Uncovered Equity Parity: New Evidence from a Copula Approach*

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Abstract

This paper finds novel evidence on the uncovered equity parity (UEP) condition by employing copula methodology with historical datasets spanning back to 1870. First, across 17 advanced countries over the 20th century, a higher equity return currency tends to depreciate in real terms at an annual frequency. Moreover, we also find a significant positive tail dependence between real equity returns differential and real exchange rate differential. That is, when real currency returns and real equity returns take extreme values, they tend to co-move in the same direction, implying a time-varying UEP condition that is also confirmed by our time-varying Student-t copula estimation. Our novel findings call for richer theoretical explanations on the UEP relationship.

JEL Classification: C32, C51, G11, G12, F21, F30
Keywords: Exchange Rate Determination, International Returns, Copulas, Tail Dependence, Dependence Structure

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1 Introduction

A recent international finance literature documents that foreign exchange rates are negatively correlated with relative stock market movements, also known as the uncovered equity parity condition (UEP), for example, see Hau and Rey (2006), Kim (2011), Curcuru *et al.* (2014), Jung (2017), and Djeutem and Dunbar (2018) among others. More specifically, the UEP argues that an increase in domestic equity returns relative to their counterparts is associated with home currency depreciation on average. This finding has important economic implications for understanding the nature of international risk sharing, capital flows, and the determination of foreign exchange rates.

Nevertheless, the UEP literature has been overlooked, mainly due to inconclusive empirical evidence and the lack of sound theories. For one thing, empirical evidence on the UEP is sparse and largely confined to relatively high-frequency data of a few advanced countries during the post-1990 period. Further, earlier empirical studies of the relationship between exchange rates and equity prices show mixed results (e.g., Branson 1983; Frankel 1983; Griffin *et al.* 2004). Theoretical attempts to explain such relationships have not reached a consensus either. Different models predict different correlations, for example, see Curcuru *et al.* (2014) and Jung (2017) for details.

We believe rigorous empirical reinvestigation based on more sample countries and a longer timespan can revive this important, yet incomplete literature. To that end, this paper empirically re-evaluates the relationship. Our empirical investigation is novel in two ways. First, our data set is larger in both cross-sectional and time dimensions. As opposed to existing studies, we employ a historical database recently constructed by Jorda *et al.* (2017). The database covers equity and currency returns both in nominal and real terms from 17 advanced countries since 1870 on an annual basis. This larger panel data set provides a more reliable testing ground for the UEP condition.

Second and more importantly, we employ a relatively new technique in investigating the relationship between currency and equity returns: copulas. The latter has been increasingly used in the finance literature to investigate correlations among financial variables. The literature has shown many benefits from employing copulas, for example, see Ning (2010) and Wang *et al.* (2013) among others. The followings are particular advantages of using copulas in our empirical investigation. First, most existing studies rely on linear correlation coefficients, for example, the Pearson correlation coefficients and/or ordinary least square estimates when estimating the relationship between currency and equity returns. This approach becomes problematic, especially when those two variables happen to take extreme values frequently; that is, the two variables follow fat-tailed distributions, particularly relevant for currency and equity returns. The reason is that linear correlation coefficients do not describe how these two variables are related during the period of extreme events, which usually draws much attention from academics and policymakers. Using copulas precisely allows us to get around this problem. It provides precise estimates of how the two variables co-move together during extreme events, *a.k.a.* the tail dependence in the literature. In addition, it also allows us to investigate whether the co-movements of the two variables during extreme events are symmetric or not, that is, whether they co-move only when they take positive (or negative) extreme values.

To reliably examine the correlations between currency and equity returns using copulas, we first construct real annual equity returns for 16 sample countries relative to the U.S. counterparts. We also construct real annual currency returns measured as an annual change in real currency value against the U.S. dollar for the 16 sample countries. Then, we specify marginal models for the two returns by using the ARMA-GARCH models with Student-t errors for the marginal distributions and the Student-t copula function for the joint model. In particular, the ARMA-GARCH model specification is used to obtain the marginal distribution of these two variables, and then they are used to examine the tail dependence by copula functions.

Through several tests based on the copula methodology, we first find the overall negative correlations between *relative* real annual currency returns and *relative* real annual equity returns; that is, the UEP condition prevails overall in our sample. These correlations also turn out to be statistically significant in most pairs. This particular finding is of vital importance because, to our best knowledge, it is the first evidence that the UEP relationship is relevant not just during the post-1990 period, but over the last century.

Another novel finding in this study is that there exists a significant positive tail dependence between the two returns for every single pair of countries in our sample. In other words, whenever these two returns take extreme values, they tend to occur simultaneously with similar signs. It also turns out that the tail dependence is symmetric for every single pair of sample countries, meaning the degree of co-movements between relative currency and relative equity returns does not vary across market downturns and upturns.

These new findings are important in many aspects. First, they imply the time-varying correlation between relative real currency returns and relative real equity returns in a sense that the correlation tends to be negative during tranquil times in which both returns take values close to their averages, but it becomes positive when the two returns deviate far from their means. This time-varying correlation pattern has been already theoretically predicted by Jung (2017). The idea is based on a long-run risk-type model with idiosyncratic volatilities. A relative increase in aggregate consumption uncertainty at home lowers domestic asset prices. At the same time, high aggregate consumption uncertainty acts like a negative supply shock, raising the value of domestic goods, and thus causing an appreciation of the domestic currency. However, this negative correlation between the two returns could change its sign when one country's idiosyncratic stock market volatility becomes relatively greater. The idea is that a higher idiosyncratic volatility in the home stock market increases home asset value, *a.k.a.* the Pastor and Veronesi (2006) effect, while it does not impact the aggregate domestic consumption. However, assuming a level of idiosyncratic stock market volatility is inversely related to aggregate consumption growth rate, a higher idiosyncratic volatility in home stock markets would bring about a home currency appreciation, potentially turning the correlation sign into positive.

