

PERSISTENT DEPENDENCE IN FOREIGN EXCHANGE RATES? A REEXAMINATION §

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Abstract

We test for stochastic long-memory behavior in the returns series of currency rates for eighteen industrial countries using a semiparametric fractional estimation method. A sensitivity analysis is also carried out to analyze the temporal stability of the long-memory parameter. Contrary to the findings of some previous studies alluding to the presence of long memory in major currency rates, our evidence provides wide support to the martingale model (and therefore for foreign exchange market efficiency) for our broader sample of foreign currency rates. Any inference of long-range dependence is fragile, especially for the major currency rates. However, long-memory dynamics are found in a small number of secondary (nonmajor) currency rates.

JEL codes: C22, G12

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1. Introduction

Since the breakdown of the Bretton Woods system, the volatility of exchange rates has been cited as a drawback of the floating exchange rate system. At both theoretical and empirical levels, the international trade and finance literature has stressed the effects of exchange rate uncertainty on international trade flows, pricing of exports and domestic goods, market structure (entry-exit decisions), and international asset portfolios. It is also well documented that although firms can protect themselves against short-term foreign exchange risk through hedging, they are exposed to medium- and long-term exchange rate volatility.¹ Such an exposure to foreign exchange risk could affect firms' investment decisions and therefore distort the optimal allocation of resources. Knowledge of the short- and long-term time series properties of foreign currency rates can have important implications for these issues. Additionally, such an understanding can address issues of appropriateness of models of exchange rate determination and foreign currency market efficiency and predictability.

The standard tool in analyzing the stochastic behavior of exchange rates has been the autoregressive integrated moving average (ARIMA) model. Along these lines, a large body of past research (see, for example, Baillie and Bollerslev (1989)) documents that foreign currency rates are best characterized as pure unit-root (random-walk or martingale) processes, thus making predictability of exchange rate movements impossible. The failure of linear univariate and structural exchange rate models to

¹ There are limitations and costs associated with firms' hedging strategies. For example, size and limited maturity of forward contracts may make it difficult for firms to hedge their foreign exchange risk.

improve upon the predictive accuracy of random-walk forecasts motivated many researchers to turn to nonlinear models.² Engel and Hamilton (1990) use a Markov switching model for exchange rate changes while Diebold and Nason (1990) and Meese and Rose (1990) use variants of local regression, a nearest-neighbor nonparametric technique. Kuan and Liu (1995) use feedforward and recurrent artificial neural networks to produce conditional mean forecasts of foreign exchange rates. Meese and Rose (1991) estimate structural models of exchange rate determination using a variety of nonparametric techniques. The success of these studies to explain exchange rate movements has been very limited, thus leaving the martingale model as the leading characterization of the data generating process of exchange rates.

More recently, some researchers have argued against the martingale hypothesis by pointing to the possibility of long-memory (fractional) dynamic behavior in the foreign currency market.³ The long-memory, or long-term dependence, property describes the high-order correlation structure of a series. If a series exhibits long memory, persistent temporal dependence exists even between distant observations. Such series are characterized by distinct but nonperiodic cyclical patterns. As long memory creates nonlinear dependence in the first moment of the distribution and therefore generates a potentially predictable component in the series dynamics, its presence in foreign currency rates would cast doubt on the weak form of foreign exchange market efficiency. The price of an asset determined in a weak-form efficient market should follow a martingale process in which each price change is unaffected by its predecessor and has no memory. As long memory implies significant autocorrelations between

² Absence of risk-neutral behavior, the nature of the policy regime, time deformation, and misspecification of the functional form of the structural exchange rate model are some of the plausible sources of nonlinearity in foreign exchange rates.

