5), we need to test whether the threshold parameter is statistically significant, whether $\alpha_1 = \alpha_2$ and $\beta_1 = \beta_2$ which is the hypothesis of no threshold effect, and whether each $\beta = 1$, which is the hypothesis of UIP. We expect the deviations from UIP to be smaller in the low uncertainty regime, when $q_{it} < \gamma$, than in the high uncertainty regime, when $q_{it} \geq \gamma$. Next, we need to determine the number of uncertainty thresholds in this model. To this end, we perform a set of sequential tests -a test of no threshold against one threshold, a test of one threshold versus two thresholds, a test of two thresholds versus three thresholds, and so on. We can proceed this way because the regimes in this framework are observable *ex-post*.

Threshold regression models have been very popular in applied econometrics for many years now. Our interest in these models reflects our conviction that certain economic relationships are better characterized by non-linear specifications. In particular, the threshold regression models provide a versatile and straightforward framework to model the relationship between a threshold-dependent variable and another variable. The regression sample is split into two or more "regimes" based on the threshold value of an observed variable q_{it}, and the regression coefficients are allowed to differ across regions.

Our framework is more general than the one used by Ismailov and Rossi (2018). First, we apply the sample split jointly to the estimation of the Fama regression parameters, in contrast to the exogenous sample split following *ad hoc* rules that these authors perform.

Second, in our framework, the number of regimes in which the sample could be split might exceed two -as dictated by the sample. Third, we are using a panel regression with fixed effects, which in comparison with a country-specific regression model should deliver better results when the country sample is not that heterogenous. Lastly, we estimate an *ex-ante* Fama regression model as opposed to an *ex-post* Fama regression model.

Parameters estimation

The within transformation suggested by Hansen (1999) is given by

$$(\widehat{s}_{it+h} - s_{it})^{+} = (\alpha_1 - \alpha_2)1(q_{it} \leq \gamma)^{+} + \beta_1(i_{h,it} - i^{*}_{h,it})^{+} + \beta_2(i_{h,it} - i^{*}_{h,it})^{\pm} + e^{+}_{it+h}, \quad (7)$$

where $(\widehat{s}_{it+h} - s_{it})^{+} = \widehat{s}_{it+h} - s_{it} - T^{-1}\sum_{t=1}^{T}(\widehat{s}_{it+h} - s_{it})$, $1(q_{it} \leq \gamma)^{+} = 1(q_{it} \leq \gamma) - T^{-1}\sum_{t=1}^{T} 1(q_{it} \leq \gamma)$, $(i_{h,it} - i^{*}_{h,it})^{+} = (i_{h,it} - i^{*}_{h,it})1(q_{it} \leq \gamma) - T^{-1}\sum_{t=1}^{T}(i_{h,it} - i^{*}_{h,it})1(q_{it} \leq \gamma)$, $(i_{h,it} - i^{*}_{h,it})^{\pm} = (i_{h,it} - i^{*}_{h,it})1(q_{it} > \gamma) - T^{-1}\sum_{t=1}^{T}(i_{h,it} - i^{*}_{h,it})1(q_{it} > \gamma)$, and $e^{+}_{it+h} = e_{it+h} - T^{-1}\sum_{t=1}^{T} e_{it+h}$; note that this latter equation is simply the original threshold panel regression model (5) after removing individual-specific means.[9]

Next, let

$$X_i(\gamma) = \begin{bmatrix} 1(q_{i1} \leq \gamma)^{+} & (i_{h,i1} - i^{*}_{h,i1})^{+} & (i_{h,i1} - i^{*}_{h,i1})^{\pm} \\ 1(q_{i2} \leq \gamma)^{+} & (i_{h,i2} - i^{*}_{h,i2})^{+} & (i_{h,i2} - i^{*}_{h,i2})^{\pm} \\ \vdots & & \\ 1(q_{iT} \leq \gamma)^{+} & (i_{h,iT} - i^{*}_{h,iT})^{+} & (i_{h,iT} - i^{*}_{h,iT})^{\pm} \end{bmatrix};$$

$$Y_i = \begin{bmatrix} (\widehat{s}_{i1+h} - s_{i1})^{+} \\ (\widehat{s}_{i2+h} - s_{i2})^{+} \\ \vdots \\ (\widehat{s}_{iT+h} - s_{iT})^{+} \end{bmatrix}; \quad \text{and} \quad e^{+}_{i} = \begin{bmatrix} e^{+}_{i1+h} \\ e^{+}_{i2+h} \\ \vdots \\ e^{+}_{iT+h} \end{bmatrix};$$

be the stacked mean corrected data and error terms for a given country i. Then, the stacked data and errors for the panel data model (7) are given by

[9] Note that given the nature of the panel threshold model, α_1 and α_2 cannot be recovered directly. that is, because the within transformation produces $\alpha_1(1(q_{it} \leq \gamma) - T^{-1}\sum_{t=1}^{T} 1(q_{it} \leq \gamma)) + \alpha_2(1(q_{it} > \gamma) - T^{-1}\sum_{t=1}^{T} 1(q_{it} > \gamma)) = (\alpha_1 - \alpha_2)(1(q_{it} \leq \gamma) - T^{-1}\sum_{t=1}^{T} 1(q_{it} \leq \gamma))$, whereas we use the fact that $1(q_{it} > \gamma) = 1 - 1(q_{it} \leq \gamma)$.

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix}; X(\gamma) = \begin{bmatrix} X_1(\gamma) \\ X_2(\gamma) \\ \vdots \\ X_n(\gamma) \end{bmatrix}; \quad \text{and} \quad e = \begin{bmatrix} e_1^+ \\ e_2^+ \\ \vdots \\ e_n^+ \end{bmatrix}.$$

The estimation procedure involves several steps starting from a given γ, within the empirical support of the threshold variable -in our case the macroeconomic uncertainty variable. The coefficients $\alpha_1 - \alpha_2$, β_1, and β_2 can then be estimated using ordinary least squares, conditional on the given value for γ

$$\widehat{\theta}(\gamma) = (X(\gamma)'X(\gamma))^{-1}X(\gamma)'Y, \tag{8}$$

where $\theta = (\alpha_1 - \alpha_2, \beta_1, \beta_2)'$, and the regression residuals are given by

$$\widehat{e}(\gamma) = Y - X(\gamma)\widehat{\theta}(\gamma); \tag{9}$$

finally, the sum of squared errors to be minimized is

$$S(\gamma) = \widehat{e}(\gamma)'\widehat{e}(\gamma). \tag{10}$$

The minimization of this sum of squared errors is carried out using a grid search over the threshold variable space, as proposed by Hansen (2000). This involves constructing an evenly spaced grid on the empirical support of macroeconomic uncertainty, q_{it}, and minimizing the concentrated sum of squared errors (10). Finally, once $\widehat{\gamma}$ the optimal threshold parameter, is obtained, the slope coefficient estimates are $\widehat{\alpha}_1 - \widehat{\alpha}_2 = \widehat{\alpha}_1(\widehat{\gamma}) - \widehat{\alpha}_2(\widehat{\gamma})$, $\widehat{\beta}_1 = \widehat{\beta}_1(\widehat{\gamma})$, and $\widehat{\beta}_2 = \widehat{\beta}_2(\widehat{\gamma})$. It is important to note that other more conventional gradient algorithms are not applicable to this case as the criterion function (10) is generally not smooth.

Inference

When there is a threshold effect $(\alpha_1 \neq \alpha_2)$ or $(\beta_1 \neq \beta_2)$, then the threshold estimate $\widehat{\gamma}$ is a consistent estimator for γ_0 (the true value of γ), and it has an asymptotic distribution, which is nonstandard (Hansen, 2000). Thus, the best way to produce confidence intervals for the threshold parameter is to form the no rejection region using the likelihood ratio statistic for the test on $\widehat{\gamma}$ (Hansen, 2000). To test the null hypothesis H_0: $\gamma = \gamma_0$, the likelihood ratio test is to reject large values of $LR(\gamma_0)$ where

$$LR(\gamma) = nT\frac{S(\gamma) - S(\widehat{\gamma})}{S(\widehat{\gamma})}, \tag{11}$$

where $S(\gamma)$ is defined in (10), and nT is the sample size.

The LR test converges in distribution as $n \to \infty$, for a fixed T, to a random variable ξ with distribution function $P(\xi \leq z) = (1 - exp(-z/2))^2$. Furthermore, the distribution function ξ has the inverse

$$c(\rho) = -2ln(1 - \sqrt{1 - \rho}), \tag{12}$$

where ρ is the significance level. The "no-rejection region" for a confidence level $1 - \rho$ is the set of values of γ such that $LR(\gamma) \leq c(\alpha)$. This is found by plotting $LR(\gamma)$ against γ and drawing a flat line at $c(\alpha)$.