To further test Jung (2017)'s hypothesis using copulas, we estimate time-varying correlation coefficients based on the time-varying Student-t copula approach. Then, we test the marginal effect of relative stock return volatility on the time-varying correlation coefficients by using linear regression analysis. We find concrete evidence that the UEP condition becomes weaker during more volatile periods. This finding supports the hypothesis of Jung (2017), because a less negative correlation (or even a positive correlation) is observed during the period of high economic uncertainty. One may concern that this result could be merely a spurious correlation. If large inflation surprises are not fully incorporated into nominal equity and currency prices in a synchronous manner, then, one could expect to obtain a spurious positive correlation between the real exchange rate and the real stock return differential. Moreover, periods of high stock market uncertainty may coincide with periods during which the link between inflation and stock/currency prices becomes weak. Thus, periods of high stock market volatility may just be those periods where the spurious positive correlation shows up most strongly. In order to address this issue, we also perform robustness check in two ways. First, we test whether the volatility of the inflation differential is statistically correlated with the time-varying correlation coefficient in a panel setup. Second, we also test whether the fixed exchange regime has any statistically significant effect on the time-varying correlation coefficient. Both tests confirm that our evidence is not driven by the spurious correlation.

Our novel findings have new implications for the UEP literature. The main mechanism behind the UEP hitherto proposed in the literature is based on portfolio rebalancing: when foreign equity markets outperform, domestic investors reshuffle their portfolio towards domestic stocks due to incomplete FX risk hedging, causing a home currency appreciation.[1] Our findings suggest that this may not be the only channel through which the UEP relationship emerges. If portfolio rebalancing was the only driving force behind the UEP, one would expect a stronger negative relationship between currency and equity returns in the event of a higher idiosyncratic stock market volatility, generally associated with higher FX risk hedging demand. However, our results show the exact opposite. Thus, our new evidence points to the possibility that a mechanism other than the portfolio rebalancing based on

[1] Curcuru *et al.* (2014) empirically show that this kind of investing behavior is asymmetric. They find that equity investors flow out of stock markets with relatively better performance, but they do not flow into markets with relatively poor performance.

incomplete FX risk hedging might be a major driving force for the UEP relationship. As Jung (2017) hinted, we believe further empirical and theoretical research on how the UEP is connected to various types of market uncertainties could be a new fruitful research avenue.

The rest of this paper is organized as follows. Section 2 summarizes the related literature. Section 3 introduces a copula function and our model specifications. Section 4 provides a description of the data and and discusses our estimation results. Finally, section 5 offers concluding remarks.

2 Literature Review

Our study is related to several lines of previous work. Most importantly, the relationship between relative real equity and currency returns has been most intensively documented in the UEP literature. Empirical papers in this line of research include Kim (2011), Melvin and Prins (2015), Curcuru *et al.* (2014), Griffin *et al.* (2004), Pavlova and Rigobon (2007), Chabot *et al.* (2014), and Cenedese *et al.* (2015). Although these studies show different dependence structures in the equity-currency pairs, they all share one commonality: linear correlation estimators have been employed for empirically evaluating the dependence structure. In addition, none of these studies document the time-varying nature of equity-currency correlations and how this time-varying property transpire. Our paper, to our best knowledge, is the first to document the time-varying dependence structure and how the latter is related to stock market volatilities. Jung (2017) is an exception worth noting. He documents that a negative relationship between real equity and real currency returns during normal times can become a positive relationship during times of relatively higher aggregate economic uncertainty. However, his evidence is based on OLS estimators. Our copula methodology corrects the drawbacks from linear correlation coefficients.

Theoretical attempts to account for either a positive or negative relationship between real equity and real currency returns have been made in the literature too (e.g., Hau and Rey 2006; Kim 2011; Melvin and Prins 2015; Jung and Pyun (2016); Geromichalos and Jung (2018); Camanho *et al.* (2019)). Among the theoretical models that predict the UEP, portfolio rebalancing acts as a main driver for the negative correlation between relative currency and equity returns. A higher rate of return on foreign equities relative to domestic ones poses a foreign exchange rate (FX) risk threat to domestic investors faced with incomplete FX risk hedging opportunities. Thus, they repatriate foreign equity holdings, thereby creating an upward price pressure upon the domestic currency, that is, home currency appreciation. Curcuru *et al.* (2014) empirically show and argue that portfolio rebalancing may be driven by factors other than FX risk exposure.

Meanwhile, other strands of literature also point to the possibility of a positive correlation (e.g., Griffin *et al.* 2004; Pavlova and Rigobon 2007; Chabot *et al.* 2014; Cenedese *et al.* 2015). For instance, based on the same portfolio balance idea, Pavlova and Rigobon (2007) argue that demand shocks could generate the positive correlation. The main idea is that a positive demand shock at home would improve the country's terms of trade due to a home bias assumption of domestic goods. Consequently, the domestic currency would appreciate, which in turn boost domestic stock values relative to foreign ones, eventually leading to the positive correlation. Martin (2013) also argues that the failure of UEP can arise within a two-country framework where two countries significantly differ in terms of country size. As mentioned earlier, our empirical results support none of these existing hypotheses but lend support for the hypothesis of Jung (2017) which states that idiosyncratic stock market volatility drives time-varying correlations of the real equity and currency returns.

This paper also relates to the broader copula literature on the dependence structure between the equity market and the FX market, for example, Ning (2010) and Wang *et al.* (2013) among others. Although this line of research is similar to our study, these studies do not focus on the *relative* currency returns. In estimating the dependence structure, they evaluate the dependence structure between local currency values against the U.S. dollar and the local country's own stock returns, not relative to the U.S. counterparts. In addition, we are the first to exploit time-varying copula estimates in the area of international finance. The time-varying copula approach is also frequently used in energy and financial markets, following the methodology of Patton (2006b). Examples include the studies for dynamic dependence between Brent crude oil price and stock markets in European countries (e.g., Aloui *et al.* 2013); between Chinese and international stock markets (e.g., Wang *et al.* 2011); between the BRIC countries and developed country equity markets (e.g., Kenourgios *et al.* 2011); and between Korea and Thailand stock market indices (e.g., Busetti and Harvey 2011).