³ Long-memory methods have been applied extensively to financial asset price series: for stock prices (Lo (1991)), futures prices (Barkoulas, Labys, and Onochie (1999)), commodity prices (Barkoulas, Labys, and Onochie (1997)), Eurocurrency deposit rates (Barkoulas and Baum (1997)), for example. See Baillie (1996) for a survey of fractional integration methods and applications in economics and finance.

distant observations, its presence entails that past returns can help predict future returns, and the possibility of consistent speculative profits arises.⁴

Applying rescaled-range (R/S) analysis to daily exchange rates for the British pound, French franc, and Deutsche mark, Booth, Kaen, and Koveos (1982) find positive long-term persistence during the flexible exchange rate period (1973-1979) but negative dependence (antipersistence) during the fixed exchange rate period (1965-1971).⁵ More recently, Cheung's (1993) findings strengthen the evidence that persistent dependence characterizes the behavior of foreign exchange markets during the managed floating regime. Using spectral regression and maximum likelihood methods, Cheung finds support for long-memory behavior in weekly returns series for the British pound, Deutsche mark, Swiss franc, French franc, and Japanese yen over the period 1974 to 1987. However, he also finds that impulse responses are generally insignificant and that short- and longer-horizon long-memory forecasts fail to improve upon the naive random-walk forecasts.

This study extends previous research on foreign exchange long-memory dynamics in three respects. First, the sample employed spans a longer time period and therefore incorporates more information regarding the low-frequency (long-term) behavior of foreign exchange rates. Second, the sample is not restricted to the major currencies, but is much more comprehensive, including currency rates for eighteen industrial countries. And third, a sensitivity analysis is performed to analyze the robustness properties and temporal stability of the long-memory (fractional

⁴ The presence of fractional structure in asset returns raises a number of theoretical and empirical issues. As long memory represents a special form of nonlinear dynamics, it calls into question linear modeling and invites the development of nonlinear pricing models at the theoretical level to account for long-memory behavior. Mandelbrot (1971) observes that in the presence of long memory, the arrival of new market information cannot be fully arbitrated away and martingale models of asset prices cannot be obtained from arbitrage. In addition, pricing derivative securities with martingale methods may not be appropriate if the underlying continuous stochastic processes exhibit long memory. Statistical inferences concerning asset pricing models based on standard testing procedures may not be appropriate in the presence of long-memory series.

⁵ The classical rescaled-range (R/S) method has a number of drawbacks (see Lo (1991)).

differencing) parameter for the foreign currency rates. We use the Gaussian semiparametric method to estimate the long-memory parameter. Contrary to previous findings of strong persistence, our evidence strongly favors the martingale model against long-memory alternatives in the foreign currency markets, thus supporting the market efficiency hypothesis in its weak form. The sensitivity analysis suggests that any evidence of long memory is temporally unstable, especially for major currency rates. However, persistent dependence appears to characterize the temporal behavior of three secondary (nonmajor) currency rates.

The rest of the paper is constructed as follows. Section 2 presents the fractional model and the Gaussian semiparametric method for estimating the fractional parameter. Data, empirical estimates of the fractional parameter, and the results of the sensitivity analysis are reported and discussed in Section 3. We summarize and conclude in Section 4.

2. Fractional Differencing Modeling and Estimation

The model of an autoregressive fractionally integrated moving average process of order (p, d, q) , denoted by ARFIMA (p, d, q) , with mean μ , may be written using operator notation as

$$\Phi(L)(1-L)^d(y_t - \mu) = \Theta(L)u_t, \quad u_t \sim \text{i.i.d.}(0, \sigma_u^2) \quad (1)$$

where L is the backward-shift operator, $\Phi(L) = 1 - \phi_1 L - \dots - \phi_p L^p$, $\Theta(L) = 1 + \vartheta_1 L + \dots + \vartheta_q L^q$, and $(1-L)^d$ is the fractional differencing operator defined by

$$(1-L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k-d)L^k}{\Gamma(-d)\Gamma(k+1)} \quad (2)$$