With regard to the estimates of the slope parameters, the panel threshold regression model conditional on a given threshold parameter is just a linear regression model. Therefore the asymptotic distribution of the estimates of the slope parameters converges to the traditional normal distribution as $n \to \infty$, for a fixed T.

Testing for threshold effects

It is critical to determine whether the threshold effect is statistically significant or not. The null hypothesis of no threshold effects in (4) can be represented by the linear constraint $H_0 : \alpha_1 = \alpha_2$ and $\beta_1 = \beta_2$. However, under the null hypothesis, H_0, the threshold γ is not identified, so classical tests have non-standard distributions. For this reason, Hansen (1999, 2000), suggest a bootstrap to simulate the asymptotic distribution of the likelihood ratio test for this model so that the p-values constructed from the bootstrap procedure are asymptotically valid.

Hence, under the null hypothesis of no threshold, the panel data model (4) is

$$\widehat{s}_{it+h} - s_{it} = \mu_i + \alpha_1 + \beta_1(i_{h,it} - i^*_{h,it}) + e_{it+h}, \tag{13}$$

where the parameter β_1 can be estimated using ordinary least squares (after making the within transformation), yielding estimate of $\widehat{\beta}_1$, and residuals $\widehat{e}$. Let $S_0 = \widehat{e}'\widehat{e}$ be the sum of squared residuals of the linear panel data model. In this case, the likelihood ratio test of H_0 is based on

$$F = nT\frac{S_0 - S(\widehat{\gamma})}{S(\widehat{\gamma})}; \tag{14}$$

moreover, the null hypothesis is rejected if the percentage of draws for which the simulated statistic exceeds the actual value is less than a given critical value.

2.3 Data

We collect data for a sample of advanced and emerging market economies. The country composition of this sample is determined by data availability. In particular, we are constrained by the availability of the macroeconomic uncertainty variable, which is a crucial variable in this project. Another constraint is the need for a balanced panel as the threshold model cannot yet be estimated for an unbalanced panel.

Our database comprises monthly information for fourteen countries or regions for the period 2003:1-2018:12. The list of countries includes Australia, Canada, Chile, China, Colombia, the European Union (which we treat as a country), Hong Kong, India, Japan, Korea, Mexico, Singapore, Sweden, and the United Kingdom. Our baseline regression requires information on the following variables: spot bilateral exchange rates, survey-based bilateral exchange rate forecasts, three-month deposit interest rates on domestic and foreign currencies, and domestic and foreign macroeconomic uncertainty. The database starts in 2003:01, as for some countries there is no macroeconomic uncertainty data available before this date.

The spot exchange rates and the three-month domestic and foreign currency deposit interest rates were obtained from Bloomberg and Datastream, the exchange rate forecasts from the Consensus Forecast, and the domestic and foreign uncertainties from the Economic Policy Uncertainty website. In all cases but Sweden, foreign currency refers to the US dollar. In the case of Sweden, foreign currency refers to the euro. This is because the anchor or reference currency for the countries in the sample is either the dollar or the euro (see, for instance, Ilzetzki et al., 2019). Table 1 reports summary statistics for each country, for averages across currencies, and the pooled data.

As in several UIP studies, we use the deposit interest rate in domestic currency since residents usually favor such deposits. One concern with these rates is that they can be affected by capital controls, regulations, and local taxes. However, with the advent of financial integration, these distortions have become less important. This is particularly true for the sample of countries and period included in this study. In other studies (see, for example, Bussière et al., 2018), offshore interest rates are utilized. Unfortunately, these interest rates are only available for a small number of countries and periods.

As noted earlier, in this study we focus on the *ex-ante* Fama regression model. We do so because we are using survey-based exchange rate expectations and, thus, we drop the assumption of rational expectations. Other papers that use survey-based exchange rate data include Bussière et al. (2018) and Chinn and Frankel (2019). The survey-based exchange rate expectations are obtained from Consensus Forecast. The consensus forecast in period t, for a given country and variable, is a simple average of the forecasts for that period provided by each participating forecaster. Each consensus forecast report is usually the result of the surveys of several international and local economists. Some of these economists represent global firms such as Goldman Sachs, JP Morgan, and HSBC or regional branches such as Citigroup Japan, while others are more country-specific, such as the University of Toronto in the case of Canada.

Table 1: Summary statistics

Variable	*Expected exchange rate change*				*Interest rate differentials*				*Economic uncertainty*			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Australia	5.3	10.7	-26.2	37.0	2.4	1.5	-0.8	5.1	102.4	61.2	25.7	337.0
Canada	1.4	6.7	-18.8	23.1	0.2	0.8	-1.5	2.2	162.2	91.2	40.4	449.6
Chile	2.3	10.7	-45.4	27.4	2.2	1.9	-0.4	6.5	99.6	43.1	31.6	282.8
China	-2.0	5.1	-13.6	13.6	1.8	2.4	-3.2	6.5	177.5	144.8	26.1	935.3
Colombia	5.7	14.4	-40.7	52.6	4.3	1.7	0.7	8.5	98.3	36.4	35.6	256.8
European Union	2.6	7.6	-14.7	21.7	-0.4	1.2	-3.2	2.1	156.4	68.0	47.7	433.3
Hong Kong	0.4	0.8	-1.3	2.6	-0.4	0.5	-2.1	0.2	134.5	65.9	31.5	425.4
India	-1.0	6.6	-23.5	14.3	5.4	2.5	0.4	10.6	94.0	52.1	24.9	283.7
Japan	0.2	10.4	-28.0	24.6	-1.5	1.6	-5.1	-0.1	103.7	32.9	48.4	236.8
Korea	-2.0	8.4	-39.0	24.7	1.8	1.5	-0.7	4.9	133.9	61.3	37.3	391.8
Mexico	0.2	11.0	-40.4	30.0	3.5	1.2	0.2	5.9	71.1	54.2	8.5	428.7
Singapore	-0.4	6.2	-14.7	20.3	-0.6	0.9	-3.4	0.6	122.7	56.9	47.9	351.3
Sweden	-5.4	5.2	-23.6	12.6	0.2	0.6	-0.6	1.9	91.9	19.4	53.7	156.7
United Kingdom	2.7	7.1	-16.9	22.3	0.6	1.2	-1.9	3.3	218.1	159.0	30.5	1141.8
Average	0.7	7.9	-24.8	23.4	1.4	1.4	-1.5	4.2	126.2	67.6	35.0	436.5
Pool	0.7	9.0	-45.4	52.6	1.4	2.5	-5.1	10.6	126.2	86.8	8.5	1141.8

Notes: Annualized values (percent). SD stands for standard deviation.

The consensus forecast has been widely used in many empirical studies; this survey data is found to be more precise than the random walk forecast and the forward rate forecast (Novotný and Raková, 2011) and that do not follow rules of thumb related to interest rate differentials or the forward exchange rate (Stavrakeva and Tang, 2015). Moreover, Batchelor (2001) finds that the Consensus Economics provide better forecasts -in terms of mean absolute error and root mean square error- than those provided by the Organization for Economic Co-operation and Development and International Monetary Fund.

Macroeconomic uncertainty is proxied by the news-based index of economic policy uncertainty (EPU). This index (Baker et al., 2016), originally developed for the United States, reflects newspaper reporting frequency of the following three items: (1) “economy” or “economic”; (2) “uncertain” or “uncertainty”; and (3) “deficit”, “Federal Reserve”, “legislation” or “White House”. The index was relatively low in the run-up to the Great Recession, with an average of 90 in the period 2003:1-2008:8, and remained relatively high during the recovery from this recession, with an average of 139 in the period 2008:9-2018:12. Similar indexes have been constructed for twenty-four countries around the world. Several of these countries, however, are members of the European Union. As mentioned, the EPU is available for some countries starting in 2003:1. Because of these considerations and other data problems in a few countries, we end up with a sample of fourteen countries for the period 2003:1-2018:12. We have chosen the EPU over other uncertainty indicators because of its coverage, timeliness, and popularity in empirical macroeconomics.

To assess the robustness of our main findings, we use information about capital controls, exchange rate regimes, inflation rates, and terms of trade. These variables are likely to affect the time-varying risk premium (Farhi and Werning, 2014) and, thus, the UIP in a framework with risk-averse agents. The capital controls information is obtained from Fernández et al. (2016). In particular, we use the overall restrictions index -which is an average of the overall inflow restrictions index and the overall outflow restrictions index. The values of the overall restrictions index are between 0 and 1, where 0 means that there are no capital inflow or outflow restrictions, and 1 means that there are many capital inflow and outflow restrictions.