3 Measuring dependence

3.1 Marginal distribution model

Our estimation is conducted based on two-step procedures. In the first step, we estimate the marginal distributions and standardized residuals of each variable in the first step; then, we estimate copula parameters using the estimated marginal models. Our return series are serially correlated with fluctuated volatilities; hence, this study adopts the autoregressive moving-average with generalized autoregressive conditional heteroscedasticity (ARMA-GARCH) model. The standard GARCH model introduced by Bollerslev (1986) allows not only the characterization of volatility clustering and time-varying volatility, but also the removal of serial dependence in our return series. In particular, the marginal model for our time series, r_t, can be specified as an ARMA(2,2)-GARCH (1,1) model in equation 1:

$$r_t = c + \phi_1 r_{t-1} + \phi_2 r_{t-2} + \psi_1 \varepsilon_{t-1} + \psi_2 \varepsilon_{t-2} + \varepsilon_t \tag{1}$$

$$\sigma_t^2 = \omega + Crisis_t + \alpha_r \varepsilon_{t-1}^2 + \beta_r \sigma_{t-1}^2, \tag{2}$$

where ϕ and ψ are the autoregressive (AR) and moving average (MA) parameters respectively. Note that the conditional variance σ_t^2 depends not only on past innovations, but also past conditional variances. Finally, the distribution of the error term ε_t is as follows:

$$\sqrt{\frac{\nu}{\sigma_t^2(\nu-2)}}\varepsilon_t \overset{\text{i.i.d.}}{\sim} t_v,$$

where t_ν is a Student-t distribution with degrees of freedom ν, and σ_t^2 evolves according to the specification in equation 2.

3.2 Copula

A linear correlation coefficient is one of the most frequently used methods to measure dependence. The statistic shows the average distance from the mean over marginal distributions. However, it is well known that the simple correlation measure has many theoretical flaws. According to Wang *et al.* (2013), first, the correlation coefficient is calculated based on a linear relationship between two random variables, and thus, it is not able to measure non-linear dependence. Second, the statistic is variant under strictly monotonic transformation, so the log transformation could lead us to obtain different correlation estimates when using two returns series in level. Lastly, it is unable to distinguish between dependence in bullish and bearish markets or for different sized market movements. As an alternative, recently, an analytical framework using copula has been considered in the financial economics and in practice.

The Sklar (1959)'s theorem indicates that the joint distribution of any two random variables, $G_{XY}(x, y)$, can be represented by a copula with marginal functions $G_X(x)$ and $G_Y(y)$ as follows:

$$G_{XY}(x, y) = C(G_X(x), G_Y(y)).$$

In particular, the unique copula function is a multivariate distribution function defined with uniform marginals U and V, such that $C(\varphi, \xi) = Pr[U \leq \varphi, V \leq \xi]$, where $\varphi = G_X(x)$ and $\xi = G_Y(y)$. The copula can extract dependence structure from marginal distributions and thus, the dependence is invariant under the monotonic transformation of the random variables. An advantage of the use of a copula is indeed to measure tail dependence, which indicates the propensity that two random variables are at the left and right tails of the joint distribution. As documented by Reboredo (2012), the dependence coefficients at the left (lower) and right (upper) tails can be represented by a copula as follows:

$$\lambda_L = \lim_{\varphi \to 0} \Pr[X \leq G_X^{-1}(\varphi) | Y \leq G_Y^{-1}(\varphi)] = \lim_{\varphi \to 0} \frac{C(\varphi, \varphi)}{\varphi} \quad (3)$$

$$\lambda_U = \lim_{\varphi \to 1} \Pr[X \geq G_X^{-1}(\varphi) | Y \geq G_Y^{-1}(\varphi)] = \lim_{\varphi \to 1} \frac{1 - 2\varphi + C(\varphi, \varphi)}{1 - \varphi} \quad (4)$$

where G_X^{-1} and G_Y^{-1} are the inverse marginal distributions (CDF) of the two random variables, X and Y. If $\lambda_U = \lambda_L > 0$, then symmetric tail dependence exists. Similarly, if $\lambda_U \neq \lambda_L > 0$, then asymmetric tail dependence exists. For a further discussion of a copula function, see Aloui *et al.* (2013).

In our empirical analysis, we employ the bivariate Student-t copula which is defined by:

$$C(\varphi, \xi | \rho, \nu) = \int_{-\infty}^{t_\nu^{-1}(\varphi)} \int_{-\infty}^{t_\nu^{-1}(\xi)} \frac{\Gamma((\nu+2)/2)/\Gamma(\nu/2)}{\nu\pi t(\tilde{x};\nu) t(\tilde{y};\nu)\sqrt{1-\rho^2}} \left(1 + \frac{\tilde{x}^2 + \tilde{y}^2 - 2\rho\tilde{x}\tilde{y}}{\nu(1-\rho^2)}\right)^{-\frac{\nu+2}{2}} dsdt \quad (5)$$

where $\rho \in (-1, 1)$ is the correlation coefficient, $t(.;\nu)$ is the PDF of a Student-t random variable with ν degrees of freedom, and $\tilde{x}$ and $\tilde{y}$ are the corresponded inverse Student-t CDFs of φ and ξ (i.e. $\tilde{x} = T^{-1}(\varphi; \nu)$, and $\tilde{y} = T^{-1}(\xi; \nu)$).

Similar to a Gaussian copula, a Student-t copula function is a family of the elliptical copulas, which is frequently used in empirical analysis because of its easy implementation. Both copula functions are useful in measuring symmetric tail dependence, but the normal copula has no tail dependence. However, this Student-t copula is capable of capturing symmetric tail dependence, in which extreme joint positive and negative observations occur with the same probability. The Student-t copula is more flexible because it allows us to select its shape parameters in the model application (see Embrechts *et al.* (2003)).

3.3 Time-varying copula

The tail dependence evolution can be identified by using a time-varying Student-t copula function. We estimate time-varying dependence parameter, ρ_t, instead of unconditional correlation coefficients (i.e. ρ), on the basis of the following function:

$$\rho_t = \widetilde{\Lambda}\left(\omega_\rho + \beta_\rho \cdot \rho_{t-1} + \alpha_\rho \cdot \frac{1}{J}\sum_{j=1}^{J} T_\nu^{-1}(\varphi_{t-j}) \cdot T_\nu^{-1}(\xi_{t-j})\right), \tag{6}$$

where $\widetilde{\Lambda} = \tanh(x/2)$, and $T_\nu^{-1}(\cdot)$ is the inversed function of the student-t cumulative distribution with degree of freedom ν. ρ_t allows to capture the dynamics of dependence for a pair because the dependence parameter varies over time. In our empirical analysis, following Patton (2006b), we impose J to equal to 2 under the assumption that correlation ρ_t follows an ARMA(1,2) process. Note that this evolution equation can capture the possible persistence and variation in the dependence parameters by incorporating $\rho_{t-1}, T_\nu^{-1}(\varphi_{t-j})$, and $T_\nu^{-1}(\xi_{t-j})$ as regressors. For more details about time-varying copulas, see Patton (2006b).