with $\Gamma(\cdot)$ denoting the gamma function. The parameter d is allowed to assume any real value. The arbitrary restriction of d to integer values gives rise to the standard autoregressive integrated moving average (ARIMA) model. The stochastic process y_t is both stationary and invertible if all roots of $\Phi(L)$ and $\Theta(L)$ lie outside the unit circle and $|d| < 0.5$. Assuming that $d \in (0, 0.5)$ and $d \neq 0$, Hosking (1981) shows that the correlation function, $\rho(\cdot)$, of an ARFIMA process is proportional to k^{2d-1} as $k \rightarrow \infty$. Consequently, the autocorrelations of the ARFIMA process decay hyperbolically to zero as $k \rightarrow \infty$ which is contrary to the faster, geometric decay of a stationary ARMA process. For $d \in (0, 0.5)$, $\sum_{j=-n}^n |\rho(j)|$ diverges as $n \rightarrow \infty$, and the ARFIMA process is said to exhibit long memory, or long-range positive dependence. The process is said to exhibit intermediate memory (anti-persistence), or long-range negative dependence, for $d \in (-0.5, 0)$. The process exhibits short memory for $d = 0$, corresponding to stationary and invertible ARMA modeling. For $d \in [0.5, 1)$ the process is nonstationary (having an infinite variance) but it is mean reverting, as there is no long-run impact of an innovation on future values of the process.

We estimate the long-memory parameter using Robinson's Gaussian semiparametric method. Robinson (1995) proposes a Gaussian semiparametric estimate, GS hereafter, of the self-similarity parameter H , which is not defined in closed form. It is assumed that the spectral density of the time series, denoted by $f(\cdot)$, behaves as

$$f(\xi) \sim G \xi^{1-2H} \text{ as } \xi \rightarrow 0^+ \quad (3)$$

for $G \in (0, \infty)$ and $H \in (0, 1)$. The self-similarity parameter H relates to the long-memory parameter d by $H = d + 1/2$. The estimate for H , denoted by \hat{H} , is obtained through minimization of the function

$$R(H) = \ln \hat{G}(H) - (2H - 1) \frac{1}{\nu} \sum_{\lambda=1}^{\nu} \ln \xi_{\lambda} \quad (4)$$

with respect to H , where $\hat{G}(H) = \frac{1}{\nu} \sum_{\lambda=1}^{\nu} \xi_{\lambda}^{2H-1} I(\xi_{\lambda})$, $I(\xi_{\lambda})$ is the periodogram of y_t at frequency ξ_{λ} , and ν is the number of Fourier frequencies included in estimation (bandwidth parameter). The discrete averaging is carried out over the neighborhood of zero frequency and, in asymptotic theory, ν is assumed to tend to infinity much slower than T . The GS estimator is $\nu^{1/2}$ -consistent and the variance of the limiting distribution is free of nuisance parameters and equals $1/4\nu$. The GS estimator appears to be the most efficient semiparametric estimator developed so far. It is also consistent and has the same limiting distribution under conditional heteroscedasticity (Robinson and Henry (1999)).

3. Data and Long-memory Results

3A. Data

The data set consists of U.S. dollar nominal rates of weekly frequency for the Canadian dollar, Deutsche mark, British pound, French franc, Italian lira, Japanese yen, Swiss franc, Netherlands guilder, Swedish krona, and Belgian franc and of monthly frequency for the Austrian schilling, Danish krone, Luxembourg franc, Norwegian krone, Finnish markka, Greek drachma, Portugese escudo, and Spanish peseta. The

sample period covers the post-Bretton Woods period of the floating exchange rate system. See the Appendix for details of data and sources. All subsequent analysis is performed on the first logarithmic differences (returns) of the exchange rate series.

