A Reconsideration of the Failure of Uncovered Interest Parity for the U.S. Dollar

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VERY PRELIMINARY!!!

Abstract

We re-examine the time-series evidence for failures of uncovered interest rate parity on short-term deposits for the U.S. dollar versus major currencies of developed countries at short-, medium- and long-horizons. The evidence that interest rate differentials predict foreign exchange risk premiums is fragile. The relationship between interest rates and excess returns is not stable over time and disappears altogether when nominal interest rates are near the zero lower bound. However, we do find evidence that year-on-year inflation rate differentials consistently predict excess returns – when the U.S. dollar inflation rate has been relatively high, subsequent returns on U.S. deposits tend to be high. We interpret this evidence as being consistent with hypotheses that posit that markets do not fully react initially to predictable changes in future monetary policy. This evidence is not strong, so we should not rule out the possibility that excess returns are not predictable at all.

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Uncovered interest parity under rational expectations is the hypothesis that there is no foreign exchange risk premium, or that the expected excess returns on foreign bonds is equal to zero. It is usually expressed algebraically as:

$$(1) \qquad E_t s_{t+1} - s_t = i_t - i_t^*$$

where s_t is the log of the exchange rate expressed as the home currency price of foreign currency, i_t is the interest rate on a riskless one-period deposit or security in the home country, and i_t^* is the analogous interest rate in the foreign country.

The uncovered interest parity puzzle arises an econometric test from Fama (1984) that estimates the slope (and intercept) parameters in the regression:[1]

$$(2) \qquad s_{t+1} - s_t = \alpha + \beta\left(i_t - i_t^*\right) + u_t\,,$$

where α and β are parameters to be estimated and u_t is an error term. One implication of the null hypothesis of uncovered interest parity (hereinafter referred to as UIP) is $\alpha = 0$ and $\beta = 1$.

By a simple algebraic transformation, this regression is equivalent to one that regresses the ex post excess return on foreign bonds on the home minus foreign interest rate differential:

$$(3) \qquad s_{t+1} - s_t + i_t^* - i_t = \alpha + \gamma\left(i_t - i_t^*\right) + u_t$$

If equations (2) and (3) are estimated by ordinary least squares, the estimates of the intercepts are identical, and the slope coefficient estimates are related as $\gamma = \beta - 1$. In this formulation, the null of UIP requires $\alpha = 0$ and $\gamma = 0$.

A very large literature has tested UIP with such regressions, especially for the U.S. dollar. The "UIP puzzle" or the "Fama puzzle" refers to the finding that the slope coefficient in equation

[1] Bilson (1981) is an earlier published paper that performs this test of uncovered interest parity.

(3) is usually found to be negative and often less than -1, This means when the home interest rate is high, the excess return on the foreign deposit tends to be low.[2]

We reconsider these econometric tests. It has been previously noted that when equation (3) is estimated in subsamples, the slope coefficient estimate is not stable over time. For example, Bekaert and Hodrick (2018) present rolling regressions on monthly data, using five-year estimation windows, for the U.S. dollar relative to the euro, the British pound and the Japanese yen. That study finds considerable instability in the slope parameter estimates.

We also undertake such an exercise for the U.S. dollar against the major world currencies, with an extended sample. In addition, in assessing the statistical significance of the slope coefficient estimate, we take into account, and correct for, the potential small sample bias first noted by Stambaugh (1999). When we do so, we find that the evidence for a UIP puzzle is weak. The slope coefficients vary widely over subsamples. They tend to be negative in the period before the global financial crisis, but generally are not significant using the bias-corrected tests. After 2007, the point estimates of the slope coefficient are positive, but the standard errors are quite large so the null of $\gamma = 0$ cannot be rejected.

We also consider the correlation of the interest rate differential on the excess return from rolling over short term bonds. At the "medium" horizon, we estimate:

$$(4) \qquad \sum_{j=1}^{12} s_{t+j+1} - s_{t+j} + i^*_{t+j} - i_{t+j} = \alpha_M + \gamma_M \left(i_t - i^*_t \right) + u^M_t$$

In this case, we find more evidence of statistical significance, but not stability of the slope coefficient. The estimates of γ_M are found to be negative prior to 2007 and positive afterward.

Then we consider the expected return from rolling over short term bonds over a long horizon by estimating:

$$(5) \qquad E_t \left(\sum_{j=1}^{\infty} s_{t+j+1} - s_{t+j} + i^*_{t+j} - i_{t+j} \right) = \alpha_L + \gamma_L \left(i_t - i^*_t \right) + u^L_t \, .$$

[2] See Engel (1996, 2014) for surveys of these tests of UIP.

The dependent variable in this regression is constructed from vector autoregressions, as described below. Our findings here in sub-samples are fragile, as they depend heavily on the estimated persistence of interest rates. That is, the measured responsiveness of $E_t\left(\sum_{j=1}^{\infty} i^*_{t+j} - i_{t+j}\right)$ depends crucially on how persistent the interest differential is measured to be – the more persistent, the greater the response. But the persistence is estimated imprecisely in small samples. For the whole sample, we generally find γ_L is not statistically significant, though for one currency it is significantly negative and for another it is significantly positive.

What should we make of this apparent parameter instability? One possibility is suggested by West (2012). Building on the work of Engel and West (2005), that paper demonstrates that the slope coefficient estimate in the Fama regression may be nearly inconsistent if the exchange rate is generated as in a large class of present-value exchange-rate models. In those models, even ones in which uncovered interest parity is posited, the exchange rate is determined by an expected present value of current and future economic fundamental variables. West shows that as the discount factor approaches unity in value, the ordinary least squares estimate of the slope coefficient becomes inconsistent. Intuitively, when the appropriate discount factor is nearly one, the slope coefficient estimates will be unstable over sub-samples, as we find.

An alternative possibility is that the slope coefficient estimates, particularly in samples from the 1980s and 1990s, were reflecting the outcome of some underlying economic process, but that process changed in the 2000s and 2010s. Much of the literature has been devoted to building models of a foreign exchange risk premium to explain the Fama puzzle. However, that literature, in general, does not effectively account for the parameter instability of the Fama regression. Farhi and Gabaix (2016) is one approach that allows for a change in the slope coefficient, but we shall see that it is not well-suited to explaining the U.S. data. That model posits that one currency has an apparent low expected return during normal times and a high expected return during times of global economic stress. But, for example, while the slope coefficient in regression (3) is estimated to be negative consistently in the 1980s and 1990s, the sign of the regressor changes frequently for most U.S. dollar currency pairs. That implies that it is not the case that one of the currencies consistently offers an ex ante excess return over this period, in contrast to the implications of Farhi and Gabaix.

Instead, we look at the possibility that a change in how monetary policy is conducted is responsible for the inconsistent sign in regression (3) over sub-samples in rolling regressions. As inflation subsided in the high-income countries, nominal interest rates sank toward zero. At the zero lower bound, central banks introduced alternative monetary policy tools – "unconventional monetary policy (UMP)" such as forward guidance and quantitative easing. The relationship between interest rates and excess returns may have changed post-2000 because the instruments of monetary policy changed.

One strand of the literature has tried to account for the Fama puzzle by examining the market's reaction to monetary policy changes. Froot and Thaler (1990) and then Eichenbaum and Evans (1995) have suggested that there is a delayed reaction to interest rate changes engineered by monetary policymakers. When money is tightened in the home country, so $i_t - i_t^*$ rises, the home currency appreciates, so s_t falls. However, in contrast to the implications of the classic Dornbusch (1976) model that assumes UIP and rational expectations, this approach suggests that the maximum appreciation of the home currency does not occur initially when policy is changed. Instead, there is "delayed overshooting" because markets react slowly to the shock to $i_t - i_t^*$. While some market players react quickly and s_t falls, others adjust their portfolios more slowly, so that the home currency continues to appreciate beyond the initial period of the shock. s_{t+1} falls more relative to s_t, which then implies the negative relationship between $s_{t+1} - s_t$ and $i_t - i_t^*$ that Fama found empirically. This process is formally modeled in Bacchetta and van Wincoop (2010), with further implications demonstrated in Bacchetta and van Wincoop (2019), in a model in which agents find it costly to adjust their portfolios constantly, and hence the full reaction of the exchange rate to monetary policy changes does not occur immediately.

A related explanation comes from Gourinchas and Tornell (2004), which posits that investors underestimate the persistence of monetary policy changes. That is, for example when $i_t - i_t^*$ rises, investors are surprised in period $t+1$ that the increase has not dissipated more than it does on average. This surprise acts like an unanticipated tightening of monetary policy leading the home currency to be stronger at time $t+1$ than it would be under rational expectations of monetary policy.

We address the possibility that the UIP puzzle is related to monetary policy by estimating short-run, medium-run and long-run regressions that are analogous to equations (3), (4), and (5), but with year-on-year inflation differences as the regressor:

$$(6) \qquad s_{t+1} - s_t + i_t^* - i_t = \alpha + \delta\left(\pi_t - \pi_t^*\right) + u_t$$

$$(7) \qquad \sum_{j=1}^{12} s_{t+j+1} - s_{t+j} + i_{t+j}^* - i_{t+j} = \alpha_M + \delta_M\left(\pi_t - \pi_t^*\right) + u_t^M$$

$$(8) \qquad E_t\left(\sum_{j=1}^{\infty} s_{t+j+1} - s_{t+j} + i_{t+j}^* - i_{t+j}\right) = \alpha_L + \delta_L\left(\pi_t - \pi_t^*\right) + u_t^L$$

where $\pi_t - \pi_t^*$ is the home minus foreign inflation rate in the 12 months leading up to period *t*. Although all our empirical analysis uses monthly data, we employ the year-on-year inflation rates because they might better measure policymaker's expectations of inflation compared to noisy monthly inflation rates.[3]

We find consistent, but not especially strong evidence that the slope coefficients in all these regressions are negative. That finding is consistent with the stories of delayed reaction by markets, or underestimation of the persistence of monetary policy, when the monetary policy response to inflation is a contraction that causes a currency appreciation. When home inflation rises relative to foreign inflation ($\pi_t - \pi_t^*$ rises), policymakers may react immediately or with some delay to tighten monetary policy. The home currency should appreciate with a sufficient tightening, but if investors react slowly or do not correctly anticipate the persistence of policy, $s_{t+1} - s_t$ will fall more than under rational expectations and there will be predictable excess returns on the home currency.

This prediction does not necessarily depend on how monetary policy is implemented – whether interest rates are the instrument of policy or whether the central bank uses unconventional monetary policy. If the central bank can react sufficiently to inflation changes, the exchange rate behavior may be similar under either regime. In line with this, we find that the estimated slope coefficients do not change sign and are consistently negative over time.

[3] Engel et al. (2019) find evidence that monthly inflation helps predict returns in the post-2000 era for a subset of currencies considered in this study.

We estimate equations (3) - (8) over four time periods: the entire sample we have for each country (which runs from 1979:06 to 2020:02 for some countries, but for New Zealand runs only from 1999:01 to 2017:12); our longest common sample, 1989:01 to 2017:11 (except New Zealand's sample, which begins 1999:01); a pre-crisis common sample, 1989:01 – 2006:12; and a common sample that includes the low interest rate era, 2007:01-2017:11. For the short-term and medium-term regressions, (3), (4), (6), and (7), we also report rolling regression results with 10-year windows using all of the data we have for each exchange rate.[4] In all of our estimates, we use statistics that offer analytical corrections for small-sample bias and serial correlation.

All our empirical results relate to the time-series relationship between interest rates and excess returns, or inflation rates and excess returns. We do not, in other words, look at broad cross-sections of returns as in the pioneering work of Lustig and Verdelhan (2007).[5] Hassan and Mano (2019) emphasize the differing implications of cross-section and time-series tests of uncovered interest parity.

Our empirical work is all for U.S. dollar exchange rates, as the failure of UIP in time series has been shown in the literature to be stronger for the dollar than other currencies. We look at the dollar against the G10 currencies, and in our longer samples, with the German mark, French franc and Italian lira in place of the euro.

Section 1 presents our findings regarding the short-run excess returns. We present results from medium-run tests and long-run tests in sections 2 and 3, respectively. We offer some conclusions and interpretation in section 4.

1. Short-Run

We begin by presenting estimates of the Fama regression, equation (2) for the different time periods mentioned above. Stambaugh (1999) showed that in such a regression, if the regressor (the interest rate differential in this case) is serially correlated, and if innovations to the regressor are correlated with the innovations in equation (2), the OLS estimate of the slope coefficient as

[4] The Supplemental Appendix reports also results with 5-year rolling windows, which result in similar conclusions.
[5] See also Lustig et al. (2011, 2014), Verdelhan (2018), Menkhoff et al. (2012a, 2012b), Hassan and Mano (2019) and many others.

well as the *t*-statistic will be biased. In the tables below, we present estimates of β from equation (2) and standard errors with the bias corrections derived by Amihud and Hurvich (2004).