Given that capital inflows or outflow restrictions are slow-moving variables, we have assumed that the monthly data is the same as the yearly. The exchange rate regime data is obtained from Ilzetzki et al. (2019). They use a two-step procedure to determine the de facto degree of exchange rate flexibility. First, they determine the anchor currency for each country with the help of algorithms based on exchange rate volatility. Second, they produce a measure of exchange rate flexibility using the information on the parallel exchange market or the unified exchange rate market. Then, they classify exchange rates based on the probability of the parallel (unified) exchange rate being outside a threshold within a five-year window, and provided that the inflation rate is not higher than 40 percent. We have used the fine measure of exchange rates with values between 0 to 15.

Inflation rates are calculated based on each country's consumer price index (CPI), obtained from the IMF's International Finance Statistics. For most countries, CPI data is collected with a monthly frequency, which allows us to calculate the twelve-month inflation rates.[10] Then, we use this information to construct the inflation differential of each country vis-à-vis its anchor country. Lastly, information on each country's commodity terms of trade is obtained from Gruss and Kebhaj (2019). They construct this database using the international price variation of up to forty-five commodities, which are rolling weighted using information on each country's commodity trade data. The data is monthly and covers the period 1980:1-2018:12.

[10]For Australia, we mensualize the quarterly data. For Hong Kong and Singapore we complement the CPI data with information from Hong Kong's Census and Statistics Department and Sigapore's Department of Statistics, respectively.

3 An empirical investigation of uncertainty and UIP

In this section, we discuss our main empirical findings on the relationship between economic uncertainty and the UIP. However, before doing so, we need to assess whether the key variables in the Fama regression equation are stationary or not, as this can affect the inference. We have a panel database with a much larger time dimension in relation to the number of countries (192 months for 14 countries). In Table 2, we show the most important unit-root tests developed in the unit-root and cointegration literature. In the case of the panel unit root tests, the evidence rejects the null hypothesis of a common unit root process. Moreover, in the individual unit root test, all but one of the tests suggest that these variables are stationary. These latter tests usually exhibit more power than the previous one as each variable is assumed to follow a unit root process under the null. On this basis we conclude that the key variables in the Fama regression equation are stationary.

Table 2: Panel unit-root tests (p-values)

Method	Expected exchange rate change	Observed exchange rate change	Interest rate differentials	Economic uncertainty
Null hypothesis: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.0000	0.0000	0.0005	0.0000
ADF - Fisher Chi-square	0.0000	0.0000	0.0003	0.0000
PP - Fisher Chi-square	0.0000	0.0000	0.3695	0.0000
Null hypothesis: Unit root (assumes common unit root process)				
Levin, Lin and Chu t-stat	0.0000	0.0504	0.0648	0.0000
Breitung t-stat	0.0000	0.0000	0.0000	0.4078

Note: The tests were performed with an intercept in the specification. For the optimal lag length selection, the Akaike information criterion was used.

In principle, macroeconomic uncertainty could arise from two important sources: domestic or foreign. Both kinds of uncertainties could potentially have different implications over the Fama regression equation. Although there are several possible combinations, in our baseline scenarios, we use domestic (Country EPU), foreign (Anchored EPU), and weighted average uncertainty. The weights for each country are chosen so as to minimize the sum of squared residuals of a country-threshold Fama regression model. We use two weighted averages. The first one (Weighted 1 EPU) uses the weights obtained from country regressions using data covering the period 2003:01-2018:12. The second one (Weighted 2 EPU) uses the weights obtained from country regressions using the largest possible span, as for some of the countries the data start before 2003.

3.1 Estimation with an imposed *ad hoc* threshold

We start by reporting the regression results, using an arbitrarily chosen macroeconomic uncertainty threshold. Table 3 shows, in particular, the results of splitting the regression sample into two uncertainty regimes: "high uncertainty", which corresponds to the top quartile of the macroeconomic uncertainty values; and "low uncertainty", which includes the rest of the observations (as in Ismailov and Rossi, 2018). We focus on the slope coefficient, as the intercept drops out after the within-transformation of the model.

The first column reports the results of estimating an *ex-ante* standard Fama regression equation where uncertainty does not play any role. Consistent with the previous literature (Chinn and Frankel, 2019), in this case, the slope coefficient is positive (0.47) but statistically different from one. Next, when we split the sample into high and low uncertainty regimes following the *ad hoc* rule above, we obtain the following results. In the "low uncertainty" regime, the estimates of the slope coefficient are positive and not significantly different from one, except when using the second uncertainty measure (Anchored EPU). In the "high uncertainty" regime, the estimate of the slope coefficient is negative and significantly different from one. These results are broadly in line with those reported in Ismailov and Rossi (2018).

Table 3: Panel data estimation with an imposed threshold

	Linear estimation	Threshold estimation			
		Country EPU	Anchored EPU	Weighted 1 EPU	Weighted 2 EPU
$\widehat{\beta}$	0.473**	-	-	-	-
	(0.166)				
$\widehat{\alpha}_1 - \widehat{\alpha}_2$	-	-0.020**	-0.010**	-0.017**	-0.012**
		(0.005)	(0.004)	(0.005)	(0.004)
Low uncertainty					
$\widehat{\beta}_1$	-	0.761	0.698*	0.767	0.834
		(0.174)	(0.169)	(0.172)	(0.171)
High uncertainty					
$\widehat{\beta}_2$	-	-0.425**	-0.226**	-0.494**	-0.463**
		(0.211)	(0.228)	(0.232)	(0.214)
Threshold	-	150.449	154.763	160.259	154.432
Observations	2674	2674	2674	2674	2674
Countries	14	14	14	14	14
Period	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12

Notes: Heteroscedasticity and autocorrelation consistent (HAC) standard errors are in parentheses, lag length is set to $T^{\frac{1}{4}}$. * and ** denote statistical significance at the 10 and 1 percent level, respectively, for the individual null hypotheses of an intercept equal to zero and a slope equal to 1. Weighted 1 and Weighted 2 are computed by minimizing the sum of squared residuals for each country in its own and the common samples, respectively.

However, these findings raise important questions. First, is it justified to split the sample into two *ad hoc* regimes? In other words, is the threshold Fama regression model superior to the Fama regression model? Second, is the optimal uncertainty threshold value that which splits the sample between the top uncertainty quartile and the rest, as in Ismailov and Rossi (2018)? Third, can the presence of more than two regimes be ruled out? In the next subsection, we discuss these questions.

3.2 Test for threshold effects

Are there macroeconomic uncertainty threshold effects in the Fama regression equation? To address this question, we need to test for the existence of a threshold effect in the panel Fama regression equation using the F test given in equation (14). This step typically involves estimating equation (5) and computing the residual sum of squares for the different uncertainty threshold. We conduct the test for the existence of uncertainty threshold effects using a sample of fourteen countries over the period 2003:01-2018:12. We use 1000 bootstrap replications to perform the threshold effect tests.

The results of the test for threshold effects are shown in Table 4. The null hypothesis of no threshold effect against a single threshold can be rejected in all cases at the five percent significance level, and in all but one case at the one percent significance level. For instance, the F test statistic for a single threshold when using the domestic (foreign) uncertainty as a threshold variable is 93.6 (81.9), with a bootstrap p-value of 0.005 (0.059). These results indicate that the test for an uncertainty threshold is highly significant regardless of the uncertainty proxy. Therefore, there is strong evidence that macroeconomic uncertainty affects the Fama equation by splitting the regression sample into two regimes. In addition, we perform tests for the existence of two or more threshold effects, which implies that the sample should be split into three or more uncertainty regimes. These tests, which are not reported here, suggest that there are no additional thresholds beyond the one we have reported.

3.3 Confidence interval of the threshold estimate

Next, we construct a confidence interval for the estimated uncertainty threshold. In particular, the point estimates of the threshold parameter and their asymptotic 90 and 99 percent confidence intervals are reported in Table 5 for the four uncertainty proxies. The two regimes separated by the threshold estimate are denoted as low and high uncertainty regimes, respectively. The asymptotic confidence intervals for the threshold parameter are tight, which indicates high precision in the estimation. Note that the threshold estimates and the corresponding confidence interval are much smaller than those obtained under the *ad hoc* rule (3), suggesting the unfitness of the later.