3B. Long-memory Estimates

Before proceeding with the empirical evidence, we briefly make the distinction between short- and long-term dependence. Short-term dependence, or short memory, describes the low-order correlation structure of a series and is typified by quickly declining autocovariances in the time domain and significant power at high frequencies in the frequency domain. For a short-memory process, events from the distant past have negligible effect on the present. On the other hand, the long-memory, or long-term dependence, property characterizes the behavior of the series' long-lagged autocovariances. If a series exhibits long memory, there are significant correlations even between observations widely separated in time (the correlations of the series are not summable); such behavior is indicated by hyperbolically declining autocovariances in the time domain. A shock to the series persists for a long time (has a long-lasting impact), even though it eventually dissipates. For all practical purposes, a long-memory process may be considered to have an infinite span of statistical interdependence. In the frequency domain, long memory is indicated by the fact that the spectral density becomes unbounded as the frequency approaches zero. Standard ARIMA processes cannot exhibit long-term dependence as they can only describe the short-run behavior of a time series.

GS estimates of the fractional exponent for the exchange rate series are reported in Table 1.⁶ In order to check the sensitivity of our results to the choice of bandwidth, or

⁶ Another frequently used periodogram-based method to estimate the fractional differencing parameter d is the spectral regression method suggested by Geweke and Porter-Hudak (GPH, 1983). The GPH fractional exponent estimates are broadly consistent with the GS estimates for our sample exchange rate

number of harmonic frequencies used in estimation, we report d estimates for $\nu = T^{0.50}$ and $\nu = T^{0.55}$.⁷ Concentrating on the major currencies, there is no evidence of long memory in any of the returns series with the exception of the French franc. For the Italian lira, rejection of the unit-root null hypothesis is obtained but it is restricted to a particular estimation window size, thus lacking robustness. This evidence for the major currency rates does not confirm the long-memory evidence reported in Booth et al. (1982) and Cheung (1993). For the remaining currencies, consistent evidence of long memory is apparent for the Danish krone, Luxembourg franc, Portuguese escudo, and Spanish peseta. For the Belgian franc, Swedish krona, Finnish markka, and Greek drachma, weak evidence of fractional dynamic behavior is found, but only for a specific estimation window size. For all other exchange rate series, the martingale hypothesis is robust to long-memory alternatives.

The overall evidence can be summarized as follows. The returns series for major currencies appear to be short-memory processes, which exhibit a rapid exponential decay in their impulse response weights. There is no convincing evidence that these series are strongly autocorrelated, which could give rise to improved predictability.⁸ However some evidence of long-term dependence appears to characterize the temporal patterns of some nonmajor currencies.

series and our inferences therefore remain unaltered. The GPH results are not reported here but they are available upon request from the authors.

⁷ Monte Carlo simulations have shown that such bandwidth choices provide a good balance in the trade-off between bias (which tends to increase with bandwidth) and sampling variability (which tends to decrease with bandwidth). Henry and Robinson (1999) provide heuristic approximations of the minimum mean squared error optimal bandwidth. Inferences drawn below remain unaltered for other plausible bandwidth choices.

⁸ Alternative estimation methods of long-memory models include Sowell's (1992) exact maximum likelihood method, Fox and Taquq's (1986) frequency domain approximate maximum likelihood method, and the conditional sum of squares (CSS) method (Chung and Baillie (1993)). The maximum likelihood methods are computationally burdensome, especially in light of the repeated estimation in the sensitivity analysis, and rely on the correct specification of the high-frequency (ARMA) structure to obtain consistent parameter estimates. Given the near whiteness of the exchange-rate returns series, the periodogram-based method employed here is not likely to suffer from biases due to the presence of strong short-term dependencies in the series dynamics (Agiakloglou, Newbold, and Wohar (1993)). Since the main finding in this study is the absence of long memory in exchange rate series, its validity should not be questioned on the basis of the particular estimation method employed here as the presence of any high-frequency dependencies would only bias the inference toward finding long memory.