Table 1 presents estimates based on the full sample for each currency and includes the sample dates. Recall that a finding that $\beta \neq 1$ constitutes a rejection of uncovered interest parity, which is equivalent to $\gamma \neq 0$ in equation (3). Moreover, for comparability with the subsequent tests we present as well as with the literature, recall that the literature has tended to find that when $i_t - i_t^*$ increases, there is a decline in the excess return on foreign bonds, $s_{t+1} - s_t + i_t^* - i_t$. That is, the literature usually finds $\beta < 1$ (and frequently, $\beta < 0$), which, given that $\gamma = \beta - 1$, is equivalent to $\gamma < 0$ ($\gamma < -1$).

The exchange rates we examine are the Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), German mark (DEM), French franc (FRF), GBP (British pound), Italian lira (ITL), Japanese yen (JPY), Norwegian krone (NOK), New Zealand dollar (NZD), and Swedish krona (SEK). We convert the mark, French franc and lira into euros using the euro using the conversion rates at the time of origination of the euro in January 1999.

All the estimated slope coefficients are less than one, consistent with the literature. However, using the bias-corrected estimates, we find that the 95 percent confidence interval contains unity for all but five of the currencies (CAD, CHF, DEM, GBP, and JPY.) Hence, we find with our full sample that the evidence against UIP is not as strong as has been previously reported in the literature.

The estimates reported in Table 1 use the full sample we have for each currency. Not all currencies have LIBOR rates for the entire period 1979:06 – 2020:02. That data is available only for CAD, DEM, FRF, GBP, ITL, and JPY. Note that three of these currencies converted into the euro. Table 2 reports the results for the longest common sample of the currencies, 1989:01 – 2017:11 (except NZD, for which the interest rate data begin in 1999.)

The findings from Table 2 are like those of Table 1. All the estimated slope coefficients are less than one (with the exception of NOK, which is 1.005.) Only two of the confidence intervals exclude the UIP null – for the German mark and Japanese yen. There are two reasons for the differences between Tables 1 and 2. First, Table 2 has no data prior to 1989, and the Fama puzzle was stronger in the data in the 1980s. Second, because the sample is shorter, the standard errors are larger in Table 2.

In fact, when we split the common sample into the pre-Global Financial Crisis (GFC) and the period that includes the GFC, we find the slope coefficient estimates are dramatically different. Table 3 reports estimates of equation (2) for the period 1989:01 – 2006:12, and Table 4 reports the estimates for the 2007:1 – 2017:11 period. In the earlier time period, all the point estimates for the slope coefficient lie below one, though the 95 percent confidence intervals exclude unity only for CAD, CHF, JPY, and NZD. In other words, the findings are almost identical to the full sample results reported in Table 1.[6] On the other hand, all the slope coefficients in the later period are estimated to be positive, but, importantly, the confidence intervals are very wide and all contain unity.

In Figures 1 – 11, we report estimates of the slope coefficient and 95 percent confidence intervals using 10-year rolling regressions.[7] These Figures highlight the instability of the coefficient estimate of the Fama regression. In the graphs, the dates along the horizontal axis mark the beginning of each 10-year sample. The blue shaded areas represent the time periods in which the estimated slope coefficient is significantly less than one at the five percent level. The pink areas are when the estimated coefficient is less than one, but not significantly so. The green areas are dates in which the estimated coefficient is greater than one. The purple areas are times in which the slope coefficient is significantly greater than one at the five percent level.

The picture that emerges is fairly incoherent, and that is the important lesson. While the Fama puzzle arises from findings that the slope coefficient is significantly less than one, for most of the currencies the time periods over which that is true are relatively short and concentrated in the pre-2000 period. Most of the time, the 95 percent confidence interval includes unity. For some of the currencies, such as the New Zealand dollar, there are extended periods of time for which the estimated coefficient is greater than one.

We do not perform any joint tests of significance, but it is notable that the estimated slope coefficients rise during the latter part of the sample for all the currencies. There are two possible interpretations of these graphs of rolling estimates of the slope coefficient: The first is that the parameter estimate is very unstable, and there is no true underlying relationship between $i_t - i_t^*$

[6] Table 1 reports that the slope coefficient is less than one for the German mark in the full sample, while in the 1989:01 – 2016:12 sample, the 95 percent confidence interval does barely contain one.

[7] The Supplemental Appendix reports results from rolling regressions with 5-year windows. They are similar to those we report in the text with 10-year windows, but the confidence intervals are wider.

and $s_{t+1} - s_t + i_t^* - i_t$ estimated by regression (2). This possibility is consistent with West's (2012) observation that the parameter estimate is nearly inconsistent as the discount factor in present value models of the exchange rate approaches one. The second possibility is that there is a significant change in the underlying economic relationship between interest rates and excess returns, but we have not detected statistical significance because we have not used a joint test of significance, and because the 10-year window is relatively short.

We can ask if there are some regularities in the data that can account for this rise in the estimated slope coefficient. Figures 12-22 plot the estimated slope coefficients from the 10-year rolling Fama regressions and the inverse of the variance of $i_t - i_t^*$ estimated over the same 10-year time window.[8]

These graphs show a clear and strong positive correlation between the reciprocal of the variance of $i_t - i_t^*$ and the slope coefficient estimates from rolling regressions of equation (2). Table 5 confirms this by reporting estimates of the correlation between the slope coefficient from these rolling regressions beginning with 1989:1, and various measures of the volatility of $i_t - i_t^*$, using both 5-year and 10-year windows.

What economic forces lead to this pattern of correlations? One explanation that has been advanced for the puzzling finding of $\beta < 1$ in the Fama regression is that there is a "peso problem" or the market is incorporating the possibility of a "rare disaster". Farhi and Gabaix (2016) offer a model of such a phenomenon. That model posits that high-interest rate currencies incorporate a risk premium during "good times" because they are currencies that will depreciate greatly during times of global uncertainty. Thus, the finding of $\beta < 1$ in the Fama regression arises both because the high-interest-rate currency has a higher expected return than lower-interest-rate currencies, and because of a peso problem in which the sample that contains only good times does not incorporate periods in which the high-interest-rate currency has a large depreciation. During bad times, this same currency has a high interest rate, but the currency depreciates, leading to a slope coefficient less than one in the Fama regression.

Figures 23-25, however, demonstrate some difficulties with this interpretation for the variation in the slope coefficient estimate from equation (2) for the U.S. dollar. The figures plot

[8] Note in this version of the paper, the time axis now has the beginning of the window rather than the end of the time window as in Figures 1-11.

the interest rates for the U.S. and the other countries. The problem, as the graphs illustrate, is that there is not a sustained period in which the U.S. is either the low-interest-rate currency or the high-interest-rate currency in the pre-2007 period. That is, we cannot identify the dollar as, for example, a low-interest-rate currency that is expected to appreciate during times of global uncertainty. Sometimes its interest rate is lower than each of the other countries, and sometimes it is higher. The graphs do reveal that the interest rate of Japan, and to a lesser extent Switzerland, were consistently lower than that of the U.S. pre-2007, but the puzzling behavior of the slope coefficient in regression (2) applies to U.S. dollar regressions, not yen or Swiss franc regressions.

We also can see in Table 6 that the correlation of the slope coefficients from the Fama regression with the market measure of uncertainty, VIX, are not as high as those reported in Table 5. That is, we would expect under the peso problem/rare disaster explanation a strong negative correlation between the Fama coefficient and VIX in the 5-year or 10-year moving average, but that is not the case in fact.

We tentatively offer a different interpretation. As is well known and confirmed by Figures 23-25, nominal interest rates in these high-income countries were near zero or below beginning very soon after the onset of the GFC. At such low levels, interest rates are no longer the most useful policy instrument for central banks. Instead, they implemented a variety of unconventional policies such as quantitative easing and forward guidance. Our hypothesis is that the change in the slope coefficient in the Fama regression is related to this change in the principle monetary policy instrument. Indeed, post-2007, while the slope coefficient estimates are positive, the confidence intervals are very wide. We think possibly the interest rate differentials are simply a misleading guide to relative monetary policy stance in this era. After 2007, U.S. interest rates, while historically close to zero, were higher than in most other countries. At the same time, the Federal Reserve pursued unconventional monetary policies more aggressively than most other countries, and so their overall stance may have been more accommodative.

In other words, prior to the GFC, the finding of $\beta < 1$ in equation (2) could be explained by the models of "delayed reaction" to monetary policy changes. When the Fed, for example, tightened monetary policy, i_t, and hence $i_t - i_t^*$ increased, which led to an immediate appreciation of the dollar (a drop in s_t.) However, perhaps because markets did not perceive how persistent the decline in the interest rate differential would be, or perhaps because expectations are sticky, or perhaps because portfolio adjustment is costly, or perhaps because of balance sheet constraints,

the initial appreciation was not the maximum appreciation. Exchange rates continued to fall, so $s_{t+1} - s_t + i_t^* - i_t$ fell when $i_t - i_t^*$ increased.

That same slow reaction to monetary policy changes may have been at work in the post-2007 era, but monetary policy stance is not well captured by the interest rate differential. To shed some potential light on the subject, we estimated equation (6). The regressor in this equation is $\pi_t - \pi_t^*$, the difference in the year-on-year inflation rate in the U.S. relative to the foreign country. Our notion is this: year-on-year inflation is a proxy for policymakers' expectations of inflation. When $\pi_t - \pi_t^*$ rises, the U.S. will very soon tighten monetary policy relative to the foreign country. Then, following the logic of the previous paragraph, delayed reaction by markets will lead to high returns on dollar assets relative to the foreign country, implying a negative slope coefficient in this regression.

We report estimates for the same time periods as we have for the Fama regression. As with the Fama regression, these coefficient estimates and standard errors are bias-corrected using the statistics of Amihud and Hurvich (2004).

The full-sample results are reported in Table 7. Australia and New Zealand are absent from this table because those countries do not report monthly inflation rates.

We can see that all the estimated slope coefficients are negative, with the exception of France (with a slope of 0.001). Additionally, most are significantly negative at the 10 percent level (in a two-sided test.) The results are not overwhelmingly strong, allowing for the possibility that these findings are simply noise, but we note that the fact that all slope coefficients save one are negative is evidence of a strong pattern.

Table 8 reports the outcome of estimating equation (6) using the longest common sample, 1989:1 – 2017:11. In this common sample, the findings are quite strong. All the slope coefficient estimates are negative, and all but three (for Japan, Norway, and Switzerland) are significantly negative at the five percent level. The coefficient in the Swiss regression is significantly negative at the 10 percent level. The stronger findings over this time period, which excludes the 1980s, perhaps reflects the stronger commitment of central banks to target inflation post-1989:1.

Importantly, when we look at subsamples of the 1989:1 – 2017:11 period, the story is not much changed. The number of significant coefficient estimates is reduced because the sample is shorter, but in both the 1989:1 – 2006:12 period and the 2007:1 – 2017:11 period, the estimated slope coefficients are all negative (with the sole exception of Japan in the latter period, where the coefficient is slightly positive), as Tables 9 and 10 demonstrate.

Figures 26-34 present the slope coefficient estimates from rolling regressions of equation (6). Here we see that the coefficient estimates tend to be consistently negative for all the countries for almost the entire sample after the mid-1980s. In these figures, the dates along the *x*-axis are the starting dates for each 10-year regression window. The areas shaded blue are for a slope coefficient that is significantly negative at the 5 percent level. Pink areas represent sample periods for which the slope coefficient is negative but not significant at the 5 percent level. Green areas are for times of positive coefficient estimates – none of which are significant at the 5 percent level for any time period.

The overwhelming impression from these graphs is that the slope coefficient estimates of equation (6) are negative. There are very few periods of positive coefficients. For a few currencies, the estimated coefficient is positive for a short window early in the sample (that is, 10-year estimation windows beginning in the early 1980s.) That window is longer for the Norwegian krone. The latter part of the sample for the Japanese yen also produces some positive coefficient estimates. But overall, the picture is clear that higher $\pi_t - \pi_t^*$ is associated with lower ex post returns on the foreign currency, $s_{t+1} - s_t + i_t^* - i_t$. Even during periods in which the Fama puzzle was seen to hold, prior to 2007, the empirical regularity from this regression is much more consistent. That is, year-on-year inflation is a better predictor of excess returns than the nominal interest rate differential, even prior to 2007.