Additional information about the threshold estimates, and their confidence intervals,

Table 4: Tests for threshold effects

	Threshold estimate	Test F	Bootstrap p-value	Critical values
Country uncertainty as a threshold variable	115.930	93.595	0.005	41.612 $^{1/}$ 51.488 $^{2/}$ 83.160 $^{3/}$
Anchored uncertainty as a threshold variable	84.549	81.900	0.059	66.877 $^{1/}$ 85.630 $^{2/}$ 139.543 $^{3/}$
Weighted 1 uncertainty as a threshold variable	114.316	107.603	0.005	44.846 $^{1/}$ 55.869 $^{2/}$ 89.473 $^{3/}$
Weighted 2 uncertainty as a threshold variable	114.676	117.249	0.004	44.604 $^{1/}$ 57.902 $^{2/}$ 97.645 $^{3/}$

Note: 1/, 2/ and 3/ critical values at 10%, 5% and 1%, respectively. We used 1000 bootstrap replications for the test.

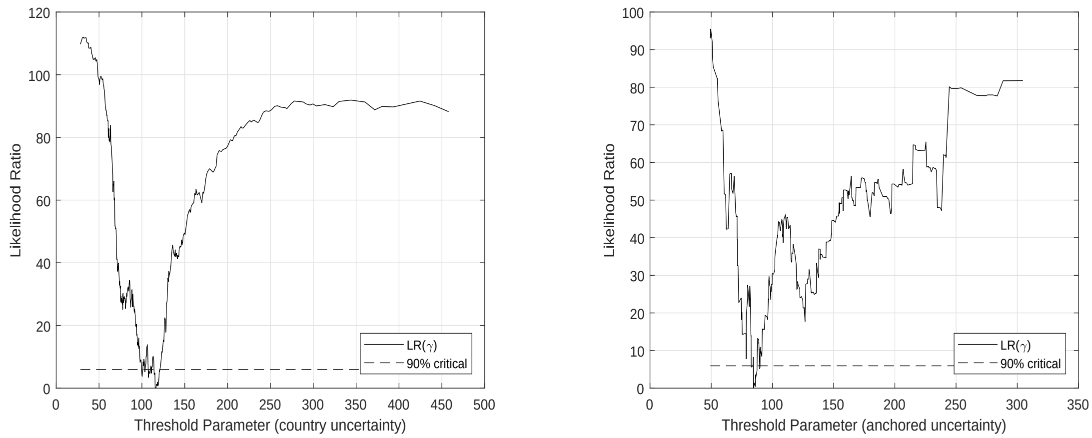
Table 5: Asymptotic confidence interval in threshold model

Threshold variable	Threshold estimate	90% confidence interval	99% confidence interval
Country uncertainty	115.930	[99.657 ; 120.577]	[97.584 ; 122.661]
Anchored uncertainty	84.549	[82.686 ; 89.915]	[78.506 ; 91.438]
Weighted 1 uncertainty	114.316	[75.486 ; 129.419]	[75.184 ; 129.938]
Weighted 2 uncertainty	114.676	[114.676 ; 128.112]	[113.014 ; 128.563]

is provided in Figure 1. We obtain the two panels by plotting the concentrated likelihood ratio function $LR(\gamma)$ of the threshold parameter when using the domestic and foreign uncertainty proxies, respectively. The function is minimized at zero when the estimated thresholds are $\widehat{\gamma} = 115.9$ and $\widehat{\gamma} = 84.6$. We obtain similar results when using the weighted uncertainty measures. The estimation precision is high because the 90 percent confidence interval, the set of values below the dotted line in Figure 1, is rather small across the threshold parameter space. None of the 90 percent confidence intervals include the *ad hoc* threshold obtained from using the procedure in Ismailov and Rossi (2018).

Figure 1: Confidence interval construction for threshold

(a) Estimation with country uncertainty (b) Estimation with anchored uncertainty



3.4 Slope estimation results

In the panel threshold Fama regression model, the slope coefficients in the two uncertainty regimes should be different. Table 6 reports the estimates of the slope coefficient for the low uncertainty and high uncertainty regimes. In the low uncertainty regime, the estimate of the slope coefficient is not significantly different from one at the one percent level in all but the foreign uncertainty proxy scenario. In contrast, in the high uncertainty regime, the estimate of the slope coefficient is negative (except for the foreign uncertainty proxy) and significantly different from one in all cases. This finding confirms our a priori belief that the deviations from UIP tend to be more severe in more uncertain regimes.

The results also suggest that macroeconomic uncertainty in the anchoring country does not seem as important as domestic uncertainty. First, there is evidence of a strong threshold effect (significant at the one percent level) when using the domestic and weighted average proxies of macroeconomic uncertainty. The evidence is weaker when using the foreign uncertainty proxy, whereby the threshold effect is significant at the 10 percent level. Second, the estimates of the slope parameters suggest different conclusions when using the domestic and weighted average proxies of macroeconomic uncertainty vis-à-vis the foreign one. In the first case, there is acceptance of the UIP condition; in the latter, it is rejected.

The point estimates of the slope coefficient in the threshold regression models are higher and closer to one than those observed using the *ad hoc* threshold model. Why would domestic uncertainty be more important than foreign uncertainty? In principle, there are no good theoretical reasons why this should be so. It seems that in the panel, survey-based exchange rate forecast and interest rate differentials are more reactive to

Table 6: Panel data estimation with an estimated threshold

	Linear estimation	Threshold estimation			
		Country EPU	Anchored EPU	Weighted 1 EPU	Weighted 2 EPU
$\widehat{\beta}$	0.473**	-	-	-	-
	(0.166)				
$\widehat{\alpha}_1 - \widehat{\alpha}_2$	-	-0.021**	-0.023**	-0.018**	-0.016**
		(0.005)	(0.005)	(0.004)	(0.004)
Low uncertainty					
$\widehat{\beta}_1$	-	1.031	1.501*	1.128	1.134
		(0.175)	(0.267)	(0.177)	(0.174)
High uncertainty					
$\widehat{\beta}_2$	-	-0.390**	0.009**	-0.297**	-0.337**
		(0.185)	(0.178)	(0.184)	(0.182)
Threshold estimate	-	115.930	84.549	114.316	114.676
99% confidence interval	-	[97.6 , 122.7]	[78.5 , 91.4]	[75.2 , 129.9]	[113.0 , 128.6]
Test for threshold effects	-	0.005	0.059	0.005	0.004
Observations	2674	2674	2674	2674	2674
Countries	14	14	14	14	14
Period	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12

Notes: Heteroscedasticity and autocorrelation consistent (HAC) standard errors are in parentheses, lag length is set to $T^{\frac{1}{4}}$. The test for threshold effects shows the probability value for the null hypothesis of $\widehat{\alpha}_1 = \widehat{\alpha}_2$ and $\widehat{\beta}_1 = \widehat{\beta}_2$; we used 1000 bootstrap replications for the test. * and ** denote statistical significance at the 10 and 1 percent level, respectively, for the individual null hypotheses of an intercept equal to zero and a slope equal to 1.

changes in domestic uncertainty than in foreign ones, as the latter is common to virtually all the countries in the sample.

The evidence also suggests that the panel threshold Fama regression model is preferred to the panel Fama regression one. In all cases, the null hypothesis of a Fama linear model is rejected in favor of the threshold regression Fama model with two regimes, whereby the slope estimates in each regime are statistically different from each other. It is worth noting that the difference in constant estimates is significantly different from zero; as mentioned earlier, a non-zero constant is usually related to the presence of differentiated taxes, constant exchange risk premium, among other variables.

3.5 Importance of high and low uncertainty regimes

These findings beg the following questions: what fraction of the observations belong to each uncertainty regime? Which countries are more susceptible to experiencing a high uncertainty regime? Table 7 provides information that addresses these questions for the different proxies of macroeconomic uncertainty. First, for the domestic and weighted average uncertainty proxies, the model establishes that between 40.8 and 50 percent of the observations in the sample belong to the high uncertainty regime. This fraction is much higher than the 25 percent assumed in Ismailov and Rossi (2018). The foreign uncertainty proxy, in contrast, suggests that 80 percent of the sample correspond to the high uncertainty regime.

Second, in terms of the individual countries, we note that more than 60 percent of the observations for Canada, the European Union, and the United Kingdom are in the high uncertainty regime. In contrast, more than 60 percent of the observations for Chile and India are in the low uncertainty regime. These results are consistent since most of the observations pertain to the post-Great Recession period, as we will discuss. As noted earlier, there is evidence of important deviations of the CIP during this period.