3C. Sensitivity Analysis

To ascertain the robustness and temporal stability properties of the long-memory coefficient, a sensitivity analysis is performed on each exchange rate series. The analysis of subsamples should provide us with insights as to whether long memory is a genuine feature of the data generating process underlying the foreign exchange rate series. It will also enable us to compare our findings with those reported in earlier studies. We apply the GS method to an initial sample of exchange-rate changes spanning the period 1974 to 1983 and then on samples generated by adding twenty-six weekly observations, so that the fractional exponent is reestimated every six months until the full sample period is exhausted.⁹

Figures 1 through 5 graph the t -statistics corresponding to the GS fractional exponent estimates over subsamples for the British pound, Deutsche mark, Swiss franc, French franc, and Japanese yen: the five major currencies examined by Cheung. If the analysis is restricted to the 1974-1987 sample period investigated by Cheung, the GS results obtained here do confirm his long-memory evidence on the five major currency returns series. With increasing sample size, however, there does not appear to be any consistent evidence favoring long memory, across both window size and time, for almost all major currency rates. Only for the French franc rejections of the no long-memory null hypothesis are invariably obtained over time. Therefore, the long-memory evidence for the major currency rates generally vanishes when the sample period is expanded, thus suggesting temporal parameter instability.

Based on the results of the sensitivity analysis, the exchange rate series analyzed by Cheung appear to be short-memory processes over the extended sample periods. His

⁹ The same procedure was performed on the monthly data, with qualitatively similar results.

evidence of long memory appears to be a function of the particular sample period used in his analysis and does not generalize to a temporally expanded data set. Over time, the presence of long memory ranges from very weak and sporadic to nonexistent. This temporal instability of the long-memory evidence helps explain Cheung's negative findings based on impulse response function analysis and out-of-sample forecasting. If long memory is not a robust feature of the stochastic behavior of major foreign currency rates, then fitting an ARFIMA model to the series is unlikely to produce superior out-of-sample forecasts as compared to benchmark random-walk forecasts. In summary, the evidence supports the martingale model—and the market efficiency hypothesis in its weak form—for major foreign currency rates over the floating exchange rate period (with the French franc being the only exception).

For the rest of the currencies, generally consistent, stable evidence of long-term persistence is obtained for the Luxembourg franc, Portugese escudo, and Spanish peseta and weaker evidence for the Greek drachma. The sensitivity analysis produces negative evidence for long memory for all other foreign currency rates with any long-memory evidence being sporadic and fragile.¹⁰

The observed deterioration in the overall evidence of persistent dependence over time could well reflect the increasing breadth and sophistication of foreign currency markets in the past decade. It could also reflect the reduced role of central bank interventions in the foreign exchange market in the 1990s. Additionally, the development of active spot, futures, and options markets in secondary currencies and the development of financial markets in a number of emerging economies has led to greater efficiencies in global currency markets. These trends are consistent with martingale behavior.

¹⁰ The corresponding figures for these currencies are not presented here but are available on request from the authors.

IV. Conclusions

Using Robinson's Gaussian semiparametric estimator, we test for stochastic long memory in the returns series for currencies of eighteen industrial countries. For major currency rates previously studied in the literature, there is no convincing evidence in support of long-memory dynamics. A sensitivity analysis suggests that, when evidence of long memory is obtained, it is sporadic and generally temporally unstable. The evidence of long memory in major currency rates reported in Booth et al. (1982) and Cheung (1993) would appear to be an artifact of the sample period and currencies considered in those studies. For all but three of the broader set of currencies analyzed here, we find that the unit-root hypothesis is robust to long-memory alternatives, providing strong support for martingale behavior of currency rates and, therefore, for foreign exchange market efficiency.