The copula parameters can be usually estimated in two different methods in the literature: inference-function-for-margins (IFM) and exact maximum likelihood (EML). IFM is more widely used than the EML method because the latter requires heavy computational burden than the former in the high dimensional estimations. Therefore, following Patton (2006a) and Patton (2006b) the copula parameters of our interest are estimated by two step procedures of the IFM method. In the first step, we estimate the parameters in the marginal distributions by using the maximum likelihood. In the second step, given the estimated parameters in the first step, we estimate the copula parameters by using the Student-t copula function.[2] The standard errors of the parameters are estimated by applying the bootstrap method.

4 Empirical Results

4.1 Data

Our dataset is from the Jorda-Schularick-Taylor macro-history database of Jorda *et al.* (2017). The sample of countries, namely, Australia, Belgium, Canada, Denmark, Finland,

[2]Note that the particular copula function is selected based on the model selection criteria. They are available upon request.

France, Germany, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the UK, and the USA. The dataset covers a period of 147 years from 1870 to 2016. In particular, we use three different time series, : nominal stock price index, consumer price index, and nominal exchange rates, measured as a price of $US 1 in units of local currency. All the time series data are based on average yearly values.

The *real* yearly stock market returns between years t and $t-1$ for country i, that is, R_t^i, is calculated as follows:

$$R_t^i = \ln(SI_t^i) - \ln(SI_{t-1}^i) - \left\{\ln(CPI_t^i) - \ln(CPI_{t-1}^i)\right\},$$

where SI_t^i is the nominal stock market index for year t of country i and CPI_t^i is the CPI of country i for year t. Then, the US *relative* real yearly stock market returns of the U.S. against a country i from year $t-1$ to t, that is, $R_t^{US,i}$, is defined as follows:

$$R_t^{US,i} = R_t^{US} - R_t^i$$

Similarly, the yearly change in *real* FX rates of country i's currency relative to the U.S. dollar from $t-1$ to t, that is, Δq_t^i, is calculated as

$$\Delta q_t^i = \left\{\ln(FX_t^i) - \ln(FX_{t-1}^i)\right\} - \left\{\ln(CPI_t^i) - \ln(CPI_{t-1}^i)\right\} + \left\{\ln(CPI_t^{U.S}) - \ln(CPI_{t-1}^{U.S})\right\},$$

where FX_t^i is the nominal local currency price per unit of U.S. dollars, e.g., £/\$, for year t. For instance, if Δq_t^i happens to be positive, then this means U.S. dollars appreciate against a local currency in real terms between year $t-1$ and t.

Table 1 reports the descriptive statistics for Δq_t^i. On average, Δq_t^i for most countries is negative, but close to zero, except for Australia and Portugal. We firstly examine the normality of our time series by using the Jarque-Bera test. Based on the values in the J-B column, we can reject the null hypothesis of a normal distribution of Δq_t^i for all countries at the 1% significance level. This implies non-normal distributions of Δq_t^i. Table 1 also reports three common statistical tests for ARCH effects, serial correlation, and unit root test using

Engle's Lagrange multiplier statistic test, Ljung-Box test, and augmented Dickey-Fuller test, respectively. The Ljung-Box test statistic indicates that serial correlation does not exist for Δq_t^i of Australia, Canada, Finland, Germany, and the UK. In addition, ARCH effects are not found in the return series of Denmark, France, Germany, Italy, Netherlands, Portugal, Spain, and Sweden. However, Δq_t^i for all the countries is classified as a stationary process.

In general, the summary statistics suggest that serially independent standardized residuals should be obtained as a first step to precisely analyze the dependence structure. Descriptive statistics and distributional features of $R_t^{US,i}$ are presented in Table 2. Similar to the findings in Table 1, $R_t^{US,i}$ is not normally distributed for most country pairs. Ljung-Box test statistics indicate the existence of serial correlation in all countries, except for France, Italy, and Japan during the sample period. The results of Engle's Lagrange multiplier test only show the existence of the ARCH effect in $R_t^{US,i}$ of Canada, France, Italy, and the UK. $R_t^{US,i}$ obtained by our formulas above is stationary for all the sample countries. Similar to Δq_t^i, the summary statistics in Table 2 support our marginal model specification by the ARMA-GARCH model.

4.2 Results for the marginal models

In the first step, we fit the ARMA-GARCH model with Student-t errors to yearly returns. In particular, the model specification for each country is determined based on the evidence reported in Tables 1 and 2. Table 3 reports the results for the marginal models when considering Δq_t^i. At the first glance, we observe that the parameter estimates of autocorrelation up to a maximum lag of two are statistically significant. We also find evidence of the presence of significant ARCH effects and of significant leverage effects for Δq_t^i, which implies that conditional volatility is highly affected by its past returns path.

The estimation results in Table 3 support the existence of volatility dependencies for Δq_t^i. The positive parameter estimates by the GARCH effect test in the table indicate that negative return shocks have more impact on volatility than positive shocks. The currency market reacts more when bad news occurs. The error structure may vary between normal