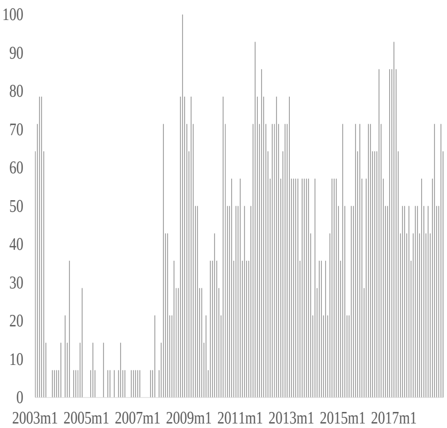
Table 7: Percentage of observations in each regime by country

Variable	*Country uncertainty*		*Anchored uncertainty*		*Weighted 1 uncertainty*		*Weighted 2 uncertainty*	
	Low	High	Low	High	Low	High	Low	High
Australia	70.8	29.2	20.3	79.7	54.2	45.8	64.6	35.4
Canada	37.0	63.0	20.3	79.7	43.8	56.3	42.2	57.8
Chile	72.4	27.6	20.3	79.7	69.3	30.7	70.8	29.2
China	46.4	53.6	20.3	79.7	45.8	54.2	45.8	54.2
Colombia	72.9	27.1	20.3	79.7	62.0	38.0	53.1	46.9
European Union	32.3	67.7	20.3	79.7	30.7	69.3	37.0	63.0
Hong Kong	44.8	55.2	20.3	79.7	44.8	55.2	45.8	54.2
India	72.9	27.1	20.3	79.7	71.4	28.6	71.9	28.1
Japan	68.8	31.3	20.3	79.7	62.0	38.0	57.3	42.7
Korea	45.3	54.7	20.3	79.7	43.8	56.3	44.8	55.2
Mexico	91.7	8.3	20.3	79.7	59.4	40.6	67.7	32.3
Singapore	54.2	45.8	20.3	79.7	53.1	46.9	53.1	46.9
Sweden	90.6	9.4	15.6	84.4	30.7	69.3	30.7	69.3
United Kingdom	29.2	70.8	20.3	79.7	28.6	71.4	53.1	46.9
Full sample	59.2	40.8	20.0	80.0	50.0	50.0	52.7	47.3

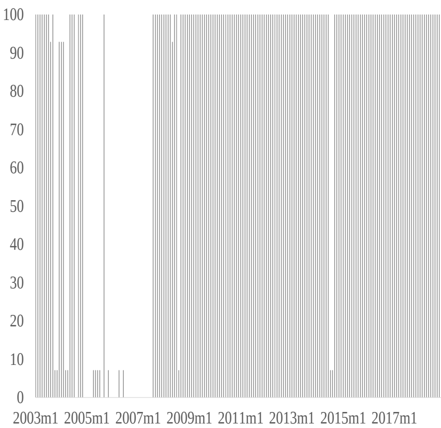
What is the time pattern of these uncertainty regimes? Figure 2 shows the evolution over time of the fraction of countries in the high uncertainty regime. We focus on the cases where we use the domestic and weighted uncertainty proxies. The charts suggest that the low uncertainty regime is mostly concentrated in the period of the run-up to the Great Recession, except for a short bout of uncertainty in 2003, which is consistent with the literature on the great moderation. The high uncertainty regime is, in contrast, concentrated in the period around and following the Great Recession. This is certainly the case of Canada, the European Union, and the United Kingdom. The post-Great Recession period, however, does not show a uniform pattern-as months of high uncertainty are followed by months of low uncertainty. Bussière et al. (2018), also report a break in their Fama regression results, starting with the great financial crisis. However, they do not link this break to uncertainty since they use a linear model.

Figure 2: Percentage of contries in a high uncertainty regime over time

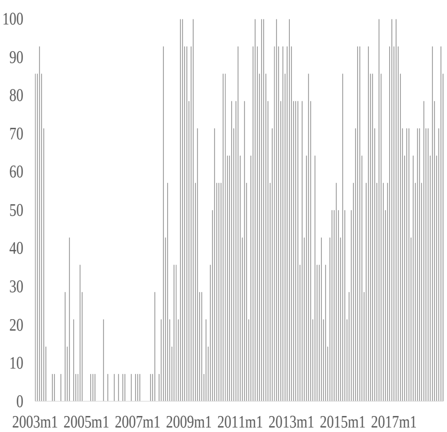
(a) Country uncertainty



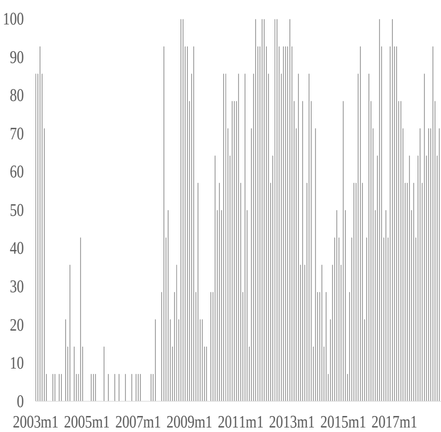
(b) Anchored uncertainty



(a) Weighted 1 uncertainty



(b) Weighted 1 uncertainty



4 Robustness

In this section, we examine the robustness of our main findings to the inclusion of additional controls, and to changes in the maturity of the asset and the estimation method.

4.1 Adding additional control variables

As noted earlier, some argue that the failure of UIP might be due to the omission of certain regressors that could be related to the risk premium. In this section, we examine five of these variables: macroeconomic uncertainty, capital controls, exchange rate flexibility, inflation differentials, terms of trade, and global common factors.

In addition to using macroeconomic uncertainty as a threshold variable, we include uncertainty as an additional regressor. This will allow us to assess whether uncertainty has a significant effect on the expected change in the nominal exchange rate beyond its effect as a threshold variable. Bussière et al. (2018) include the VIX as an additional regressor to explore this possibility. Table 8 reports the main results of this exercise. The estimate of the uncertainty parameter is positive and statistically significant (different from zero), albeit numerically unimportant, in the relevant cases. Moreover, the slope estimates of UIP are closer to 1 than our benchmark estimates reported in Table 6. This suggests that uncertainty affects the Fama regression model mainly through its effect as a threshold variable.

Table 8: Panel data estimation with uncertainty as a regressor

	Linear estimation	Threshold estimation			
		Country EPU	Anchored EPU	Weighted 1 EPU	Weighted 2 EPU
Uncertainty/1000	0.041*	0.048*	-0.152*	0.057**	0.023
	(0.024)	(0.027)	(0.055)	(0.031)	(0.045)
$\widehat{\beta}$	0.445**	-	-	-	-
	(0.165)	-	-	-	-
$\widehat{\alpha}_1 - \widehat{\alpha}_2$	-	-0.015**	-0.035**	-0.011*	-0.014**
		(0.006)	(0.006)	(0.006)	(0.006)
Low uncertainty					
$\widehat{\beta}_1$	-	1.026	1.432*	1.056	1.125
		(0.175)	(0.252)	(0.172)	(0.175)
High uncertainty					
$\widehat{\beta}_2$	-	-0.376**	0.007**	-0.403**	-0.345**
		(0.185)	(0.176)	(0.190)	(0.182)
Threshold estimate	-	115.930	85.969	128.525	114.676
99% confidence interval	-	[100.4 , 122.7]	[84.5 , 96.4]	[75.5 , 129.9]	[113.0 , 129.9]
Test for threshold effects	-	0.002	0.054	0.001	0.002
Observations	2674	2674	2674	2674	2674
Countries	14	14	14	14	14
Period	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12

Notes: Heteroscedasticity and autocorrelation consistent (HAC) standard errors are in parentheses, lag length is set to $T^{\frac{1}{4}}$. The test for threshold effects shows the probability value for the null hypothesis of $\widehat{\alpha}_1 = \widehat{\alpha}_2$ and $\widehat{\beta}_1 = \widehat{\beta}_2$; we used 1000 bootstrap replications for the test. * and ** denote statistical significance at the 10 and 1 percent level, respectively, for the individual null hypotheses of an intercept equal to zero and a slope equal to 1. The linear estimation includes the own country uncertainty; the others uncertainty measures give pretty similar results. For the additional control, the null is that its coefficient estimate is equal to zero.

Next, we include capital controls as an additional regressor in the Fama equation. Capital controls have been used by countries, regardless of their exchange rate regimes, to mitigate the exchange rate effects of a sudden stop or a capital inflow surge. Farhi and Werning (2014) show that this policy makes sense even in the economies with flexible exchange rate regimes, as optimal capital controls take the form of temporary taxes when there are outflows and subsidies when there are inflows -thus helping mitigate the effect on the nominal exchange rate. When we include the proxy of international capital control restrictions developed by Fernández et al. (2016) as a regressor, we find evidence that these controls tend to appreciate the domestic currency. This effect is statistically significant (different from zero; Table 9). Despite this, the importance of macroeconomic uncertainty as a threshold variable remains unchanged from our baseline regression.