The Supplemental Appendix reports estimates from regressions that include both interest rate differentials and year-on-year inflation rate differences:

$$(9) \qquad s_{t+1} - s_t + i_t^* - i_t = \alpha + \gamma_1 \left(i_t - i_t^* \right) + \gamma_2 \left(\pi_t - \pi_t^* \right) + u_{t+1} .$$

The econometrics literature does not provide analytical corrections for bias in the coefficient estimates and standard errors when there is more than one regressor, as is the case here. However,

based on the OLS estimates and Newey-West standard errors, we can draw the following inferences. First, the evidence for a negative relationship between $i_t - i_t^*$ and $s_{t+1} - s_t + i_t^* - i_t$ all but disappears when the inflation differential is included in the regression. That is, the coefficient point estimates, γ_1, are not usually negative during any subsample, and are rarely significantly negative. On the other hand, the evidence for a negative relationship between $\pi_t - \pi_t^*$ and $s_{t+1} - s_t + i_t^* - i_t$ remains strong even when $i_t - i_t^*$ is included in the regression. This suggests the following interpretation: The usual finding that the slope coefficient is less than one in the Fama regression, (2), really is picking up the reaction to monetary policy. The inflation rate over the previous 12 months, $\pi_t - \pi_t^*$ is a stronger measure of monetary policy stance than the interest rate differential. When controlling for year-on-year inflation, there is little evidence of additional explanatory power from $i_t - i_t^*$ except perhaps in the 1979-1988 period for currencies for which we have data. When inflation targeting became more central to monetary policy, both before and after 2007 when interest rates were very low and unconventional monetary policy became more common, $i_t - i_t^*$ has little explanatory power for excess returns once relative inflation is controlled for.

We also estimated versions of equation (9) with the constraint imposed of $\gamma_2 = -\gamma_1$. One could interpret this as a regression of excess returns on a proxy for real interest rate differentials. As Engel (2016) notes, almost all the theoretical literature on the Fama puzzle builds models in which excess returns are related to real, rather than nominal, interest rate differentials. If $\pi_t - \pi_t^*$ is considered a measure of expected inflation over the next month, then $i_t - i_t^* - \left(\pi_t - \pi_t^*\right)$ is a measure of the ex ante real interest rate differential. Even if $\pi_t - \pi_t^*$ is not an excellent measure of inflation expectations, we can still think of these regressions as "inflation adjusted" regressions, that may take into account the problem that nominal interest rates are higher during times of high inflation.

These results are also reported in the Supplemental Appendix. Here, we can use the Amihud and Hurvich (2004) corrections for small-sample bias because there is only one regressor in each regression, $i_t - i_t^* - \left(\pi_t - \pi_t^*\right)$. We can summarize the findings as follows: When using the whole sample, for those countries whose data goes back as far as 1979, the estimated slope coefficient is negative, and usually significantly negative. In the common sample of 1989:01-

2017:11, the slope coefficient is generally not significant, and the sign is about evenly split between positives and negatives. In the 1989:01 – 2006:12 sub-sample, almost all the coefficient estimates are negative, but few are statistically significant. In the 2007:01- 2017:11 period, almost all the coefficients are positive, with a few being statistically significant. The bottom line is that these regressions do not really alter our conclusions. It appears in the pre-2007 period, the interest rate is a predictor, though somewhat weak, of excess returns. When expressed in inflation-adjusted terms, the predictive power is a bit stronger than when only the nominal interest rate differential is used. In the post-2007 period, $i_t - i_t^* - \left(\pi_t - \pi_t^*\right)$ is positively related to $s_{t+1} - s_t + i_t^* - i_t$. We infer that the difference between the two periods is perhaps related to the fact that interest rates were the main instrument of monetary policy before 2007, but much less so afterward.

2. Medium Run

In this section, we consider estimates of equations (4) and (7). The dependent variable in these regressions can be interpreted as the return on an investment strategy of buying foreign exchange, investing in one-month foreign-currency deposits, rolling those deposits over for 12 months then converting the gross investment back into dollars compared to the return from rolling over one-month dollar deposits for 12 months. Our purpose for looking at the medium horizon is to assess whether these predicted excess returns are persistent, which may shed further light on why returns might be predictable.

These regressions are also subject to the bias in parameter estimates and standard errors originally noted by Stambaugh (1999) but are also subject to the problems attendant with "long-horizon" returns regressions. We make use of the bias corrections in the recent study of Boudoukh et al. (2020), using Newey-West standard errors.

We consider the same four estimation periods as we did for our short-run return regressions: the entire sample we have for each country; our longest common sample, 1989:01 to 2017:1; a pre-crisis common sample, 1989:01 – 2006:12; and a common sample that includes the low interest rate era, 2007:01-2017:11.[9]

[9] Again, we note that New Zealand's sample does not begin until 1999.

These results are reported in Tables 11 – 14. For the full sample in Table 11, all the estimated coefficients are negative, except that for the Italian lira. As the short-term interest differential for the U.S. relative to the foreign country increases ($i_t - i_t^*$), the excess return on the foreign investment falls. These coefficients are significantly less than zero at the five percent level for six of the currencies, and at the ten percent level for one more. The findings for this relationship are stronger than what we found over the full sample for the short-run returns in the Fama regression.

The findings are similar when we use our longest common sample, as reported in Table 12. Here all the point estimates of the slope coefficient are negative, and five are significantly less than zero at the five percent confidence level. These findings are echoed in Table 13 for the pre-GFC sample of 1989:01 – 2006:12. All the slope coefficient estimates are negative except for the Italian lira, and seven are significantly (at the five percent level) negative.

The findings are dramatically reversed in the post-2007:01 sample reported in Table 14. There, all the estimated coefficients from regression (4) are positive. Four are significantly positive at the five percent level, and the dollar/euro slope coefficient is significant at the ten percent level.

Compared to the short-run Fama regressions, the outcome of the medium-run regressions show a more dramatic shift. Before 2007, there is strong evidence of a negative slope across the currencies, but after 2007 the evidence is strong in favor of a positive slope.

We also perform rolling regressions, reported in Figures 35 – 45, which highlight this sudden shift. The horizontal axis gives the starting date for each 10-year estimation window. The blue-shaded areas represent a slope coefficient significantly negative at the 5 percent level. Pink areas are for sample periods for which the slope coefficient is negative but insignificant at the 5 percent level. The area is shaded green for times of positive coefficient estimates that are not significant, and purple when the coefficient is positive and significant.

The graphs all show a large swing in the coefficient estimates in the later part of the sample compared to the earlier part. For almost all the currencies, that shift begins with 10-year samples that start in the early 2000s, which coincides with samples in which near-zero interest rates become predominant. In samples that are primarily drawn from the low-interest rate era, the slope coefficients are positive, and usually significantly so. We can conclude that we see the same parameter instability as in the Fama regressions, but with more evidence of a shift in regime from

negative to positive coefficients. That is, the finding of the shift in sign of the slope coefficient is more likely to be a genuine shift in the relationship rather than just sampling error.

We turn next to estimates of equation (7), in which excess medium-term returns is again the dependent variable, and year-on-year inflation is the regressor. We report the slope parameter estimates and standard errors in Tables 15 – 18 for the different time periods.

The most striking takeaway from these tables is that all the slope coefficient estimates for all the currencies and time periods are negative, apart from the French franc and British pound for the full sample, which are marginally positive. The latter two estimates come from samples that begin in 1979. As we have seen with the one-month excess returns, the empirical evidence that increases in $\pi_t - \pi_t^*$ predict declines in excess returns on foreign deposits is weaker when the 1980s are included in the sample. If our working hypothesis is correct, this can be explained by the fact that inflation targeting by central banks was not as strongly followed in the 1980s as in later periods.

In Table 15, which is for the full sample period for each currency, the estimated value of the slope parameter is strongly significantly negative for six of the nine currencies (and insignificant but negative for the lira.) In Table 16, which presents evidence for the 1989:01 - 2017:01 period, all parameter estimates are negative, and the 95 percent confidence interval excludes zero for six of them. For the period 1989:01 – 2006:12, the findings are similar. For the later period when interest rates were near zero, the coefficient estimates are all negative, though fewer are statistically significant.

Figures 46-54 show the slope estimates from rolling regressions with 10-year windows. The figures show that the estimated slope coefficient is negative almost all of the time for all of the currencies, with very few exceptions. For some currencies, windows that start in the early 1980s yield positive parameter values, and the Japanese yen and Norwegian krone show a few more periods of positive parameters than the other currencies, but these are the exceptions to the rule.

Figures 55-63 offer some perspective into the channel through which inflation is generating expected excess returns. These charts plot the parameter estimates of λ_k from the regressions:

$$(10) \qquad s_{t+k} - s_{t-1} = \alpha + \lambda_k \left(\pi_t - \pi_t^* - \left(\pi_{t-1} - \pi_{t-1}^* \right) \right) + \varepsilon_{t+k}, \quad k = 0,1,2,\ldots$$

Note that the dependent variable is the change in the exchange rate from time $t-1$ to time $t+k$ (not the change in time *t* to $t+k$.) For example, when $k=0$, λ_0 gives us the association between the change in the exchange rate between $t-1$ and *t* and changes at time *t* in the inflation rate differential.

We can give a causal explanation to these graphs that is consistent with our hypothesis about delayed reaction to monetary policy, or underestimation of the persistence of monetary policy. For each Figure, the first panel shows estimates of (10) for the pre-GFC period of 1989:01 – 2006:12, and the second graph for the period 2007:01 – 2017:11. With the notable exception of Japan, the graphs show a consistent pattern. In the first place, λ_0 is positive. Our interpretation is that when inflation rises at time *t*, central banks do not immediately undertake contractionary policy. But then we find that the λ_k quickly turn negative, as one would expect if monetary policymakers were targeting inflation, as a tighter monetary policy leads to an appreciation. However, the maximum appreciation does not occur immediately, but instead many months later. If investors were adjusting their portfolios continuously to their desired level, and if they had rational expectations of the persistence of monetary policy, the maximum appreciation should occur as soon as the market recognizes that policy will be tightened. Although these graphs are not literally impulse response functions to monetary policy changes or even to news about inflation, they have that flavor. They show us that exchange rates react slowly to changes in inflation in ways that can be anticipated. We know that these predictable exchange rate changes are not mirrored in interest rate changes, and hence there are predictable excess returns.

We note that the pattern holds well in both periods, pre- and post-2007:01. Even though the preferred monetary policy instruments changed, the exchange rate reaction to changes in year-on-year inflation is very consistent across time.

3. Long-Run

To understand the regressions with expected long-run returns as the dependent variable, equations (5) and (8), take expectations of the "medium-run" regressions. For example, to motivate (5), begin by taking the expectation at time *t* of the dependent variable in equation (4), summing up returns until *k* periods in the future:

$$E_t\left(\sum_{j=1}^{k} s_{t+j+1} - s_{t+j} + i^*_{t+j} - i_{t+j}\right)$$

Now subtract the unconditional mean changes in exchange rates, and the unconditional mean interest rate differential:

$$E_t s_{t+k} - s_t - k\overline{\left(s_{+1} - s\right)} - E_t\sum_{j=0}^{k-1}\left(i_{t+j} - i^*_{t+j} - \left(\overline{i - i^*}\right)\right)$$

Then take the limit as *k* goes to infinity:

(11) $$\lim_{k\to\infty}\left[E_t s_{t+k} - s_t - k\overline{\left(s_{+1} - s\right)}\right] - E_t\sum_{j=0}^{\infty}\left(i_{t+j} - i^*_{t+j} - \left(\overline{i - i^*}\right)\right)$$

The term $\lim_{k\to\infty}\left[E_t s_{t+k} - s_t - k\overline{\left(s_{+1} - s\right)}\right]$ is (minus) the transitory component of the exchange rate in a Beveridge and Nelson (1981) decomposition. Recall any variable with a unit root can be decomposed into a component that is a pure random walk, and a component that is transitory. We shall use a vector autoregression (VAR) to compute a measure of the transitory component of the exchange rate.

The second term on the left-hand-side is the "uncovered interest parity level" of the transitory component of the exchange rate, as defined in Engel (2016). That is, if UIP held, the exchange rate would equal to $-E_t\sum_{j=0}^{\infty}\left(i_{t+j} - i^*_{t+j} - \left(\overline{i - i^*}\right)\right)$. This can be seen by rearranging the UIP condition, (1), and iterating forward as in Engel (2016). We can also obtain an estimate of this component from the same VAR mentioned above.

We then regress the measure obtained for the expression in equation (11) on $i_t - i^*_t$ as in equation (5), or on $\pi_t - \pi^*_t$, as in equation (8).

There are two questions we must address that turn out to be very important for the estimates of the quantities in (11). First, what variables belong in the VAR that we use to produce the dependent variable? Second, how important are small sample considerations in the estimate of the VAR? As it turns out, the two questions are related, and both suggest that results based on shorter samples may not be very reliable.