Table 1: Descriptive statistics of Δq_t^i

	Obs	Mean	Median	Min	Max	Std	J-B	L-B (1)	L-B (2)	ARCH-LM(1)	ADF
Australia	146	0.001	-0.000	-0.286	0.331	0.093	40.46***	0.616	1.683	2.833*	-7.385***
Belgium	146	-0.004	-0.003	-0.562	0.721	0.152	> 100***	6.408***	6.999**	4.029**	-7.314***
Canada	146	-0.003	0.000	-0.195	0.227	0.058	58.59***	0.462	0.552	12.129***	-8.967***
Denmark	146	-0.010	-0.003	-0.240	0.617	0.104	> 100***	9.532***	9.535***	0.377	-7.804***
Finland	146	-0.019	-0.002	-0.745	1.421	0.196	> 100***	0.743	3.920	14.415***	-9.436***
France	146	-0.011	-0.000	-0.406	1.588	0.174	> 100***	5.268**	5.381*	1.065	-9.215***
Germany	144	-0.005	-0.016	-1.298	1.045	0.204	> 100***	1.961	2.789	0.874	-8.486***
Italy	146	-0.012	-0.002	-0.716	2.393	0.242	> 100***	0.035	7.351**	0.012	-10.600***
Japan	143	-0.015	-0.010	-1.878	2.698	0.302	> 100***	25.438***	26.213***	22.474***	-13.524***
Netherlands	146	-0.007	-0.002	-0.294	0.892	0.117	> 100***	10.258***	11.383***	0.428	-8.574***
Norway	146	-0.009	-0.003	-0.461	0.453	0.117	96.91***	6.245***	8.469***	3.229*	-8.916***
Portugal	146	0.001	-0.001	-0.409	0.592	0.116	> 100***	2.628*	4.690*	0.256	-8.960***
Spain	146	-0.008	-0.001	-0.780	0.881	0.162	> 100***	5.439**	11.141***	0.058	-9.642***
Sweden	146	-0.011	-0.001	-0.412	0.337	0.104	38.08***	5.960***	11.598***	1.972	-9.614***
Switzerland	146	-0.004	-0.006	-0.247	0.258	0.094	7.539**	9.364***	11.352***	15.257***	-9.010***
UK	147	-0.003	-0.000	-0.237	0.347	0.093	50.78***	0.476	1.594	12.445***	-9.337***

Note: J-B indicates the Jarque-Bera normality test. L-B (1) and L-B (2) are the Ljung-Box test for the serial correlation for one-period and two-period lags. ARCH-LM represents Engle's Lagrange multiplier statistic test for autoregressive conditional heteroscedasticity of one-period lag in our return series. ADF test shows the augmented Dickey-Fuller test statistics up to two-year lags. The null hypotheses state that ARCH effect, serial correlation, and nonstationarity do not exist. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 2: Descriptive statistics of $R_t^{US,i}$

	Obs	Mean	Median	Min	Max	Std	J-B	L-B (1)	L-B (2)	ARCH-LM(1)	ADF
Australia	145	0.022	0.001	-0.565	0.526	0.189	3.131	0.362	4.270*	0.394	-10.280***
Belgium	145	0.036	0.028	-0.710	0.620	0.197	15.3***	0.041	9.982***	0.204	-11.093***
Canada	145	0.007	0.002	-0.445	0.444	0.146	6.927***	5.684**	9.117***	3.044*	-11.166***
Denmark	124	0.003	0.007	-0.634	0.546	0.219	1.451	0.141	4.666*	0.297	-9.570***
Finland	104	-0.020	0.011	-0.723	0.971	0.299	0.884	0.107	9.837***	0.002	-9.476***
France	145	0.035	0.038	-0.476	0.783	0.224	4.451*	0.832	3.094	6.127**	-9.241***
Germany	142	0.003	0.007	-0.661	1.465	0.256	$>$ 100***	3.937**	4.657*	0.012	-9.519***
Italy	110	0.060	0.048	-0.891	1.493	0.294	$>$ 100***	0.269	4.201	26.117*	-8.983***
Japan	136	0.021	0.046	-0.652	2.612	0.367	$>$ 100***	0.837	1.334	0.006	-8.304***
Netherlands	124	0.018	0.020	-0.869	0.613	0.208	32.23***	0.934	5.587*	0.000	-9.910***
Norway	102	0.024	0.016	-0.643	0.636	0.246	0.214	0.101	6.586**	0.021	-9.174***
Portugal	87	0.055	0.033	-1.142	2.335	0.383	$>$ 100***	2.978*	3.660	0.005	-6.630***
Spain	145	0.052	0.037	-0.556	0.601	0.231	1.594	0.678	5.324*	0.266	-9.692***
Sweden	145	-0.003	0.005	-0.464	0.641	0.192	0.272	0.376	14.003***	0.705	-11.764***
Switzerland	115	0.010	-0.000	-0.528	0.460	0.175	0.065	0.102	8.385***	0.033	-9.823***
UK	145	0.019	0.014	-0.464	0.646	0.164	15.92***	2.364	6.555**	5.300**	-10.732***

Note: J-B indicates the Jarque-Bera normality test. L-B (1) and L-B (2) are the Ljung-Box test for the serial correlation for the one-period and two-period lags. ARCH-LM represents Engle's Lagrange multiplier statistic test for autoregressive conditional heteroscedasticity of one period lags in our return series. ADF test shows the augmented Dickey-Fuller test statistics up to two-year lags. The null hypotheses state that ARCH effect, serial correlation, and nonstationarity do not exist. ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

and crisis sample periods. Thus, our analysis includes time dummy variables indicating the financial market turmoils, such as World War I and II, and serious hyperinflation periods. By doing so, it is opportune to control the potential impact of global crisis periods on the conditional volatility processes. The coefficient of estimates (Crisis) are significantly positive, which strongly supports our estimation model specification for marginal distributions. Note that the degrees of freedom of the Student-t distribution is 7 to control for the possible non-normal error terms. Our selection of the degrees of freedom is on the basis of previous literature (e.g., Nikoloulopoulos and Mentzakis 2016). Table 4 presents the marginal model estimation for $R_t^{US,i}$. Considering low values of log likelihood, our marginal model specification seems to fit the sample data of $R_t^{US,i}$ to a lesser extent, and yet, the parameter estimates and their statistical significance are in line with our findings in Table 1.