Table 9: Panel data estimation with capital control indicator as a regressor

	Linear estimation	Threshold estimation			
		Country EPU	Anchored EPU	Weighted 1 EPU	Weighted 2 EPU
Capital control	-0.105**	-0.119**	-0.113**	-0.116**	-0.116**
	(0.027)	(0.027)	(0.027)	(0.028)	(0.028)
$\widehat{\beta}$	0.523**	-	-	-	-
	(0.164)	-	-	-	-
$\widehat{\alpha}_1 - \widehat{\alpha}_2$	-	-0.022**	-0.026**	-0.018**	-0.017**
		(0.005)	(0.005)	(0.004)	(0.004)
Low uncertainty					
$\widehat{\beta}_1$	-	1.101	1.465*	1.138	1.201
		(0.173)	(0.249)	(0.171)	(0.173)
High uncertainty					
$\widehat{\beta}_2$	-	-0.365**	0.025**	-0.383**	-0.300**
		(0.182)	(0.176)	(0.188)	(0.180)
Threshold estimate	-	115.930	85.969	128.525	114.676
99% confidence interval	-	[100.0 , 122.7]	[78.5 , 91.4]	[114.3 , 129.9]	[113.0 , 129.9]
Test for threshold effects	-	0.003	0.086	0.001	0.003
Observations	2674	2674	2674	2674	2674
Countries	14	14	14	14	14
Period	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12

Notes: Heteroscedasticity and autocorrelation consistent (HAC) standard errors are in parentheses, lag length is set to $T^{\frac{1}{4}}$. The test for threshold effects shows the probability value for the null hypothesis of $\widehat{\alpha}_1 = \widehat{\alpha}_2$ and $\widehat{\beta}_1 = \widehat{\beta}_2$; we used 1000 bootstrap replications for the test. * and ** denote statistical significance at the 10 and 1 percent level, respectively, for the individual null hypotheses of an intercept equal to zero and a slope equal to 1. For the additional control, the null is that its coefficient estimate is equal to zero.

How sensitive is the evolution of the nominal exchange rate to differences in the nominal exchange rate regime and inflation? A significant proportion of the literature suggests that countries with flexible exchange rate regimes should have exchange rates that are more depreciated than in countries with fixed exchange rates. To explore this possibility, we include the de facto exchange rate regime proxy constructed by Ilzetzki et al. (2019). Table 10 shows that, as predicted by the theory, there is a positive and statistically significant association between the exchange rate regime and the expected change in nominal exchange rate in all but one of the uncertainty proxies. This suggests that more flexible exchange rate regimes tend to be associated with more depreciated exchange rates.

Some authors argue that inflation is another variable that could be affecting the omitted risk premium. To explore this possibility, we include the inflation differential as another regressor in the Fama equation and find that this variable is not statistically significant (different from zero; Table 11). In these exercises, Macroeconomic uncertainty remains a robust threshold variable, and the threshold regression model is not the result of a misspecified linear regression as some might argue.

Table 10: Panel data estimation with exchange rate flexibility as a regressor

	Linear estimation	Threshold estimation			
		Country EPU	Anchored EPU	Weighted 1 EPU	Weighted 2 EPU
Exchange rate flexibility	0.003*	0.004*	0.003*	0.003**	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\widehat{\beta}$	0.462**	-	-	-	-
	(0.167)	-	-	-	-
$\widehat{\alpha}_1 - \widehat{\alpha}_2$	-	-0.020**	-0.022**	-0.016*	-0.015**
		(0.005)	(0.005)	(0.005)	(0.005)
Low uncertainty					
$\widehat{\beta}_1$	-	1.028	1.509*	1.067	1.131
		(0.175)	(0.268)	(0.173)	(0.175)
High uncertainty					
$\widehat{\beta}_2$	-	-0.402**	0.009**	-0.415**	-0.338**
		(0.185)	(0.178)	(0.190)	(0.182)
Threshold estimate	-	115.930	85.549	128.525	114.676
99% confidence interval	-	[100.4 , 122.7]	[75.3 , 91.4]	[75.5 , 129.9]	[113.0 , 129.9]
Test for threshold effects	-	0.001	0.055	0.004	0.003
Observations	2674	2674	2674	2674	2674
Countries	14	14	14	14	14
Period	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12

Notes: Heteroscedasticity and autocorrelation consistent (HAC) standard errors are in parentheses, lag length is set to $T^{\frac{1}{4}}$. The test for threshold effects shows the probability value for the null hypothesis of $\widehat{\alpha}_1 = \widehat{\alpha}_2$ and $\widehat{\beta}_1 = \widehat{\beta}_2$; we used 1000 bootstrap replications for the test. * and ** denote statistical significance at the 10 and 1 percent level, respectively, for the individual null hypotheses of an intercept equal to zero and a slope equal to 1. For the additional control, the null is that its coefficient estimate is equal to zero.

Another variable that has been associated with the evolution of the nominal exchange rates is commodity terms of trade. According to this literature, favorable commodity prices tend to be associated with more appreciated exchange rates. To examine this possibility, we include as a regressor the annual percentage change of commodity terms of trade for each country (Gruss and Kebhaj, 2019). As reported in Table 12, there is a negative and statistically significant association between the change of commodity terms of trade and the expected change in the nominal exchange rate. Perhaps more importantly, the status of macroeconomic uncertainty as a threshold variable does not change.

Including all these additional controls in the Fama regression equation delivers similar results to those discussed. The only notable change is that the inflation differential is now statistically significant, but the de facto exchange rate regime is not (see Table 13). Macroeconomic uncertainty remains a robust threshold variable.

There are other variables that we could have left out of the threshold regression model- for instance, the presence of global factors such as the Great Recession, the evolution of international oil prices, global financial conditions, etc. Controlling for such variables

Table 11: Panel data estimation with inflation differential as a regressor

	Linear estimation	Threshold estimation			
		Country EPU	Anchored EPU	Weighted 1 EPU	Weighted 2 EPU
Inflation differentials	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\widehat{\beta}$	0.522**	-	-	-	-
	(0.170)	-	-	-	-
$\widehat{\alpha}_1 - \widehat{\alpha}_2$	-	-0.021**	-0.024**	-0.018*	-0.017**
		(0.005)	(0.005)	(0.004)	(0.001)
Low uncertainty					
$\widehat{\beta}_1$	-	1.059	1.548*	1.096	1.174
		(0.182)	(0.268)	(0.179)	(0.181)
High uncertainty					
$\widehat{\beta}_2$	-	-0.357**	0.062**	-0.389**	-0.297**
		(0.187)	(0.178)	(0.193)	(0.184)
Threshold estimate	-	115.931	84.549	128.525	114.676
99% confidence interval	-	[100.0 , 122.7]	[78.5 , 91.4]	[75.5 , 129.9]	[113.0 , 129.9]
Test for threshold effects	-	0.005	0.068	0.005	0.001
Observations	2674	2674	2674	2674	2674
Countries	14	14	14	14	14
Period	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12

Notes: Heteroscedasticity and autocorrelation consistent (HAC) standard errors are in parentheses, lag length is set to $T^{\frac{1}{4}}$. The test for threshold effects shows the probability value for the null hypothesis of $\widehat{\alpha}_1 = \widehat{\alpha}_2$ and $\widehat{\beta}_1 = \widehat{\beta}_2$; we used 1000 bootstrap replications for the test. * and ** denote statistical significance at the 10 and 1 percent level, respectively, for the individual null hypotheses of an intercept equal to zero and a slope equal to 1. For the additional control, the null is that its coefficient estimate is equal to zero.

is desirable, but because there are no good proxy measures available, to achieve this we include a time-fixed effects variable, which is common to all countries in the sample. In Table 14, we report the results of including such a variable. While there is still evidence of a threshold effect, the estimate of the slope parameter in the low uncertainty regime is now statistically different from one for two of the uncertainty proxies.

4.2 Estimation with one-year forecast horizon

What happens if the Fama regression model is estimated using twelve-month deposits instead of three-month deposits? To address this question, we utilize one-year survey-based exchange rate expectations obtained from Consensus Forecast and twelve-month interest rates on domestic and foreign exchange deposits.[11] Table 15 reports the main findings of this exercise. Similar to our baseline scenario, there is evidence of an uncertainty threshold effect in the Fama regression model. The slope coefficients are closer to one in the low uncertainty regime than in the high uncertainty one. However, the estimates are

[11]For certain months, we had to complete the interest rates obtained from Bloomberg and the central banks using the SHIBOR for China, and the three-month domestic interest rate for China, Mexico and India.