Since we are interested in the response of exchange rates to interest rate changes and inflation, it seems natural that at a minimum, the VAR that we use should include exchange rates, interest rates and inflation. A key question, though, is whether we model the real exchange rate as stationary or not. Define the log of the real exchange rate as $q_t \equiv s_t + p_t^* - p_t$, where p_t is the log of the consumer price level in the U.S., and p_t^* is the log of the consumer price level in the foreign country. There is considerable disagreement in the literature about whether the real exchange rate is better modeled as converging or as containing a unit root. In fact, Engel (2000) argues that the question is in essence unresolvable without much longer time series than we use in typical studies. There are plausible reasons why the real exchange rate may be stationary but converging very slowly so that it appears to have a unit root when it does not. Conversely, even if one rejects a unit root using standard tests, there may still be a permanent component that has a small innovation variance and is only detectable in very long samples.

We settle on a VAR that contains the vector of variables $\left[q_t \quad i_t - i_t^* \quad \pi_t - \pi_t^* \right]$, but also consider a variant that uses the vector $\left[s_t - s_{t-1} \quad i_t - i_t^* \quad \pi_t - \pi_t^* \right]$. Because the interest rate differential and the inflation rate differential are more indisputably stationary, the former vector imposes that the real exchange rate is stationary, and the latter vector imposes that it is non-stationary. Recent empirical literature has settled on modeling the U.S real exchange rate as stationary (even though there may be a small permanent component), but that is persistent so that the convergence is only detectable in longer samples. We report findings based on the first vector of variables here, and report results under the non-stationarity assumption in the supplemental appendix. We emphasize results estimated from the entire sample, rather than from sub-samples, because of the slow convergence of the real exchange rate.

The second reason why using longer samples is important is because of small-sample bias in estimating the VAR. This bias is likely to be important in our analysis. From equation (11), we can see that the dependent variable depends on the response of $\lim_{k\to\infty}\left[E_t s_{t+k} - s_t - k\overline{\left(s_{+1} - s\right)} \right]$ relative to the response of $E_t \sum_{j=0}^{\infty} \left(i_{t+j} - i_{t+j}^* - \left(\overline{i - i^*} \right) \right)$ to a change in the regressor. Consider this example. Take the case in which the regressor is the interest rate differential, $i_t - i_t^*$, and suppose it turns our that the interest differential follows a first-order autoregression with serial correlation of ρ. Then

our estimate of $E_t\sum_{j=0}^{\infty}\left(i_{t+j}-i^*_{t+j}-\left(\overline{i-i^*}\right)\right)$ is given by $\frac{1}{1-\hat{\rho}}\left(i_t-i^*_t\right)$, where $\hat{\rho}$ is the estimate of ρ. It is well known that the estimate of serial correlation is biased downward. This could have important implications when $i_t-i^*_t$ is very persistent. If the true value of ρ is 0.99, but the estimated value is 0.98, the response of $E_t\sum_{j=0}^{\infty}\left(i_{t+j}-i^*_{t+j}-\left(\overline{i-i^*}\right)\right)$ to the interest rate is lowered from the true value of $100\left(i_t-i^*_t\right)$ down to $50\left(i_t-i^*_t\right)$. Such a large mismeasurement could certainly influence our determination of the sign of the effect of the dependent variable in (11).

The literature has proposed several ways of dealing with this bias in VAR estimation.[10] We found that when we used some of the corrections from the literature, we were left with VARs that had estimated roots greater than one. Here we have used the small-sample bias correction from West (2016), with which we did not encounter the root greater than one problem. However, especially in the estimates in shorter samples, the slope estimates for regressions (5) and (8) were very sensitive to small differences in the bias correction. Here we report our estimates only for the full sample for each currency because of this problem.

The estimates reported in Table 19 and 20 for the slope coefficients have the opposite sign of equations (5) and (8). That is, these regressions are of the form:

(12) $$s^T_t-s^{IP}_t=\alpha_L+\eta_L\left(i_t-i^*_t\right)+u^L_t$$

(13) $$s^T_t-s^{IP}_t=\alpha_L+\zeta_L\left(\pi_t-\pi^*_t\right)+u^L_t,$$

where $s^T_t\equiv-\lim_{k\to\infty}\left[E_ts_{t+k}-s_t-k\left(\overline{s_{+1}-s}\right)\right]$ is the transitory component of the exchange rate from the Beveridge-Nelson decomposition, and $s^{IP}_t=-E_t\sum_{j=0}^{\infty}\left(i_{t+j}-i^*_{t+j}-\left(\overline{i-i^*}\right)\right)$ is the value of the exchange rate if UIP held. In other words, a positive coefficient in these regressions is analogous

[10] See Bauer et al. (2012), Engsted and Pedersen (2014), Pope (1990).

to a negative coefficient in our previous regressions because they imply that when $i_t - i_t^*$ or $\pi_t - \pi_t^*$ increase, expected returns on foreign deposits (over the infinite horizon) rise.

All the estimated coefficients in both Tables 19 and 20 have the expected positive sign. There are three currencies for which the estimated slope is significantly positive at the one percent level (and one at the ten percent level) for equation (12) in which the interest-rate differential is the regressor. The slope estimates are all significantly positive at the one percent level for all the currencies in equation (13), which uses the year-on-year inflation rate differential as the regressor.

Interestingly, these results imply that there is not excess reaction of the exchange rate to changes in either interest rates or inflation rates, in contrast to the findings of Engel (2016). The difference is attributable to the small sample correction that increases the volatility of s_t^{IP}. That is, when the interest differential is estimated to be more persistent, the UIP value of the exchange rate becomes more volatile. Even with this correction, there is still clearly excess volatility of exchange rates, as Table 21 shows. That table reports estimates of the variance of s_t^{IP} and s_t^T, and we see in all cases that $\text{var}\left(s_t^T\right) > \text{var}\left(s_t^{IP}\right)$.

The overall picture remains the same – that inflation differentials are a stronger predictor of future excess returns than interest rate differentials, and when the U.S. inflation rate rises, the expected return on foreign deposits declines.

4. Conclusions

We find that the famous UIP puzzle is not such a robust puzzle. In fact, the slope coefficient in the Fama regression changes signs in the 2000s. This has been noted previously by, among others, Engel et al. (2019) and Bussiére et al. (2018).

One possible explanation for this parameter instability is that, in fact, excess foreign currency returns are unpredictable and the UIP puzzle is merely an illusion. West (2012) has shown that many exchange rate models actually have the implication that UIP holds but that the parameter in the Fama regression will be unstable over time.

Another possible explanation for the parameter instability is that it is related to a genuine change in economic regime. A likely suspect is the change in monetary policy operating procedures. The Fama regression falls apart just when interest rates approach the zero lower bound. We have offered an explanation for the findings based on the hypotheses of Froot and Thaler

(1990), Eichenbaum and Evans (1995), Gourinchas and Tornell (2004), and Bacchetta and van Wincoop (2010, 2019). That explanation is supported by empirical examination of the relationship between future excess returns and the current year-on-year inflation rates.

Bussiére et al. (2018) also finds that the Fama regression no longer produces a negative slope coefficient in the 2000s. However, when the dependent variable (ex post excess returns) is replaced with expected excess returns, where expectations of the future exchange rate are measured from surveys, the slope coefficient is not significantly different than one. That is, uncovered interest parity holds well if the rational expectations hypothesis is jettisoned and replaced with expectations based on surveys of foreign exchange traders (which fail the test of rational expectations.) This is consistent with the possibility that agents do not foresee the persistence of monetary policy changes, as argued by Gourinchas and Tornell (2004) and as we have explained above.

Galí (2020) finds that exchange rates underreact to interest rate changes on long-term bonds, but overreact to interest rate changes on short-term bonds. Bacchetta and van Wincoop (2019) demonstrate that this pattern may occur in a model with delayed portfolio adjustment.

We emphasize that the findings here are not definitive. The economic relationships that determine ex ante excess returns are probably too complicated to be captured in univariate regressions. Our findings do provide evidence that the Fama puzzle is not a stable relationship, and the Fama regression does not generate stable parameter estimates over time. Future research is needed to determine whether, in fact, the data support the hypothesis of delayed portfolio adjustment that may arise from barriers to reallocating assets or from biased expectations.

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Table 1

Slope Coefficient Estimates from Fama Regression, full sample

Currency	Time	# of Obs.	b	95% CI
AUD	1989/01-2017/11	347	-0.466	(-2.404, 1.473)
CAD	1979/06-2017/11	462	-1.012*	(-2.194, 0.171)
CHF	1989/01-2020/02	373	-1.302	(-3.415, 0.810)
DEM	1979/06-2020/02	488	-0.903	(-2.493, 0.687)
FRF	1979/06-2020/02	488	-0.188	(-1.563, 1.187)
GBP	1979/06-2020/02	488	-1.781**	(-3.443, -0.119)
ITL	1979/06-2020/02	488	0.439	(-0.467, 1.345)
JPY	1979/06-2020/02	488	-1.613**	(-3.045, -0.180)
NOK	1986/01-2017/11	382	0.399	(-1.118, 1.916)
NZD	1999/01-2017/12	227	0.077	(-3.904, 4.058)
SEK	1987/01-2017/11	370	0.871	(-0.948, 2.689)

Please ignore the *'s in this version of the paper. These will be corrected in subsequent versions.

Table 2

Slope Coefficient Estimates from Fama Regression, longest common sample

1989:01 – 2017:11

Currency	Time	# of Obs.	b	95% CI
AUD	1989/01-2006/12	346	-0.520	(-2.461, 1.422)
CAD	1979/06-2006/12	346	-0.328	(-1.756, 1.099)
CHF	1989/01-2006/12	346	-1.325	(-3.507, 0.858)
DEM	1979/06-2006/12	346	-0.552	(-2.645, 1.541)
FRF	1979/06-2006/12	346	-0.246	(-2.196, 1.705)
GBP	1979/06-2006/12	346	0.296	(-1.972, 2.564)
ITL	1979/06-2006/12	346	0.902	(-1.168, 2.972)
JPY	1979/06-2006/12	346	-1.128	(-2.968, 0.713)
NOK	1986/01-2006/12	346	1.005	(-0.840, 2.851)
NZD	1999/01-2006/12	226	-0.090	(-4.086, 3.906)
SEK	1987/01-2006/12	346	0.929	(-0.946, 2.805)

Please ignore the time periods and number of observations reported in this table. These are not the time periods used in these regressions. This will be corrected in subsequent versions.

Table 3

Slope Coefficient Estimates from Fama Regression, pre-GFC sample

1989:01 – 2006:12

Currency	Time	# of Obs.	b	95% CI
AUD	1989/01-2006/12	215	-0.828	(-2.779, 1.123)
CAD	1989/01-2006/13	215	-0.633	(-1.824, 0.559)
CHF	1989/01-2006/14	215	-1.530	(-3.896, 0.835)
DEM	1989/01-2006/15	215	-1.131	(-3.351, 1.088)
FRF	1989/01-2006/16	215	-0.551	(-2.593, 1.491)
GBP	1989/01-2006/17	215	0.133	(-2.415, 2.680)
ITL	1989/01-2006/18	215	0.856	(-1.486, 3.199)
JPY	1989/01-2006/19	215	-2.421**	(-4.604, -0.237)
NOK	1989/01-2006/20	215	0.705	(-1.326, 2.736)
NZD	1999/01-2006/21	95	-4.869**	(-9.248, -0.490)
SEK	1989/01-2006/22	215	0.862	(-1.160, 2.884)

Please ignore the time periods reported in this table. These are not the time periods used in these regressions. Also ignore the *s. These will be corrected in subsequent versions.

Table 4

Slope Coefficient Estimates from Fama Regression, post-2007:01 sample

2007:01 – 2017:11

Currency	Time	# of Obs.	b	95% CI
AUD	2007/01-2017/11	130	1.417	(-5.070, 7.905)
CAD	2007/01-2017/12	130	6.735	(-7.078, 20.55)
CHF	2007/01-2017/13	130	2.775	(-3.112, 8.662)
DEM	2007/01-2017/14	130	5.411	(-2.124, 12.95)
FRF	2007/01-2017/15	130	5.411	(-2.124, 12.95)
GBP	2007/01-2017/16	130	9.100**	(0.984, 17.22)
ITL	2007/01-2017/17	130	5.411	(-2.124, 12.95)
JPY	2007/01-2017/18	130	4.356**	(0.385, 8.328)
NOK	2007/01-2017/19	130	6.353*	(-0.213, 12.92)
NZD	2007/01-2017/20	130	11.271***	(3.452, 19.09)
SEK	2007/01-2017/21	130	3.255	(-2.008, 8.518)

Please ignore the time periods reported in this table. These are not the time periods used in these regressions. Also ignore the *s. And, of course, DEM, FRF and ITL results are identical in this time period because these are all for the euro. These problems will be corrected in subsequent versions.