4.3 Results for the copula model

Before estimating the time-varying dependence parameters, the bivariate Student-t copula is applied. Table 5 presents the estimation results. The dependence parameter at the mean level is negative for the most return pairs considered, except for the pair of Portugal. The strength of dependence varies across countries, ranged from -0.111 for Finland to -0.589 for Canada. However, this particular negative correlation certainly does not hold in the entire joint distribution. The relationship at the tails appears to statistically positive with moderate extreme tail dependence. Put it differently, the negative dependence reverses it sign to positive under a case where both returns deviate remarkably from their means such as financial market turmoil. In addition, the estimate for $\lambda_u = \lambda_l$ is statistically significant for every country in the table. This finding provides clear evidence of symmetric tail dependence, that is, extreme co-movements, for all the pairs. However, the strength of tail dependence is weak in a sense that every tail dependence coefficient estimate is below 0.05. For example, the estimated value of ρ for Australia is -0.230 at the mean, whereas its estimate of tail dependence coefficient is 0.007. Summing up, our baseline estimation results strongly support our conjecture that a negative (positive) co-movement exists for Δq_t^i and

Table 3: Marginal model estimation: Δq_t^i

	Australia	Belgium	Canada	Denmark	Finland	France	Germany	Italy
$AR(1)$				-0.796*	0.884***	0.810***	0.688***	0.734***
				(0.414)	(0.047)	(0.053)	(0.049)	(0.221)
$AR(2)$	0.763***	-0.573***	-0.802***					-0.162*
	(0.101)	(0.201)	(0.289)					(0.086)
$MA(1)$		0.191***		1.038**	-0.982***	-0.811***	-0.735***	-0.715***
		(0.082)		(0.424)	(0.018)	(0.101)	(0.109)	(0.211)
$MA(2)$	-0.910***	0.613***	0.729**	0.221**		-0.149	-0.175*	
	(0.051)	(0.199)	(0.336)	(0.108)		(0.095)	(0.096)	
$ARCH(1)$	0.375***	0.588***	0.192***	0.370*	0.531***	0.672**	0.835***	0.506***
	(0.113)	(0.170)	(0.069)	(0.195)	(0.198)	(0.270)	(0.313)	(0.167)
$GARCH(1)$	0.608***	0.559***	0.779***	0.459***	0.212	0.336***	0.175**	0.488***
	(0.068)	(0.051)	(0.068)	(0.157)	(0.170)	(0.102)	(0.087)	(0.078)
Crisis	4.304***	5.058***	3.698***	4.148***	5.423*	6.515***	7.334***	5.540***
	(0.820)	(1.457)	(1.260)	(0.772)	(3.010)	(0.757)	(1.290)	(1.023)
Obs.	146	146	146	146	146	146	146	146
Log likelihood	171.605	125.568	233.499	163.937	130.325	157.904	155.767	146.237

	Japan	Netherlands	Norway	Portugal	Spain	Sweden	Switzerland	UK
$AR(1)$	0.942****		0.309***	0.148*	0.260***	0.306***	0.891***	-0.298***
	(0.166)		(0.100)	(0.077)	(0.096)	(0.093)	(0.076)	(0.068)
$AR(2)$	-0.182**	0.900***		-0.609***	-0.167**	-0.185***		0.721***
	(0.087)	(0.028)		(0.233)	(0.082)	(0.083)		(0.061)
$MA(1)$	-0.837***						-0.705***	0.081***
	(0.139)						(0.118)	(0.017)
$MA(2)$		-1.013***	-0.213**	0.486			-0.270***	-0.974***
		(0.009)	(0.084)	(0.282)			(0.103)	(0.014)
$ARCH(1)$	0.400*	0.793**	0.399***	0.398***	0.294*	0.385***	0.571***	0.801***
	(0.217)	(0.313)	(0.120)	(0.150)	(0.159)	(0.127)	(0.215)	(0.253)
$GARCH(1)$	0.091	0.273**	0.600***	0.567***	0.503***	0.594***	0.474***	0.371***
	(0.064)	(0.130)	(0.053)	(0.095)	(0.151)	(0.078)	(0.106)	(0.100)
Crisis	5.077***	5.233***	5.078***	4.242***	4.063***	3.943***	3.734***	4.725***
	(0.737)	(1.076)	(1.094)	(0.877)	(0.718)	(0.948)	(1.245)	(0.966)
Obs.	143	146	146	146	146	146	146	147
Log likelihood	104.133	180.067	159.475	138.674	111.055	163.226	179.119	197.654

Note: ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively. Standard errors are in parentheses.

Table 4: Marginal model estimation: $R_t^{US,i}$

	Australia	Belgium	Canada	Denmark	Finland	France	Germany	Italy
$AR(1)$	-0.967	0.481*	-0.193**	-0.583***	0.513*	-0.693***	0.650***	
	(0.180)	(0.253)	(0.075)	(0.062)	(0.296)	(0.023)	(0.161)	
$AR(2)$	-0.722***		-0.156*	-0.944**		-0.970**		0.671***
	(0.171)		(0.094)	(0.056)		(0.023)		(0.124)
$MA(1)$	0.957***	0.466*		0.612***	0.694***	0.781***	0.754***	
	(0.220)	(0.258)		(0.094)	(0.260)	(0.010)	(0.163)	
$MA(2)$	0.553***	-0.240***		0.842***		1.008***	0.106***	-0.899***
	(0.212)	(0.094)		(0.087)		(0.011)	(0.028)	(0.090)
Obs.	145	145	145	124	104	145	145	110
Log likelihood	42.165	36.686	79.959	17.913	-19.981	20.209	-32.472	-8.476

	Japan	Netherlands	Norway	Portugal	Spain	Sweden	Switzerland	UK
$AR(1)$	-0.721***		-0.901***	0.845***	-1.013***		-0.661***	0.475**
	(0.125)		(0.048)	(0.151)	(0.065)		(0.104)	(0.221)
$AR(2)$	-0.123*	-0.152*		-0.773***	-0.907***	-0.321***	-0.253***	-0.142*
	(0.067)	(0.086)		(0.132)	(0.062)	(0.078)	(0.092)	(0.084)
$MA(1)$	0.785***		1.023***	-0.745***	1.116***		-0.866***	-0.591***
	(0.107)		(0.005)	(0.192)	(0.066)		(0.068)	(0.219)
$MA(2)$				0.589***	0.903***			
				(0.207)	(0.061)			
Obs.	138	126	102	87	145	145	117	145
Log likelihood	-29.995	23.655	1.183	-16.396	10.561	41.427	48.000	64.638

Note: ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively. Standard errors are in parentheses.