APPENDIX

For the U.S. dollar nominal rates for the Canadian dollar, Deutsche mark, British pound, French franc, Italian lira, Japanese yen, Swiss franc, Netherlands guilder, Swedish krona, and Belgian franc, the frequency of observation is weekly and the sample spans the period 01/04/1974 to 12/29/1995 for a total of 1,147 returns observations. These weekly rates represent Friday noon-time bid prices from the New York foreign exchange market and were obtained from the Federal Reserve Board of Governors. When Friday prices are not available Thursday prices are used. (The construction of the data set of weekly observations follows Cheung (1993)). For the U.S. dollar nominal rates for the Austrian schilling, Danish krone, Luxembourg franc, Norwegian krone, Finnish markka, Portugese escudo, and Spanish peseta, the frequency of observation is monthly and the sample covers the period 08/1973 to 12/1995 for a total of 268 returns observations. For the Greek drachma, the sample period starts at 04/1975 (248 returns observations) as, prior to this date, the currency was under a fixed exchange rate regime relative to the U.S. dollar. The source of the monthly exchange rates is the International Monetary Fund's *International Financial Statistics* database. Data availability dictated the choice of the frequency of observation.

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Table 1: Gaussian Semiparametric Estimates of the Fractional Differencing Parameter d for Exchange Rate Returns Series

Currency	Gaussian Semiparametric Estimates	
	$d(0.50)$	$d(0.55)$
<i>(A) Weekly Returns</i>		
Canadian Dollar	0.015 (0.172)	0.111 (1.538)
Deutsche Mark	0.071 (0.815)	0.074 (1.025)
British Pound	-0.007 (-0.080)	0.031 (0.429)
French Franc	0.177 (2.033)*	0.181 (2.508)*
Italian Lira	0.110 (1.263)	0.149 (2.064)*
Japanese Yen	0.025 (0.287)	0.095 (1.316)
Swiss Franc	0.041 (0.471)	0.068 (0.942)
Belgian Franc	0.119 (1.367)	0.146 (2.023)*
Netherlands Guilder	0.074 (0.850)	0.093 (1.288)
Swedish Krona	0.079 (0.907)	0.148 (2.050)*

Currency	Gaussian Semiparametric Estimates	
	$d(0.50)$	$d(0.55)$
	<i>(B) Monthly Returns</i>	
Austrian Schilling	0.185 (1.480)	0.202 (1.850)
Danish Krone	0.253 (2.024)*	0.228 (2.089)*
Luxembourg Franc	0.302 (2.416)*	0.284 (2.603)*
Norwegian Krone	-0.009 (-0.072)	0.090 (0.824)
Finnish Markka	0.185 (1.480)	0.257 (2.355)*
Greek Drachma	0.321 (2.486)*	0.218 (1.949)
Portugese Escudo	0.386 (3.088)*	0.299 (2.740)*
Spanish Peseta	0.266 (2.128)*	0.344 (3.153)*

Notes: The sample period is 01/11/1974 to 12/29/1995 for a total of 1,147 returns observations for the weekly currency rates. The sample period is 09/1973 to 12/1995 for a total of 268 returns observations for the monthly currency rates, except for the Greek drachma, which spans the period 04/1975 to 12/1995 for a total of 248 returns observations. $d(0.50)$ and $d(0.55)$ give the d estimates corresponding to estimation window size $v = T^{0.50}$ and $v = T^{0.55}$, respectively. The t -statistics are given in parentheses. The superscript * indicates statistical significance for the null hypothesis $d=0$ at the 5 per cent level or less.