Table 5

Correlation Between Fama Coefficient and Volatility of $i_t - i_t^*$

Currency	$var(i_t - i_t^*)$		$s.d.(i_t - i_t^*)$		$\frac{1}{var(i_t - i_t^*)}$		$\frac{1}{s.d.(i_t - i_t^*)}$	
	10-year	5-year	10-year	5-year	10-year	5-year	10-year	5-year
AUD	-0.219032	-0.0134085	-0.2775269	-0.0311605	0.3846625	0.1301551	0.3630883	0.0933806
CAD	-0.222097	-0.25052	-0.3392542	-0.3378888	0.5776892	0.3504238	0.551779	0.419812
CHF	-0.1363908	0.0110457	-0.2310677	0.0257761	0.5327361	-0.3139027	0.4649779	-0.2354246
DEM	-0.2709887	-0.2008321	-0.3899572	-0.291183	0.7270605	0.2581157	0.6492089	0.3361648
FRF	-0.1703477	-0.1781361	-0.2831697	-0.3065565	0.6843109	0.5089261	0.5807944	0.5158561
GBP	-0.2272118	-0.2696069	-0.3088093	-0.4333834	0.5170766	0.8402929	0.4777775	0.7875769
ITL	-0.0948732	-0.1450298	-0.2131551	-0.2965008	0.6360868	0.5250106	0.5235616	0.5230335
JPY	-0.6184538	-0.4791037	-0.7130964	-0.5451229	0.7649129	0.2895529	0.7809908	0.4139815
NOK	-0.2152181	-0.0802055	-0.3669302	-0.2065483	0.6950363	0.2290806	0.647934	0.3036734
SEK	0.1627654	0.1959826	0.0873281	0.1081914	0.2895565	0.150698	0.1599901	0.1016158
All	-0.1198412	-0.0934521	-0.2445278	-0.2171518	**0.5111405**	0.3821952	0.4936273	0.4138726

Table 6

Correlation Between Fama Coefficient and VIX

Currency	$corr(VIX, \hat{\beta})$	
	10-year	5-year
AUD	-0.0708334	-0.0143217
CAD	-0.4181572	-0.3873864
CHF	-0.2820189	0.0162222
DEM	-0.3387412	-0.1311715
FRF	-0.3590141	-0.1679671
GBP	-0.2121535	0.014264
ITL	-0.3681683	-0.2548278
JPY	-0.2620131	0.0346865
NOK	-0.3919516	0.0635429
NZD	-0.7100843	0.1697775
SEK	-0.4900593	0.0093962

Table 7

Slope Coefficient from Equation (6), Full Sample for Each Country

Currency	Time	# of Obs.	c	95% CI
CAD	1979/06-2017/11	450	-0.133**	(-0.259, -0.00596)
CHF	1989/01-2020/02	361	-0.333*	(-0.696, 0.0299)
DEM	1979/06-2020/02	476	-0.323***	(-0.518, -0.127)
FRF	1979/06-2020/02	476	0.001	(-0.168, 0.171)
GBP	1979/06-2020/02	476	-0.198*	(-0.395, 0.000244)
ITL	1979/06-2020/02	476	-0.020	(-0.107, 0.0666)
JPY	1979/06-2020/02	476	-0.125	(-0.332, 0.0830)
NOK	1986/01-2017/11	370	-0.105	(-0.268, 0.0586)
SEK	1987/01-2017/11	358	-0.215**	(-0.394, -0.0373)

Table 8

Slope Coefficient from Equation (6), 1989:1 – 2017:11

Currency	Time	# of Obs.	c	95% CI
CAD	1989/01-2017/11	334	-0.312**	(-0.592, -0.0312)
CHF	1989/01-2017/11	334	-0.337*	(-0.703, 0.0285)
DEM	1989/01-2017/11	334	-0.475***	(-0.782, -0.169)
FRF	1989/01-2017/11	334	-0.881***	(-1.326, -0.437)
GBP	1989/01-2017/11	334	-0.257**	(-0.500, -0.0137)
ITL	1989/01-2017/11	334	-0.390***	(-0.656, -0.124)
JPY	1989/01-2017/11	334	-0.020	(-0.244, 0.204)
NOK	1989/01-2017/11	334	-0.052	(-0.297, 0.192)
SEK	1989/01-2017/11	334	-0.234**	(-0.426, -0.0426)

Table 9

Slope Coefficient from Equation (6), 1989:1 – 2006:12

Currency	Time	# of Obs.	c	95% CI
CAD	1989/01-2006/13	203	-0.285**	(-0.505, -0.0644)
CHF	1989/01-2006/13	203	-0.268	(-0.675, 0.139)
DEM	1989/01-2006/13	203	-0.347**	(-0.689, -0.00442)
FRF	1989/01-2006/13	203	-0.988***	(-1.488, -0.487)
GBP	1989/01-2006/13	203	-0.214	(-0.506, 0.0792)
ITL	1989/01-2006/13	203	-0.308*	(-0.628, 0.0116)
JPY	1989/01-2006/13	203	-0.279	(-0.672, 0.114)
NOK	1989/01-2006/13	203	-0.027	(-0.407, 0.353)
SEK	1989/01-2006/13	203	-0.192*	(-0.386, 0.00141)

Table 10

Slope Coefficient from Equation (6), 2007:1 – 2017:11

Currency	Time	# of Obs.	c	95% CI
CAD	2007/01-2017/12	118	-0.462	(-1.206, 0.281)
CHF	2007/01-2017/12	118	-0.637	(-1.500, 0.226)
DEM	2007/01-2017/12	118	-1.128***	(-1.846, -0.409)
FRF	2007/01-2017/12	118	-1.147**	(-2.008, -0.286)
GBP	2007/01-2017/12	118	-0.606**	(-1.177, -0.0342)
ITL	2007/01-2017/12	118	-0.733**	(-1.367, -0.0989)
JPY	2007/01-2017/12	118	0.175	(-0.130, 0.479)
NOK	2007/01-2017/12	118	-0.228	(-0.635, 0.180)
SEK	2007/01-2017/12	118	-0.715*	(-1.452, 0.0209)

Table 11

Slope Coefficient from Medium-Run Regression (4), Full Sample for Each Country

Currency	Time	# of Obs.	d	95% CI
AUD	1989/01-2017/11	337	-16.985***	(-28.19, -5.781)
CAD	1979/06-2017/11	452	-8.248**	(-15.28, -1.214)
CHF	1989/01-2020/02	363	-19.324***	(-31.42, -7.230)
DEM	1979/06-2020/02	478	-16.599***	(-25.05, -8.147)
FRF	1979/06-2020/02	478	-5.533	(-14.18, 3.116)
GBP	1979/06-2020/02	478	-16.507***	(-28.56, -4.453)
ITL	1979/06-2020/02	478	1.433	(-5.887, 8.754)
JPY	1979/06-2020/02	478	-20.451***	(-28.81, -12.10)
NOK	1986/01-2017/11	372	-9.141*	(-19.77, 1.487)
NZD	1999/01-2017/12	217	-23.298	(-60.66, 14.06)
SEK	1987/01-2017/11	360	-1.177	(-15.92, 13.57)

Table 12

Slope Coefficient from Medium-Run Regression (4), 1989:01-2017:11

Currency	Time	# of Obs.	b	95% CI
AUD	1989/01-2007/11	337	-16.985***	(-28.19, -5.781)
CAD	1989/01-2007/11	337	-6.741	(-16.14, 2.658)
CHF	1989/01-2007/11	347	-19.129***	(-31.55, -6.710)
DEM	1989/01-2007/11	347	-15.641**	(-28.61, -2.677)
FRF	1989/01-2007/11	347	-13.347**	(-25.21, -1.489)
GBP	1989/01-2007/11	347	-7.199	(-22.34, 7.940)
ITL	1989/01-2007/11	347	-0.091	(-11.64, 11.46)
JPY	1989/01-2007/11	347	-22.934***	(-34.41, -11.45)
NOK	1989/01-2007/11	336	-5.180	(-17.44, 7.075)
NZD	1989/01-2007/11	217	-23.298	(-60.66, 14.06)
SEK	1989/01-2007/11	336	-0.928	(-15.90, 14.05)

Table 13

Slope Coefficient from Medium-Run Regression (4), 1989:01-2006:12

Currency	Time	# of Obs.	b	95% CI
AUD	1989/01-2006/12	216	-20.403***	(-26.45, -14.36)
CAD	1989/01-2006/12	216	-10.841***	(-15.81, -5.870)
CHF	1989/01-2006/12	216	-22.082***	(-29.70, -14.46)
DEM	1989/01-2006/12	216	-19.842***	(-27.83, -11.85)
FRF	1989/01-2006/12	216	-15.536***	(-23.19, -7.882)
GBP	1989/01-2006/12	216	-3.144	(-12.45, 6.165)
ITL	1989/01-2006/12	216	0.872	(-6.294, 8.039)
JPY	1989/01-2006/12	216	-38.961***	(-44.60, -33.33)
NOK	1989/01-2006/12	216	-6.374	(-14.52, 1.769)
NZD	1989/01-2006/12	96	-61.466***	(-73.65, -49.28)
SEK	1989/01-2006/12	216	-1.240	(-11.26, 8.776)

Table 14

Slope Coefficient from Medium-Run Regression (4), 2007:01-2017:11

Currency	Time	# of Obs	b	95% CI
AUD	2007/01-2017/11	121	1.965	(-38.36, 42.29)
CAD	2007/01-2017/11	121	82.044***	(37.34, 126.7)
CHF	2007/01-2017/11	131	14.284	(-20.63, 49.20)
DEM	2007/01-2017/11	131	38.034*	(0.0821, 75.99)
FRF	2007/01-2017/11	131	38.039*	(0.0873, 75.99)
GBP	2007/01-2017/11	131	64.430**	(14.45, 114.4)
ITL	2007/01-2017/11	131	38.034*	(0.0816, 75.99)
JPY	2007/01-2017/11	131	39.831***	(21.57, 58.10)
NOK	2007/01-2017/11	120	30.158	(-22.14, 82.46)
NZD	2007/01-2017/11	121	73.114**	(10.05, 136.2)
SEK	2007/01-2017/11	120	26.027	(-6.974, 59.03)

Table 15

Slope Coefficient from Medium-Run Regression (7), Full Sample for Each Currency

Currency	Time	# of Obs.	f	95% CI
CAD	1979/06-2017/11	440	-0.868**	(-1.692, -0.0450)
CHF	1989/01-2020/02	363	-1.957***	(-3.423, -0.490)
DEM	1979/06-2020/02	466	-2.189***	(-3.468, -0.910)
FRF	1979/06-2020/02	466	0.066	(-1.147, 1.279)
GBP	1979/06-2020/02	466	0.111	(-1.563, 1.786)
ITL	1979/06-2020/02	466	-0.138	(-0.919, 0.643)
JPY	1979/06-2020/02	466	-2.489***	(-4.069, -0.910)
NOK	1986/01-2017/11	372	-1.299***	(-2.192, -0.407)
SEK	1987/01-2017/11	360	-2.536***	(-3.657, -1.415)

Table 16

Slope Coefficient from Medium-Run Regression (7), 1989:01-2017:11

Currency	Time	# of Obs.	c	95% CI
CAD	1989/01-2007/11	337	-1.999**	(-3.849, -0.149)
CHF	1989/01-2007/11	347	-1.939**	(-3.409, -0.470)
DEM	1989/01-2007/11	347	-1.960**	(-3.452, -0.468)
FRF	1989/01-2007/11	347	-4.111***	(-6.779, -1.444)
GBP	1989/01-2007/11	347	-0.795	(-2.365, 0.775)
ITL	1989/01-2007/11	347	-2.218**	(-4.014, -0.421)
JPY	1989/01-2007/11	347	-1.447	(-3.189, 0.294)
NOK	1989/01-2007/11	336	-0.362	(-1.628, 0.905)
SEK	1989/01-2007/11	336	-2.692***	(-3.896, -1.488)

Table 17

Slope Coefficient from Medium-Run Regression (7), 1989:01-2006:12

Currency	Time	# of Obs.	c	95% CI
CAD	1989/01-2006/12	216	-1.780*	(-3.789, 0.228)
CHF	1989/01-2006/12	216	-1.972**	(-3.902, -0.0429)
DEM	1989/01-2006/12	216	-2.340***	(-4.057, -0.624)
FRF	1989/01-2006/12	216	-7.037***	(-9.833, -4.241)
GBP	1989/01-2006/12	216	-0.145	(-1.968, 1.678)
ITL	1989/01-2006/12	216	-1.885*	(-4.063, 0.293)
JPY	1989/01-2006/12	216	-4.756***	(-7.376, -2.137)
NOK	1989/01-2006/12	216	-0.825	(-3.207, 1.558)
SEK	1989/01-2006/12	216	-2.485***	(-3.716, -1.254)