Table 5: Tail Dependence: Constant Student-t Copula

	Australia	Belgium	Canada	Denmark	Finland	France	Germany	Italy
ρ	-0.230**	-0.227***	-0.589***	-0.231**	-0.111*	-0.072	-0.274***	-0.166**
	(0.095)	(0.087)	(0.082)	(0.090)	(0.081)	(0.091)	(0.077)	(0.085)
$\lambda_u = \lambda_l$	0.007*	0.007*	0.001*	0.007**	0.013**	0.016**	0.006**	0.010**
	(0.004)	(0.005)	(0.000)	(0.004)	(0.006)	(0.008)	(0.003)	(0.005)

	Japan	Netherlands	Norway	Portugal	Spain	Sweden	Switzerland	UK
ρ	-0.123*	-0.216**	-0.115*	0.159*	-0.186**	-0.198**	-0.200*	-0.294***
	(0.073)	(0.097)	(0.092)	(0.093)	(0.079)	(0.097)	(0.096)	(0.105)
$\lambda_u = \lambda_l$	0.013***	0.008*	0.013*	0.043***	0.009*	0.009*	0.009*	0.005*
	(0.005)	(0.005)	(0.007)	(0.015)	(0.005)	(0.005)	(0.006)	(0.003)

Note: ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively. Standard errors are in parentheses.

$R_t^{US,i}$ during the normal (economic turmoil) periods.

Table 6: Time-varying copula estimation results

	Australia	Belgium	Canada	Denmark	Finland	France	Germany	Italy
ω_ρ	-0.111	-0.497	-0.868***	-0.011	-0.788***	-0.385	-0.555*	-0.158
	(0.170)	(1.861)	(0.338)	(0.070)	(0.297)	(0.589)	(0.339)	(0.319)
β_ρ	-0.049	-0.001	0.140*	-0.234**	-0.214***	0.074	0.214	0.027
	(0.075)	(0.067)	(0.081)	(0.103)	(0.080)	(0.169)	(0.179)	(0.063)
α_ρ	1.209	-0.016	-2.111***	1.344***	-0.750	-0.500	-1.817***	-1.116
	(1.165)	(7.765)	(0.071)	(0.519)	(0.572)	(3.410)	(0.359)	(1.806)
Obs.	145	145	145	124	104	145	145	110
Log likelihood	0.890	5.574	6.326	13.527	6.147	1.428	3.319	3.193

	Japan	Netherlands	Norway	Portugal	Spain	Sweden	Switzerland	UK
ω_ρ	-0.004	-0.209	-0.348	-0.684*	-0.436	-0.057	0.286	-0.471
	(0.011)	(0.136)	(0.322)	(0.412)	(0.426)	(0.112)	(0.397)	(0.445)
β_ρ	-0.188***	-0.173**	-0.097	-0.073	0.120	0.133	0.175	-0.041
	(0.038)	(0.078)	(0.078)	(0.067)	(0.122)	(0.161)	(0.231)	(0.112)
α_ρ	2.277***	1.384***	-1.242	-2.032**	-0.912	1.413*	0.182	-1.027
	(0.030)	(0.475)	(1.026)	(0.095)	(2.271)	(0.729)	(1.910)	(2.154)
Obs.	138	126	102	87	145	145	117	145
Log likelihood	12.366	4.994	3.741	5.660	3.053	1.855	0.799	5.215

Note: ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively. Standard errors are in parentheses.

Table 6 presents the estimation results for the time-varying Student-t copula. The dynamics of dependence parameters for some countries are statistically significant. For example, we find statistically significant persistence in the dependence parameter (β_ρ) only for Canada, Denmark, Finland, Japan, and the Netherlands. Meanwhile, variation occurs in the dependence (α_ρ) for Canada, Denmark, Germany, Japan, Netherlands, Portugal, and Sweden. Our results confirm that in general the dependence for the considered pairs varies over time. Figure 1 displays the time path of dependence by using time-varying Student-t copula. Each panel clearly displays the dynamics of dependence during periods of severe economic turmoil, such as World War I and II, and the great depression. In fact, the figure successfully detects significant dependence variations within periods of high economic