Table 12: Panel data estimation with terms of trade as a regressor

	Linear estimation	Threshold estimation			
		Country EPU	Anchored EPU	Weighted 1 EPU	Weighted 2 EPU
Terms of trade	-0.276*	-0.264*	-0.266*	-0.258**	-0.267*
	(0.059)	(0.057)	(0.057)	(0.057)	(0.057)
$\widehat{\beta}$	0.414**	-	-	-	-
	(0.167)	-	-	-	-
$\widehat{\alpha}_1 - \widehat{\alpha}_2$	-	-0.019**	-0.021**	-0.016*	-0.015*
		(0.005)	(0.005)	(0.004)	(0.004)
Low uncertainty					
$\widehat{\beta}_1$	-	0.974	1.452*	1.010	1.075
		(0.176)	(0.267)	(0.174)	(0.175)
High uncertainty					
$\widehat{\beta}_2$	-	-0.425**	-0.033**	-0.445**	-0.379**
		(0.184)	(0.177)	(0.189)	(0.181)
Threshold estimate	-	115.930	84.549	128.525	114.676
99% confidence interval	-	[100.0 , 122.2]	[75.3 , 91.4]	[75.5 , 129.9]	[113.0 , 129.9]
Test for threshold effects	-	0.002	0.084	0.003	0.002
Observations	2674	2674	2674	2674	2674
Countries	14	14	14	14	14
Period	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12

Notes: Heteroscedasticity and autocorrelation consistent (HAC) standard errors are in parentheses, lag length is set to $T^{\frac{1}{4}}$. The test for threshold effects shows the probability value for the null hypothesis of $\widehat{\alpha}_1 = \widehat{\alpha}_2$ and $\widehat{\beta}_1 = \widehat{\beta}_2$; we used 1000 bootstrap replications for the test. * and ** denote statistical significance at the 10 and 1 percent level, respectively, for the individual null hypotheses of an intercept equal to zero and a slope equal to 1. For the additional control, the null is that its coefficient estimate is equal to zero.

statistically different from one in both uncertainty regimes, thus suggesting that the UIP condition does not hold even in the low uncertainty regime. The low uncertainty results are similar to those reported in Lee (2011).

4.3 Maximum likelihood estimation

Are our main findings robust to the estimation method? Ramírez-Rondán (2019) proposes a maximum likelihood (ML) approach to estimate a dynamic panel threshold model. Although the model we are dealing with is not strictly dynamic, this is a particular case of the family of models that can be estimated with the ML method. In order to eliminate the country-level fixed effect, we take the first difference in equation (5). This results in

$$\Delta(\widehat{s}_{it+h}-s_{it}) = (\alpha_1-\alpha_2)\Delta 1(q_{it}\leq\gamma)+\beta_1\Delta(i_{h,it}-i_{h,it})^{+}+\beta_2\Delta(i_{h,it}-i_{h,it})^{\pm}+\Delta e_{it+h}, \quad (15)$$

where $\Delta(\widehat{s}_{it+h}-s_{it}) = (\widehat{s}_{it+h}-s_{it})-(\widehat{s}_{it-1+h}-s_{it-1})$, $\Delta 1(q_{it}\leq\gamma) = 1(q_{it}\leq\gamma)-1(q_{it-1}\leq\gamma)$; $\Delta(i_{h,it}-i_{h,it})^{+} = (i_{h,it}-i_{h,it})1(q_{it}\leq\gamma)-(i_{h,it-1}-i_{h,it-1})1(q_{it-1}\leq\gamma)$; $\Delta(i_{h,it}-i_{h,it})^{\pm} =$

Table 13: Panel data estimation with controls as regressors

	Linear estimation	Threshold estimation			
		Country EPU	Anchored EPU	Weighted 1 EPU	Weighted 2 EPU
Capital controls	-0.100**	-0.112**	-0.107**	-0.112**	-0.108**
	(0.028)	(0.028)	(0.028)	(0.029)	(0.029)
Uncertainty	0.045*	0.047*	-0.149*	0.065*	0.012
	(0.024)	(0.026)	(0.056)	(0.031)	(0.044)
Terms of trade	-0.295**	-0.279**	-0.274**	-0.274**	-0.283**
	(0.060)	(0.058)	(0.059)	(0.058)	(0.058)
Inflation differentials	-0.002	-0.002*	-0.003**	-0.002*	-0.002*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Exchange rate flexibility	0.001	0.001	0.002	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\widehat{\beta}$	0.523**	-	-	-	-
	(0.166)	-	-	-	-
$\widehat{\alpha}_1 - \widehat{\alpha}_2$	-	-0.016**	-0.035**	-0.010*	-0.015*
		(0.006)	(0.006)	(0.005)	(0.006)
Low uncertainty					
$\widehat{\beta}_1$	-	1.089	1.528*	1.112	1.205
		(0.179)	(0.252)	(0.177)	(0.180)
High uncertainty					
$\widehat{\beta}_2$	-	-0.325**	0.091**	-0.330**	-0.275**
		(0.180)	(0.172)	(0.187)	(0.179)
Threshold estimate	-	115.930	85.969	127.938	114.676
99% confidence interval	-	[107.5 , 121.8]	[84.5 , 96.4]	[114.3 , 129.9]	[113.0 , 129.9]
Test for threshold effects	-	0.000	0.021	0.001	0.001
Observations	2674	2674	2674	2674	2674
Countries	14	14	14	14	14
Period	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12

Notes: Heteroscedasticity and autocorrelation consistent (HAC) standard errors are in parentheses, lag length is set to $T^{\frac{1}{4}}$. The test for threshold effects shows the probability value for the null hypothesis of $\widehat{\alpha}_1 = \widehat{\alpha}_2$ and $\widehat{\beta}_1 = \widehat{\beta}_2$; we used 1000 bootstrap replications for the test. * and ** denote statistical significance at the 10 and 1 percent level, respectively, for the individual null hypotheses of an intercept equal to zero and a slope equal to 1. The linear estimation includes the own country uncertainty; the others uncertainty measures give pretty similar results. For the additional controls, the null is that each coefficient estimate is equal to zero.

$(i_{h,it} - i_{h,it})1(q_{it} > \gamma) - (i_{h,it-1} - i_{h,it-1})1(q_{it-1} > \gamma)$; and $\Delta e_{it+h} = e_{it+h} - e_{it-1+h}$.[12]

Let the stacked data and errors for a country be noted as

$$X_i(\gamma) = \begin{bmatrix} \Delta 1(q_{i1} \leq \gamma) & \Delta(i_{h,i1} - i^*_{h,i1})^+ & \Delta(i_{h,i1} - i^*_{h,i1})^\pm \\ \vdots & \vdots & \vdots \\ \Delta 1(q_{iT} \leq \gamma) & \Delta(i_{h,iT} - i^*_{h,iT})^+ & \Delta(i_{h,iT} - i^*_{h,iT})^\pm \end{bmatrix};$$

[12]Note that given the nature of the panel threshold model, α_1 and α_2 cannot be recovered directly; that is, since the first difference produces $\alpha_1(1(q_{it} \leq \gamma) - 1(q_{it-1} \leq \gamma)) + \alpha_2(1(q_{it} > \gamma) - 1(q_{it-1} > \gamma)) = (\alpha_1 - \alpha_2)(1(q_{it} \leq \gamma) - 1(q_{it-1} \leq \gamma))$, where we use that fact that $1(q_{it} > \gamma) = 1 - 1(q_{it} \leq \gamma)$.

Table 14: Panel data estimation with time fixed effects

	Linear estimation	Threshold estimation			
		Country EPU	Anchored EPU	Weighted 1 EPU	Weighted 2 EPU
$\widehat{\beta}$	0.579*	-	-	-	-
	(0.202)				
$\widehat{\alpha_1} - \widehat{\alpha_2}$	-	-0.028**	-0.032**	-0.021**	-0.023**
		(0.005)	(0.011)	(0.005)	(0.005)
Low uncertainty					
$\widehat{\beta}_1$	-	1.341	2.153**	1.392*	1.251
		(0.214)	(0.288)	(0.216)	(0.206)
Low uncertainty					
$\widehat{\beta}_2$	-	-0.174**	0.273**	-0.140**	-0.299**
		(0.197)	(0.192)	(0.201)	(0.207)
Time dummies	✓	✓	✓	✓	✓
Threshold estimate	-	118.667	84.549	120.337	128.112
99% confidence interval	-	[97.6 , 123.1]	[84.5 , 87.4]	[114.3 , 128.5]	[113.9 , 129.0]
Test for threshold effects	-	0.000	0.003	0.000	0.000
Observations	2674	2674	2674	2674	2674
Countries	14	14	14	14	14
Period	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12

Notes: Heteroscedasticity and autocorrelation consistent (HAC) standard errors are in parentheses, lag length is set to $T^{\frac{1}{4}}$. The test for threshold effects shows the probability value for the null hypothesis of $\widehat{\alpha}_1 = \widehat{\alpha}_2$ and $\widehat{\beta}_1 = \widehat{\beta}_2$; we used 1000 bootstrap replications for the test. * and ** denote statistical significance at the 10 and 1 percent level, respectively, for the individual null hypotheses of an intercept equal to zero and a slope equal to 1.