Table 18

Slope Coefficient from Medium-Run Regression (7), 2007:01-2017:11

Currency	Time	# of Obs.	c	95% CI
CAD	2007/01-2017/11	121	-3.811**	(-7.172, -0.451)
CHF	2007/01-2017/11	131	-2.449**	(-4.796, -0.101)
DEM	2007/01-2017/11	131	-1.942	(-5.020, 1.137)
FRF	2007/01-2017/11	131	-2.169	(-6.026, 1.689)
GBP	2007/01-2017/11	131	-4.621**	(-8.124, -1.118)
ITL	2007/01-2017/11	131	-2.283	(-5.252, 0.686)
JPY	2007/01-2017/11	131	1.536	(-0.557, 3.628)
NOK	2007/01-2017/11	120	-1.074	(-2.910, 0.762)
SEK	2007/01-2017/11	120	-4.708**	(-8.850, -0.566)

Table 19

Slope Coefficient from Long-Run Regression (12), Full Sample for Each Currency

Currency	Data	Transitory Component β^T	UIP measure β^{IP}	Difference β^{T-IP}
CAD	1979/06-2017/11	-46.663***	-77.289***	30.626***
	446	(-60.11, -33.22)	(-92.39, -62.19)	(27.45, 33.80)
CHF	1989/01-2020/02	-31.791***	-57.815***	26.024***
	369	(-40.40, -23.18)	(-64.15, -51.48)	(11.22, 40.82)
DEM	1979/06-2020/02	-39.275***	-42.000***	2.725
	472	(-49.17, -29.38)	(-43, -41)	(-7.700, 13.15)
FRF	1979/06-2020/02	-22.412***	-27.617***	5.205
	472	(-29.79, -15.03)	(-32.72, -22.51)	(-1.524, 11.93)
GBP	1979/06-2020/02	-16.923**	-14.138***	-2.785
	472	(-30.18, -3.661)	(-15.11, -13.17)	(-16.97, 11.40)
ITL	1979/06-2020/02	-88.865***	-94.296***	5.431*
	472	(-102.8, -74.89)	(-112.1, -76.52)	(-0.579, 11.44)
JPY	1979/06-2020/02	-5.406	-17.053***	11.647
	472	(-17.84, 7.029)	(-20.31, -13.80)	(-3.863, 27.16)
NOK	1986/01-2017/11	-28.875***	-71.177***	42.301***
	378	(-35.56, -22.19)	(-76.33, -66.03)	(36.34, 48.26)
SEK	1987/01-2017/11	-79.322***	-85.743***	6.421
	366	(-105, -53.62)	(-119.1, -52.42)	(-3.549, 16.39)

Table 20

Slope Coefficient from Long-Run Regression (13), Full Sample for Each Currency

Currency	Data	Transitory Component β^T	UIP measure β^{IP}	Difference β^{T-IP}
β_π				
CAD	1979/06-2017/11	-1.618**	-3.805***	2.187***
	446	(-2.845, -0.392)	(-5.228, -2.383)	(1.856, 2.518)
CHF	1989/01-2020/02	-1.712*	-7.074***	5.363***
	369	(-3.440, 0.0172)	(-8.550, -5.598)	(3.547, 7.179)
DEM	1979/06-2020/02	-2.322***	-4.537***	2.214***
	472	(-3.990, -0.654)	(-5.393, -3.680)	(0.915, 3.514)
FRF	1979/06-2020/02	-1.732***	-4.682***	2.951***
	472	(-2.999, -0.464)	(-5.140, -4.225)	(2.001, 3.900)
GBP	1979/06-2020/02	-0.241	-0.513**	0.272
	472	(-1.888, 1.406)	(-0.920, -0.105)	(-1.366, 1.910)
ITL	1979/06-2020/02	-11.377***	-13.027***	1.649***
	472	(-11.78, -10.97)	(-13.47, -12.59)	(1.243, 2.056)
JPY	1979/06-2020/02	1.765*	-2.691***	4.457***
	472	(-0.0712, 3.602)	(-3.158, -2.225)	(2.274, 6.640)
NOK	1986/01-2017/11	-0.518	-4.178***	3.660***
	378	(-1.832, 0.797)	(-5.819, -2.537)	(2.773, 4.548)
SEK	1987/01-2017/11	-9.274***	-12.921***	3.647***
	366	(-11.17, -7.374)	(-14.27, -11.57)	(3.088, 4.206)

Table 21

Estimated variances of s_t^{IP} and s_t^T

Currency	Data	Obs.	$var(s_T)$	$var(s_{IP})$	$F - stat$
CAD	1979/06-2017/11	446	0.0195	0.0290	0.6705
CHF	1989/01-2020/02	369	0.0111	0.0133	0.8325
DEM	1979/06-2020/02	472	0.0232	0.0076	3.0531
FRF	1979/06-2020/02	472	0.0195	0.0092	2.1254
GBP	1979/06-2020/02	472	0.0131	0.0008	17.2414
ITL	1979/06-2020/02	472	0.1135	0.1464	0.7752
JPY	1979/06-2020/02	472	0.0252	0.0032	8.0024
NOK	1986/01-2017/11	378	0.0184	0.0333	0.5513
SEK	1987/01-2017/11	366	0.0819	0.0867	0.9440