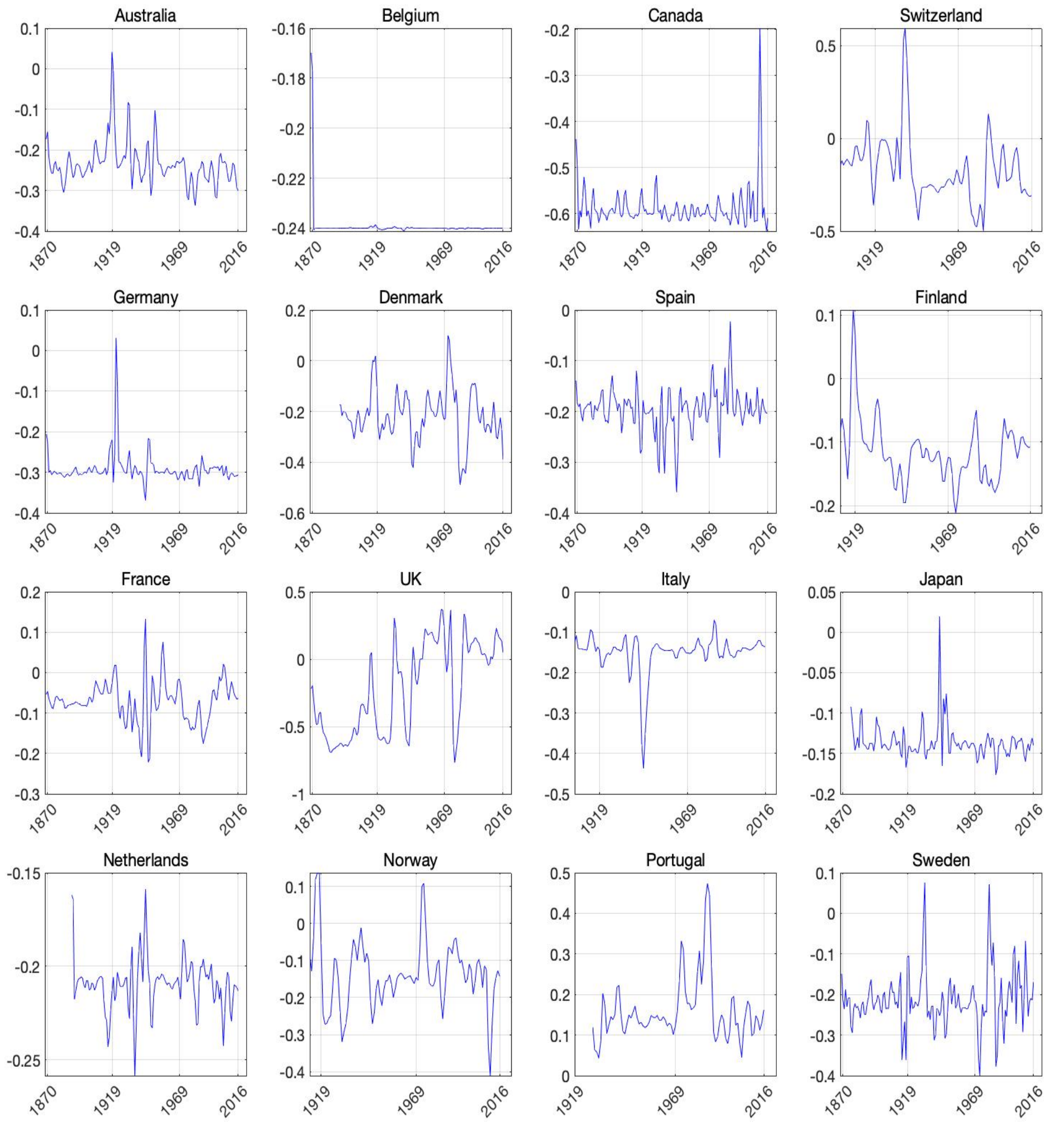

Figure 1: Time-varying Student-t copula

uncertainty. Evidently the time-varying copula gives clearer movements of the dependence structure during the sample period.

What's worth noting from Figure 1 is that the time-varying correlation shows a generally negative dependence, but not during economic crises with high uncertainty. As emphasized before, this observation is new to the literature to our best knowledge. Jung (2017) provides a possible rationale for this observation based on a long-run risks-type model with idiosyncratic stock market volatility. Our time-varying copula estimation results provide a good testing ground for this hypothesis. We assess the marginal effects of stock market volatilities on time-varying dependence parameters to see if stock market volatilities affect the time-varying dependence. In particular, a simple linear regression model is used. We regress the estimated time-varying dependence parameters on stock market volatility with robust standard errors. This regression specification is based on Jung (2017)'s model in that stock market volatility (proxied by ϵ_t^2) is a potential determinant of correlations between Δq_t^i and $R_t^{US,i}$. We also run the regression model with ($\sigma^2_{R_t^{US,i}}$) which is time-invariant in our model specification. The estimation results are reported in Table 7. We obtain the coefficient estimate of 3.922, which is statistically significant at the 1% significance level. As the volatility of stock market return differential increases, the negative dependence tends to be weaker. These findings again provide evidence that negative correlations between Δq_t^i and $R_t^{US,i}$ are confined to relatively tranquil stock market conditions.

Table 7: Volatilities on Time-Varying Dependence

	ρ_t	
$\ln \epsilon^2_{R_t^{US,i}}$	0.165***	
	(0.048)	
$\ln \sigma^2_{R_t^{US,i}}$		3.922***
		(0.212)
Obs.	2,067	2,067
adj R^2	0.009	0.181

Note: ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors are in parentheses.

Finally, one might disregard our test results as merely a spurious correlation. For instance, if nominal equity and currency prices do not fully incorporate unexpectedly large inflation surprises in a synchronous manner, then, one could expect to obtain a spurious positive correlation between the real exchange rate and the real stock return differential. Moreover, periods of high stock market uncertainty may coincide with periods of high discrepancy between inflation surprises and currency/equity prices. Thus, periods of high stock market volatility might as well be those periods where the spurious positive correlation shows up most strongly. In order to address this issue, we also perform two robustness checks. First, we regress the time-varying correlation coefficient on the volatility of the inflation differentials across countries. If the aforementioned spurious correlation bias was indeed true, one would expect to observe a positive and statistically significant coefficient on the volatility of the inflation differential. Table 8 shows coefficients on the volatility of inflation differential are statistically insignificant. It confirms that concerns over the spurious correlation bias can be dismissed. Another way to check the spurious correlation bias is to test whether the fixed exchange regime has any statistically significant effect on the time-varying correlation coefficient. It is safe to argue that the link between FX rates and inflation surprises easily breaks under the fixed FX regime. Thus, one ought to expect to observe higher positive value for ρ_t under the fixed FX regime, if such spurious correlations were indeed at play. Table 9 disregards this hypothesis. ρ_t and the fixed FX regime turn out to be uncorrelated, refuting concerns over the spurious correlation bias.

5 Conclusion

This paper employs copula methods and investigates the long history of relationship between real currency and real equity returns at an annual frequency for 17 major advanced countries, perhaps for the first time in the literature. Our investigation reveals that the UEP relationship has held true on average not just during the post-1990 period, but over the entire last century. Another surprising result of our study is that the UEP condition fails to materialize or even shift its sign during periods of severe economic uncertainties. Our

Table 8: Volatilities on Time-Varying Dependence

	ρ_t	
$\ln \epsilon^2_{R_t^{US,i}}$	0.165***	
	(0.047)	
$\ln \sigma^2_{R_t^{US,i}}$		3.906***
		(0.212)
$\ln \epsilon^2_{\Delta\pi_t^i}$	0.001	
	(0.026)	
$\ln \sigma^2_{\Delta\pi_t^i}$		0.021
		(0.016)
Obs.	2,067	2,067
adj. R^2	0.009	0.181

Note: ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors are in parentheses.

Table 9: Foreign Exchange Regimes on Time-Varying Dependence

	ρ_t
Gold Standard (1880-1914)	-0.040
	(0.046)
War and Depression (1915-1945)	-0.004
	(0.027)
Pre-Bretton Woods (1946-1960)	-0.016*
	(0.009)
Bretton Woods (1961-1971)	0.010
	(0.015)
Observations	2067
Adjusted R^2	0.017

Note: ***, **, and * denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors are in parentheses. The volatilities of inflation differentials are estimated from ARMA-GARCH model separately, and the results are available upon request.

time-varying Student-t copula estimation results lend support to this novel finding.

These findings set out a new and interesting agenda for future research. In particular, issues pertaining to how various types of economic uncertainties drive the relationship between real currency and real equity returns remain to be explored. We do hope our discoveries of this long history of potentially time-varying nature of the two returns pave the way for new lines of both empirical and theoretical exploration in this important and yet overlooked UEP literature.

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