Table 15: Panel data estimation with one-year forecast horizon

	Linear estimation	Threshold estimation			
		Country EPU	Anchored EPU	Weighted 1 EPU	Weighted 2 EPU
$\widehat{\beta}$	0.338**	-	-	-	-
	(0.089)				
$\widehat{\alpha}_1 - \widehat{\alpha}_2$	-	-0.004*	-0.003	-0.002	-0.002
		(0.002)	(0.002)	(0.002)	(0.002)
Low uncertainty					
$\widehat{\beta}_1$	-	0.614**	0.737**	0.642**	0.635**
		(0.096)	(0.094)	(0.095)	(0.093)
High uncertainty					
$\widehat{\beta}_2$	-	-0.004**	0.123**	-0.021**	-0.073**
		(0.091)	(0.091)	(0.087)	(0.085)
Threshold estimate	-	117.796	91.438	127.938	128.563
99% confidence interval	-	[115.5 , 128.3]	[84.6 , 91.4]	[117.6 , 129.9]	[126.6 , 129.9]
Test for threshold effects	-	0.009	0.031	0.007	0.005
Observations	2674	2674	2674	2674	2674
Countries	14	14	14	14	14
Period	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12

Notes: Heteroscedasticity and autocorrelation consistent (HAC) standard errors are in parentheses, lag length is set to $T^{\frac{1}{4}}$. The test for threshold effects shows the probability value for the null hypothesis of $\widehat{\alpha}_1 = \widehat{\alpha}_2$ and $\widehat{\beta}_1 = \widehat{\beta}_2$; we used 1000 bootstrap replications for the test. * and ** denote statistical significance at the 10 and 1 percent level, respectively, for the individual null hypotheses of an intercept equal to zero and a slope equal to 1.

$$Y_i = \begin{bmatrix} \Delta(\widehat{s}_{i1+h} - s_{i1}) \\ \vdots \\ \Delta(\widehat{s}_{iT+h} - s_{iT}) \end{bmatrix}; \quad \text{and} \quad \Delta e_i = \begin{bmatrix} \Delta e_{i1+h} \\ \vdots \\ \Delta e_{iT+h} \end{bmatrix};$$

with this notation, the estimation procedure starts by fixing γ at any value in the empirical support of the threshold variable. Note that for any given γ, the maximum likelihood estimation (ML) is asymptotically equivalent to the minimum distance estimator $\sum_{i=1}^{n} \Delta e_i' \Omega^{-1} \Delta e_i$; where Ω is a matrix with values of twos and minus ones in the first and second main diagonals, respectively; and zeros otherwise.

Thus, after taking the first-order condition and by setting the partial derivative equal to zero, for any given γ, the slope coefficients $\alpha_1 - \alpha_2$, β_1, and β_2 can be obtained by

$$\widehat{\theta}(\gamma) = \Big(\sum_{i=1}^{n} X_i(\gamma)' \Omega^{-1} X_i(\gamma) \Big)^{-1} \Big(\sum_{i=1}^{n} X_i(\gamma)' \Omega^{-1} Y_i \Big), \tag{16}$$

where $\theta = (\alpha_1 - \alpha_2, \beta_1, \beta_2)'$, and then, the minimum distance estimator for a given threshold parameter γ is

$$\sum_{i=1}^{n} \Delta \widehat{e}_i(\gamma)' \Omega^{-1} \Delta \widehat{e}_i(\gamma). \tag{17}$$

where $\Delta \widehat{e}_i(\gamma) = Y_i - X_i(\gamma)\widehat{\theta}(\gamma)$.

The criterion function (17) is not smooth, since we previously estimated the threshold by using a grid search across the macroeconomic uncertainty space. Once $\widehat{\gamma}$ is obtained, the slope coefficient estimates are then obtained $\widehat{\alpha}_1 - \widehat{\alpha}_2 = \widehat{\alpha}_1(\widehat{\gamma}) - \widehat{\alpha}_2(\widehat{\gamma})$, $\widehat{\beta}_1 = \widehat{\beta}_1(\widehat{\gamma})$, and $\widehat{\beta}_2 = \widehat{\beta}_2(\widehat{\gamma})$. As regards the inference of the parameter estimates and testing for threshold effects, we follow the steps of the least-squares estimation of Hansen (1999).

In Table 16, we report the results of the minimum distance estimator, which are asymptotically equivalent to the maximum likelihood estimator. Overall, the main results are very similar to those reported in Table 6. Nevertheless, all slope estimates have slightly higher values. Thus, we confirm the presence of threshold effects, the failure of UIP in the high uncertainty regime, and the holding of the UIP in the low uncertainty regime.

5 Conclusion

In this paper, we study whether macroeconomic uncertainty can help explain the uncovered interest parity puzzle. We postulate that the link between macroeconomic uncertainty and the UIP could be usefully modeled using a panel threshold regression model, where macroeconomic uncertainty is the threshold variable. Using survey-based exchange rate expectations, we find that for a different measure of macroeconomic uncertainty, there is a statistically significant macroeconomic uncertainty threshold that splits the sample into two regimes: a low-uncertainty regime and a high-uncertainty regime, respectively.

Table 16: Maximum likelihood panel data estimation

	Linear estimation	Threshold estimation			
		Country EPU	Anchored EPU	Weighted 1 EPU	Weighted 2 EPU
$\widehat{\beta}$	0.488**	-	-	-	-
	(0.032)				
$\widehat{\alpha}_1 - \widehat{\alpha}_2$	-	-0.020**	-0.022**	-0.016**	-0.015**
		(0.004)	(0.002)	(0.003)	(0.004)
Low uncertainty					
$\widehat{\beta}_1$	-	1.048	1.517**	1.093	1.148*
		(0.074)	(0.140)	(0.080)	(0.075)
High uncertainty					
$\widehat{\beta}_2$	-	-0.357**	0.037**	-0.368**	-0.305**
		(0.101)	(0.062)	(0.095)	(0.104)
Threshold estimate	-	115.930	84.475	127.938	114.676
99% confidence interval	-	[100.0 , 122.7]	[75.1 , 91.4]	[75.5 , 129.6]	[113.0 , 130.0]
Test for threshold effects	-	0.000	0.002	0.001	0.000
Observations	2674	2674	2674	2674	2674
Countries	14	14	14	14	14
Period	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12	03m01-18m12

Notes: White standard errors are in parentheses. The test for threshold effects shows the probability value for the null hypothesis of $\widehat{\alpha}_1 = \widehat{\alpha}_2$ and $\widehat{\beta}_1 = \widehat{\beta}_2$; we used 1000 bootstrap replications for the test. * and ** denote statistical significance at the 10 and 1 percent level, respectively, for the individual null hypotheses of an intercept equal to zero and a slope equal to 1.

More importantly, our analysis finds the UIP condition holds in the low-uncertainty regime but does not in the high-uncertainty one.[13] The subtle effect of macroeconomic uncertainty on UIP suggests that both the linearity of the Fama regression model and the omission of macroeconomic uncertainty from this model might be at the core of the negative empirical results widely reported in the literature. Our findings are robust to the use of different uncertainty measures, the inclusion of other control variables, changes in the maturity of the deposits, and the estimation methods.

Why does UIP hold in a low-uncertainty regime but not in a high-uncertainty one? The theoretical literature is virtually silent on this, and our findings suggest that this can be a fruitful area for future research. There are indications that macroeconomic uncertainty can affect financial market liquidity, the volume of assets traded, and excess returns in currency asset operations. Moreover, macroeconomic uncertainty also seems to affect credit market conditions. All these factors justify including macroeconomic uncertainty in the Fama regression. We have found evidence that uncertainty is a robust threshold variable. This result should inspire future theoretical efforts in the field.

[13]These econometrics results hold on average but not necessarily continuously. This means that there can be episodes where UIP fails in a low-uncertainty regime and where UIP holds in a high-uncertainty.

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