Figure 1: 10-year Rolling Regressions: AUD

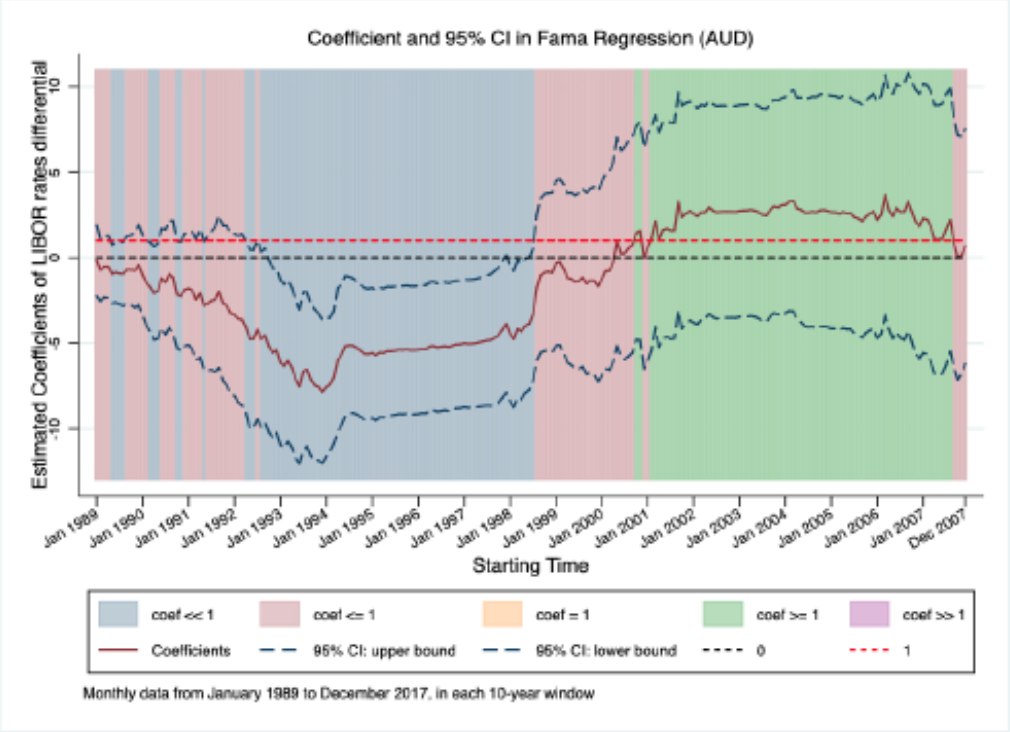


Figure 2: 10-year Rolling Regressions: CAD

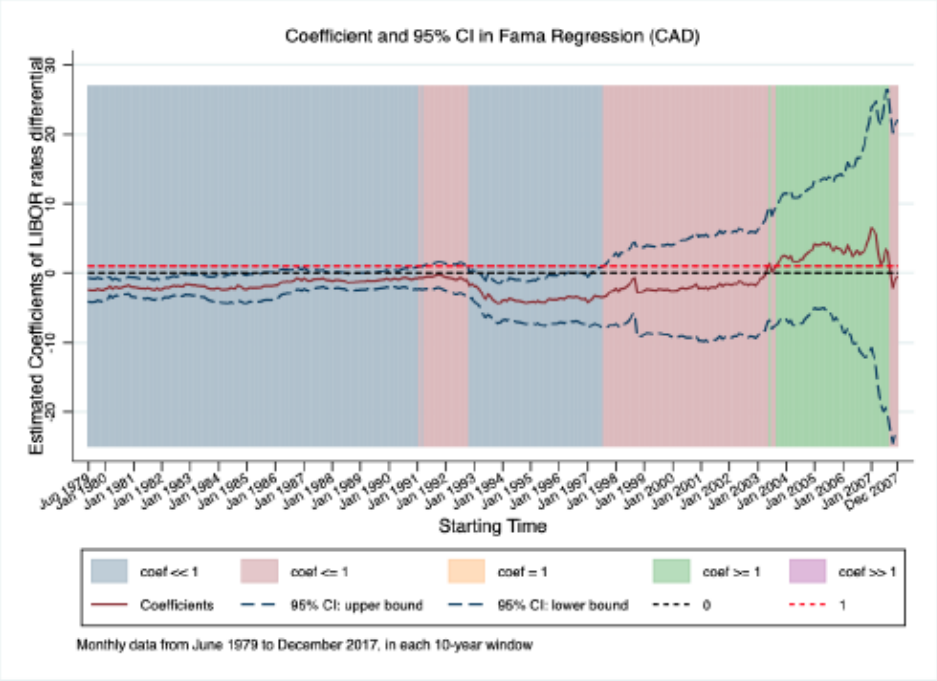


Figure 3: 10-year Rolling Regressions: CHF

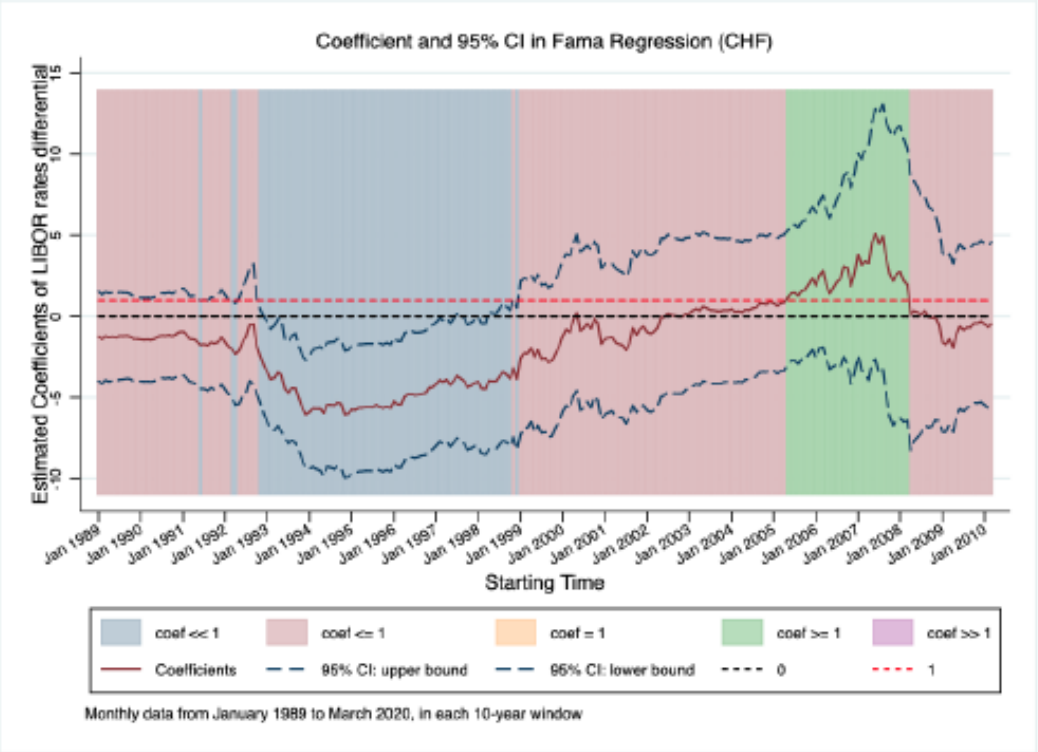


Figure 4: 10-year Rolling Regressions: DEM

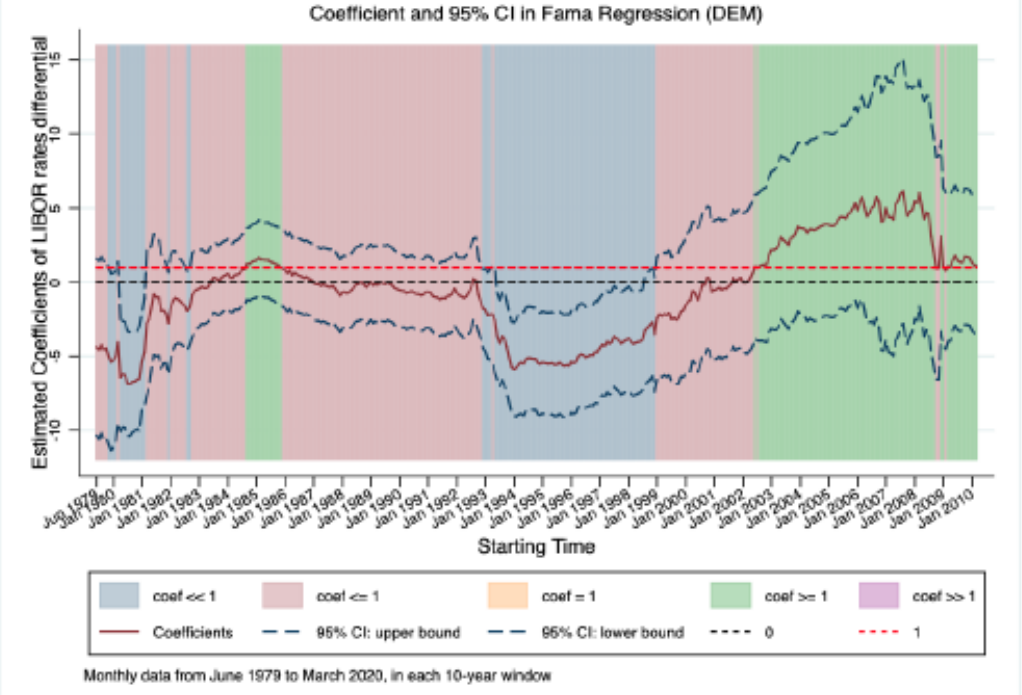


Figure 5: 10-year Rolling Regressions: FRF

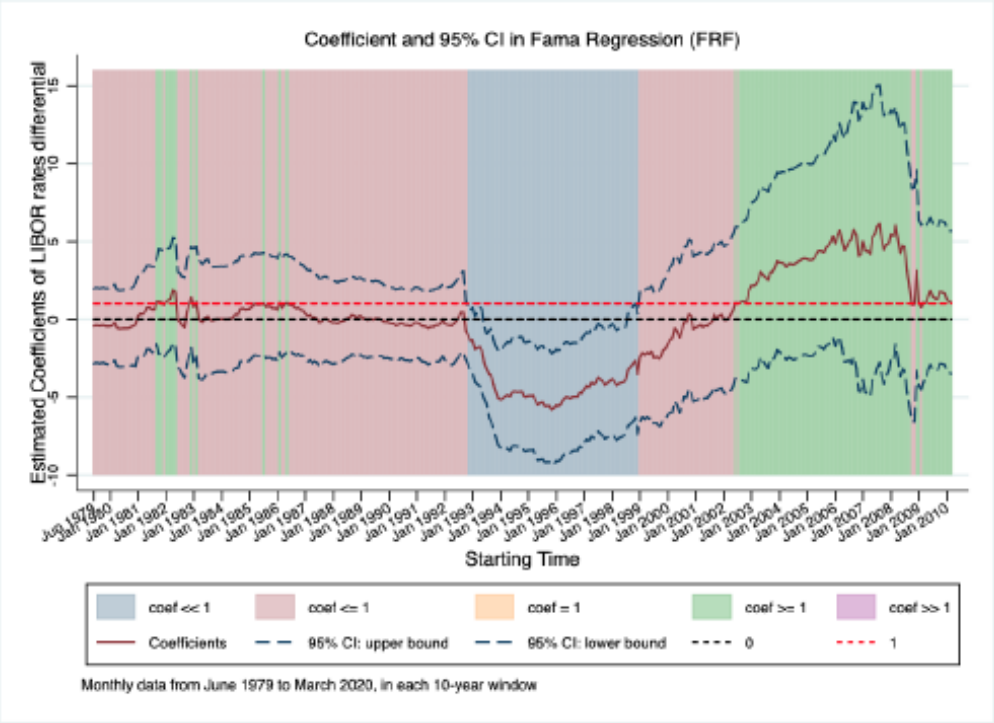


Figure 6: 10-year Rolling Regressions: GBP

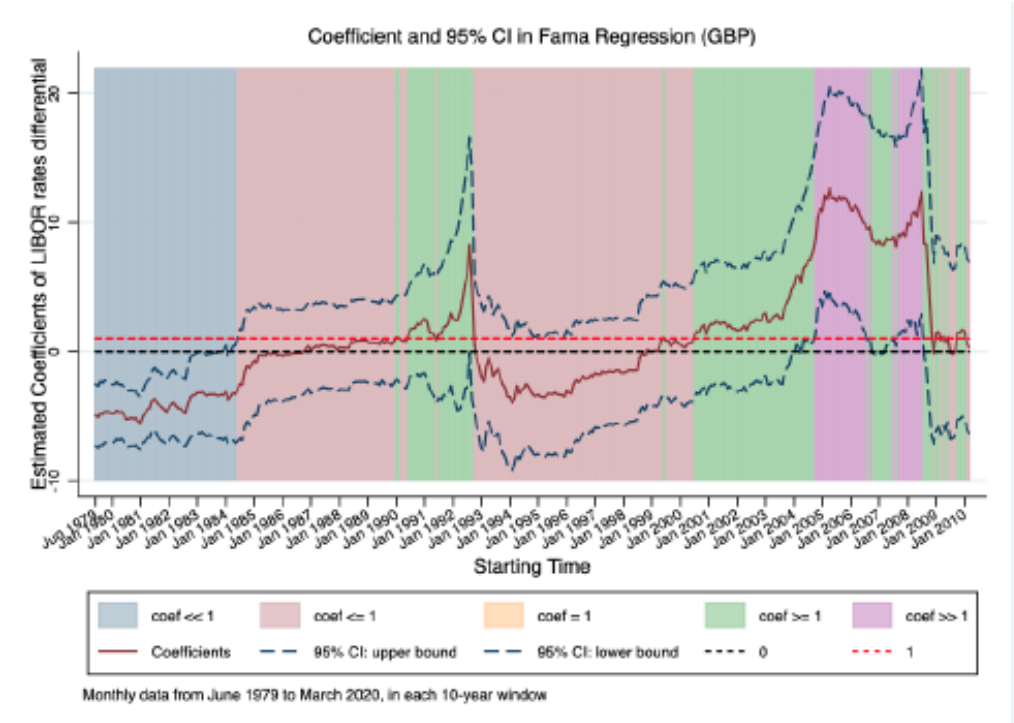


Figure 7: 10-year Rolling Regressions: ITL

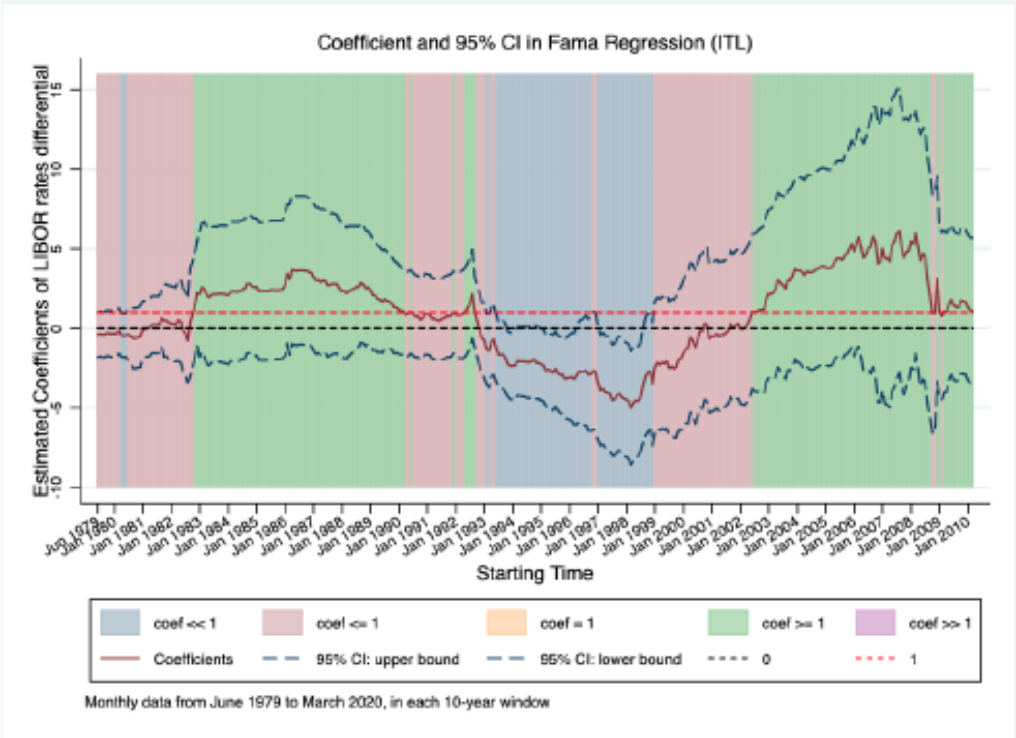


Figure 8: 10-year Rolling Regressions: JPY

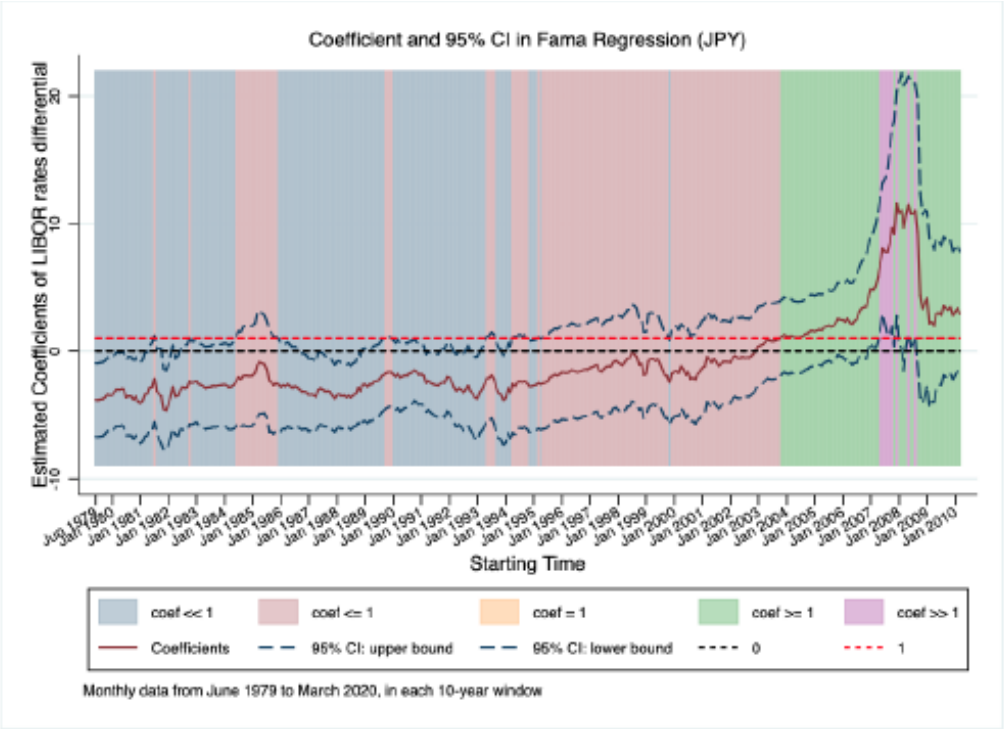


Figure 9: 10-year Rolling Regressions: NOK