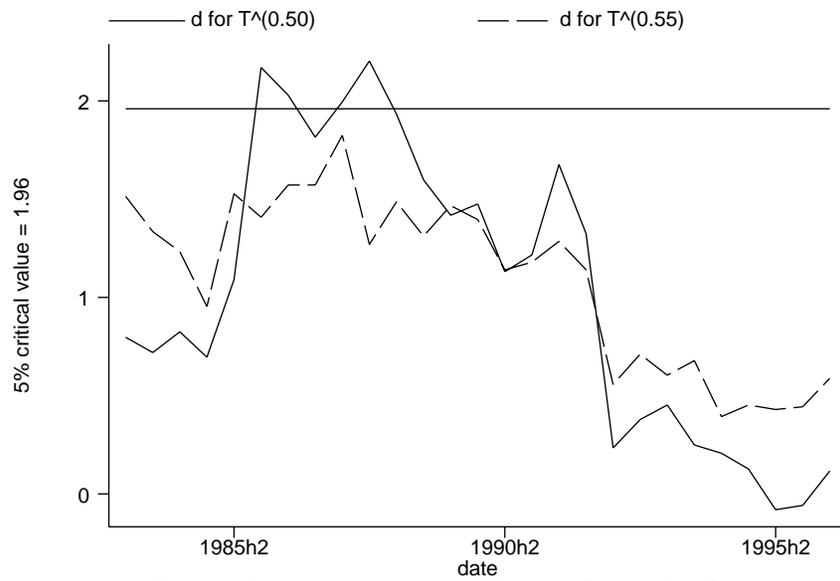


Figure 1. t-statistics for $d[\text{British Pound}] = 0$

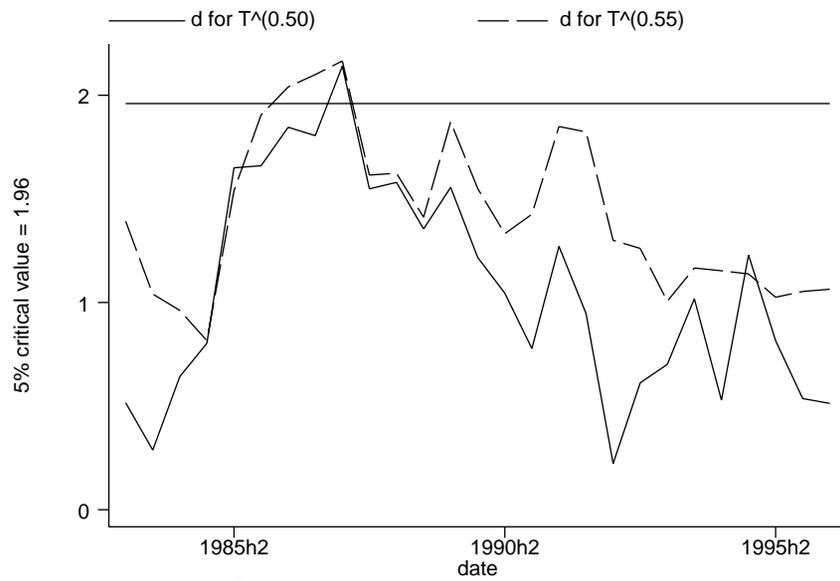


Figure 2. t-statistics for $d[\text{Deutsche Mark}] = 0$

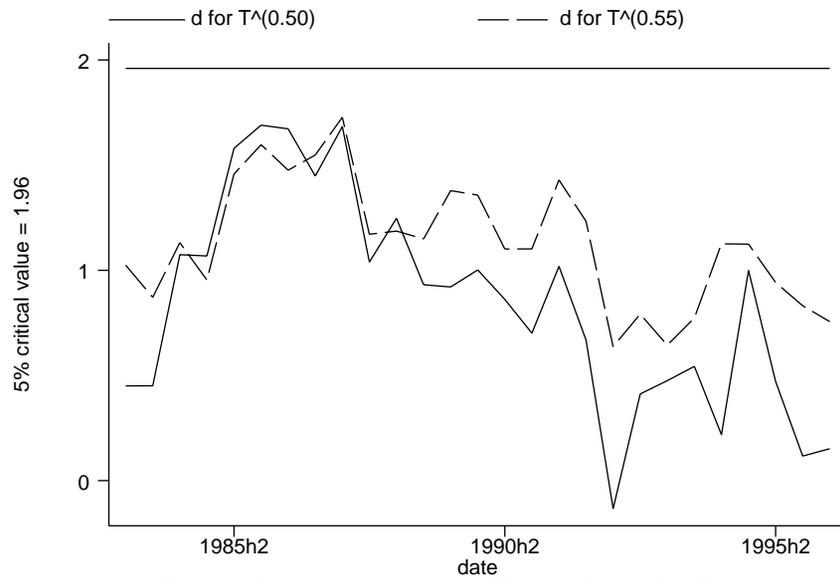


Figure 3. t-statistics for $d[\text{Swiss Franc}] = 0$

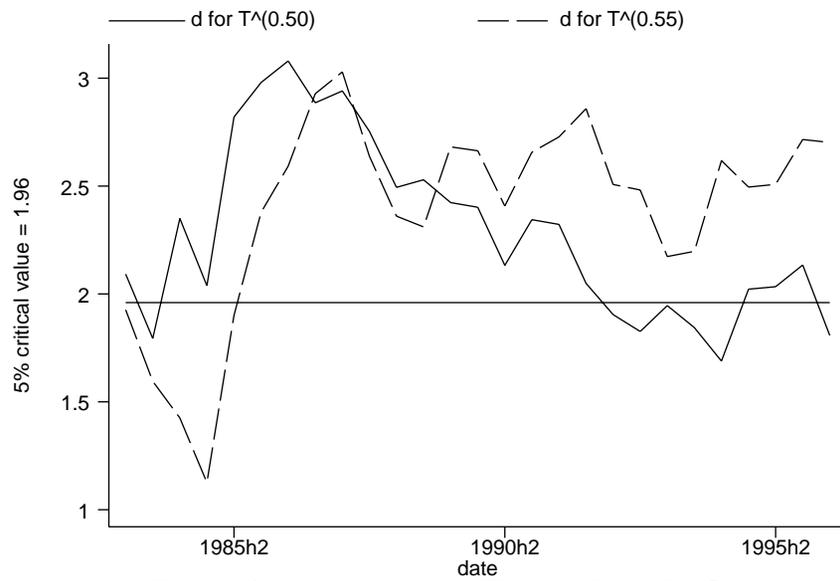


Figure 4. t-statistics for $d[\text{French Franc}] = 0$

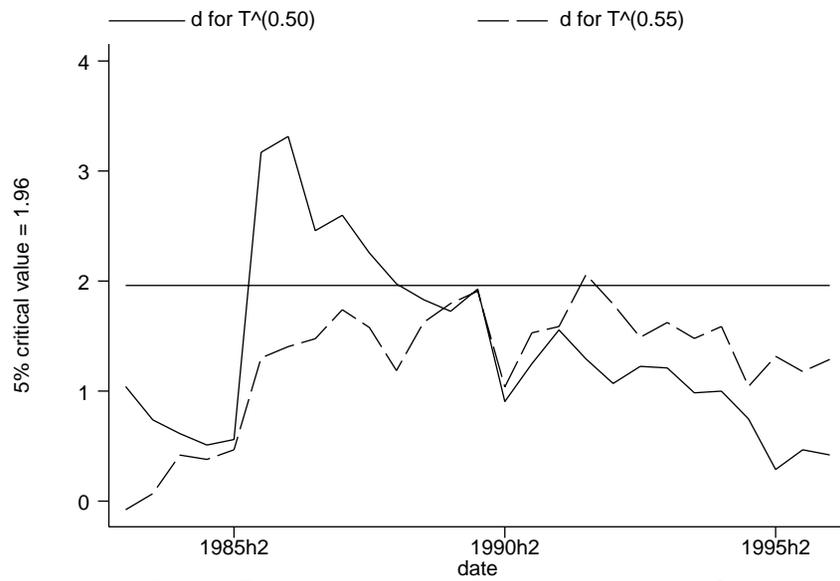


Figure 5. t-statistics for $d[\text{Japanese Yen}] = 0$