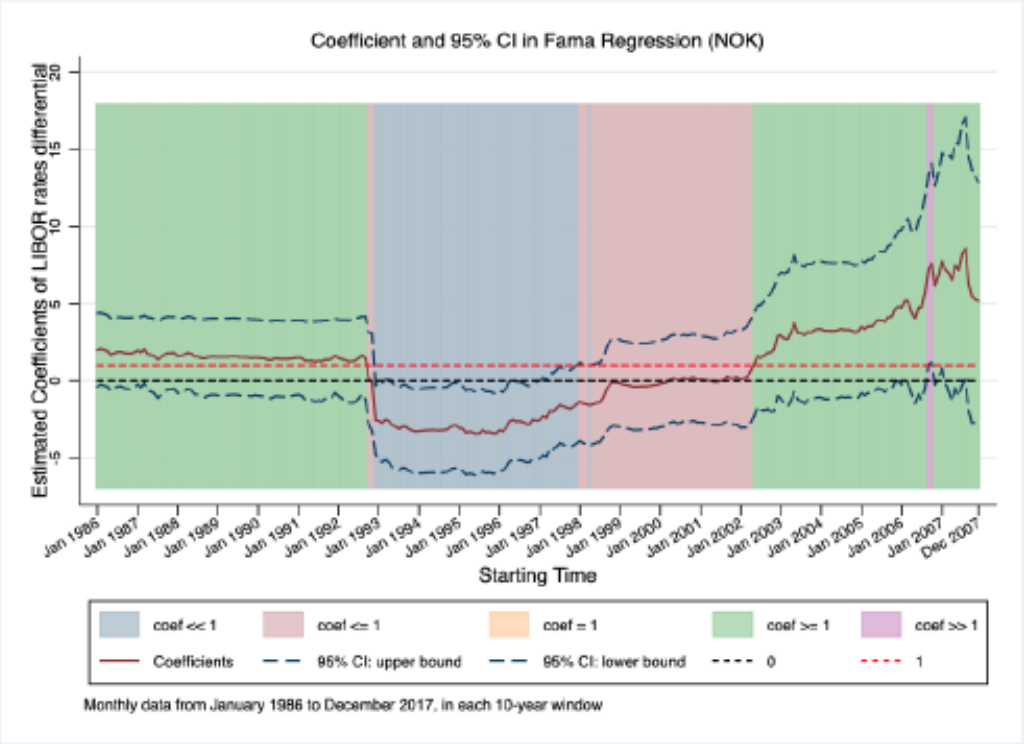


Figure 10: 10-year Rolling Regressions: NZD

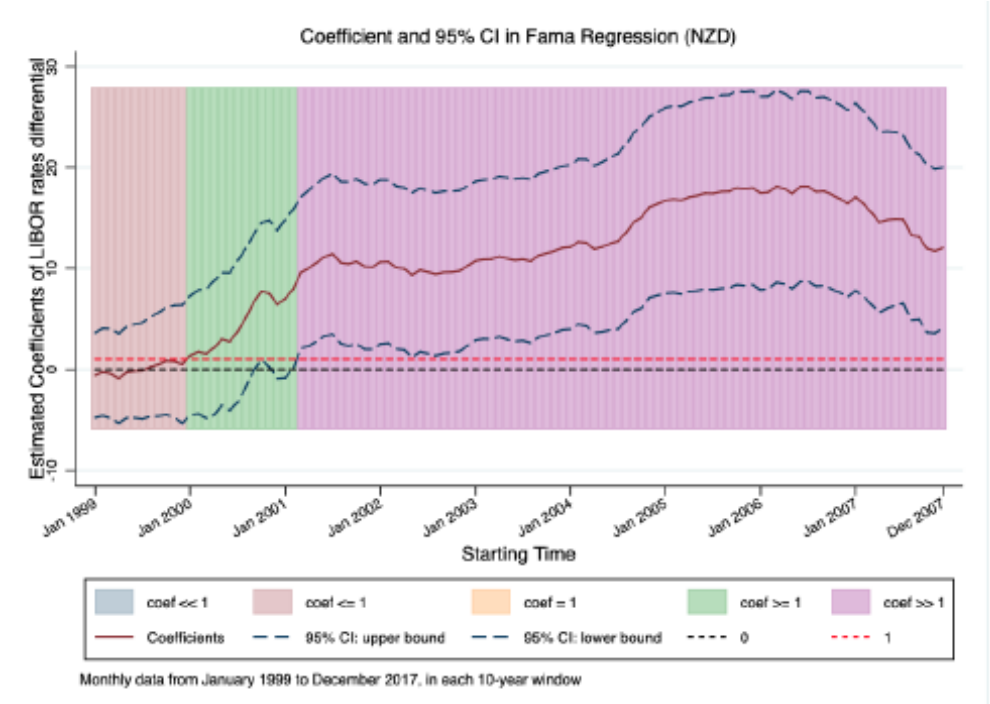


Figure 10: 10-YEAR ROLLING REGRESSION: NZD

Figure 11: 10-year Rolling Regressions: SEK

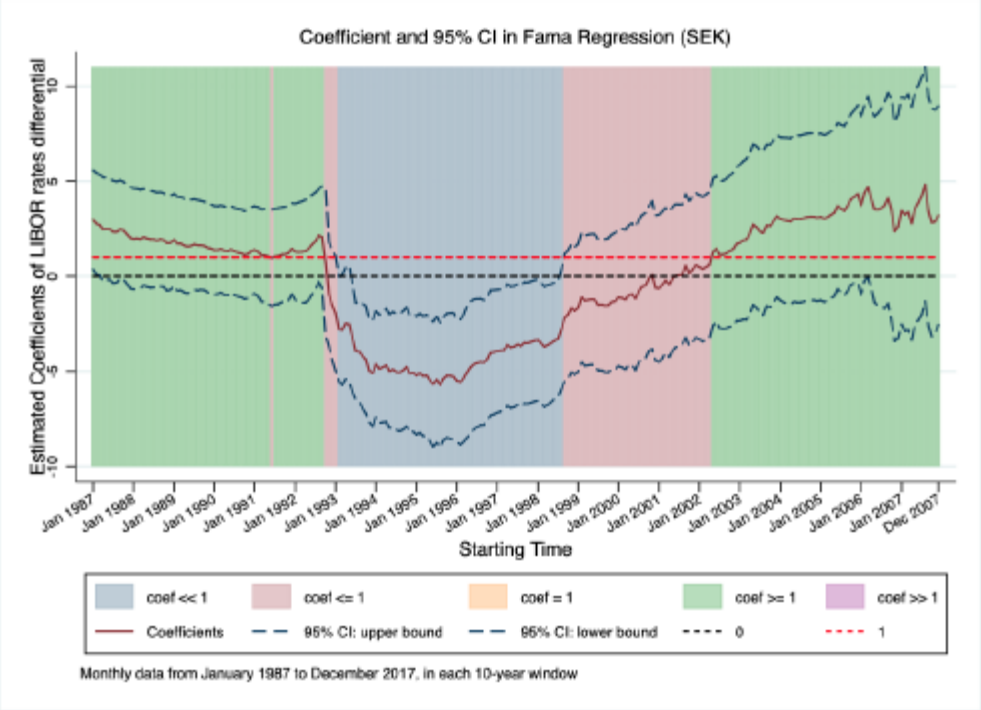


Figure 11: 10-YEAR ROLLING REGRESSION: SEK

Figure 12: Fama Slope Coefficient and Inverse of Variance of $i_t - i_t^*$: AUD

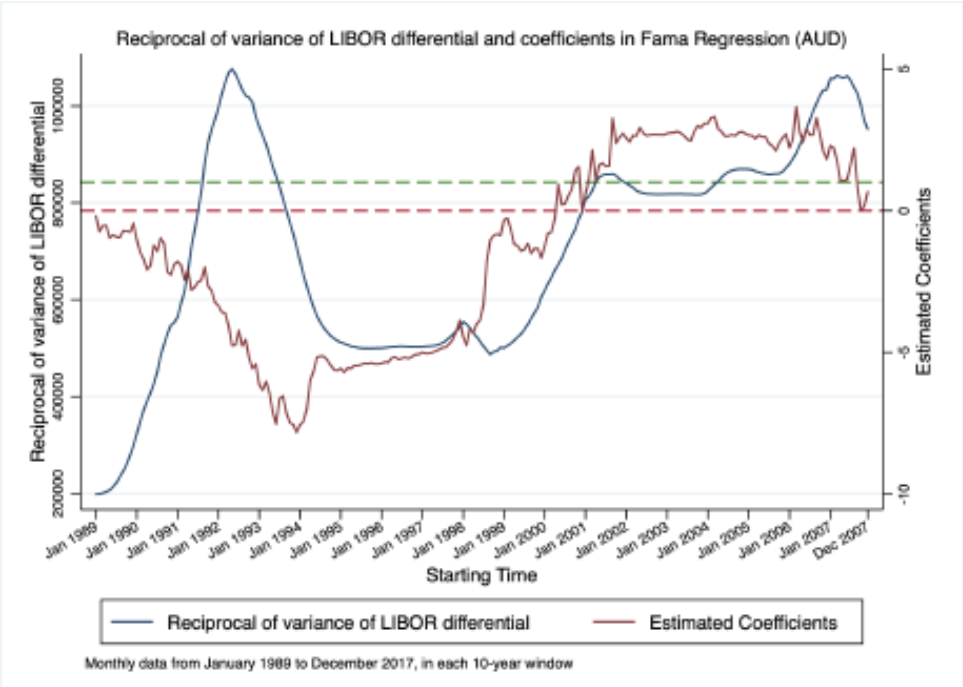


Figure 13: Fama Slope Coefficient and Inverse of Variance of $i_t - i_t^*$: CAD

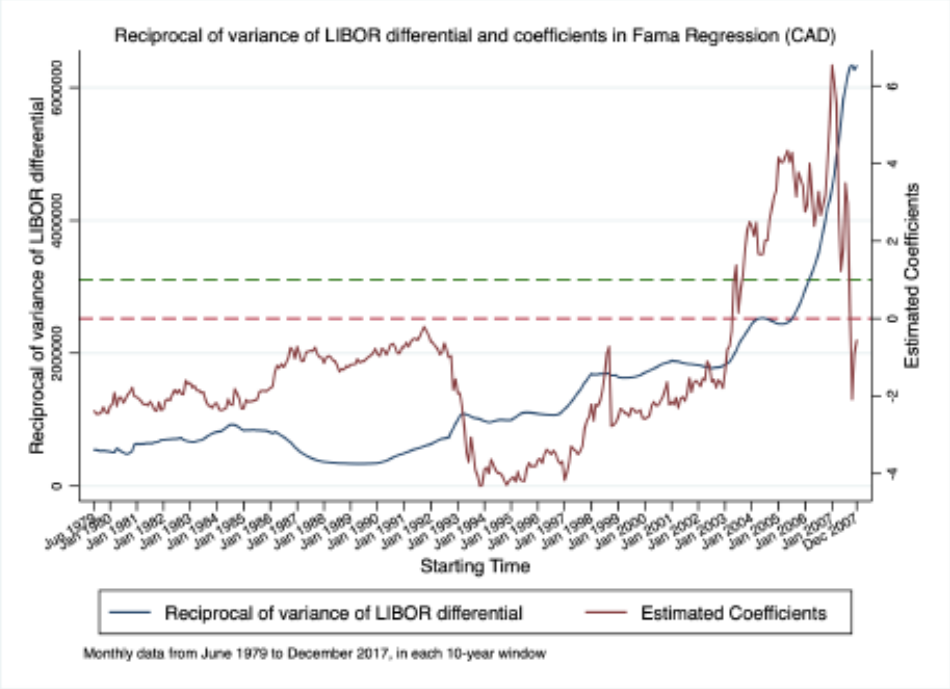


Figure 14: Fama Slope Coefficient and Inverse of Variance of $i_t - i_t^*$: CHF

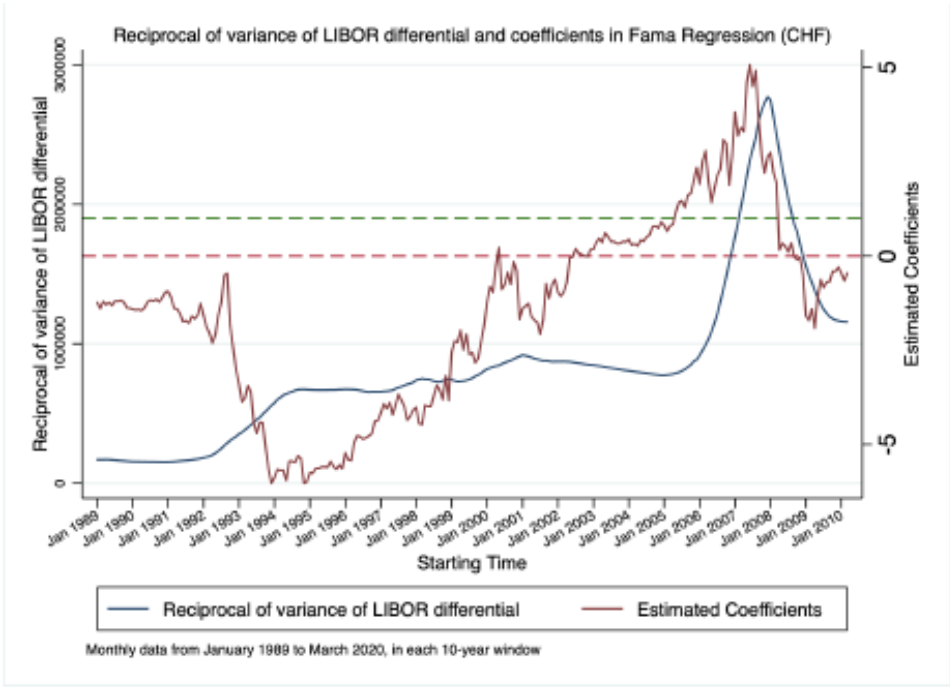


Figure 15: Fama Slope Coefficient and Inverse of Variance of $i_t - i_t^*$: DEM

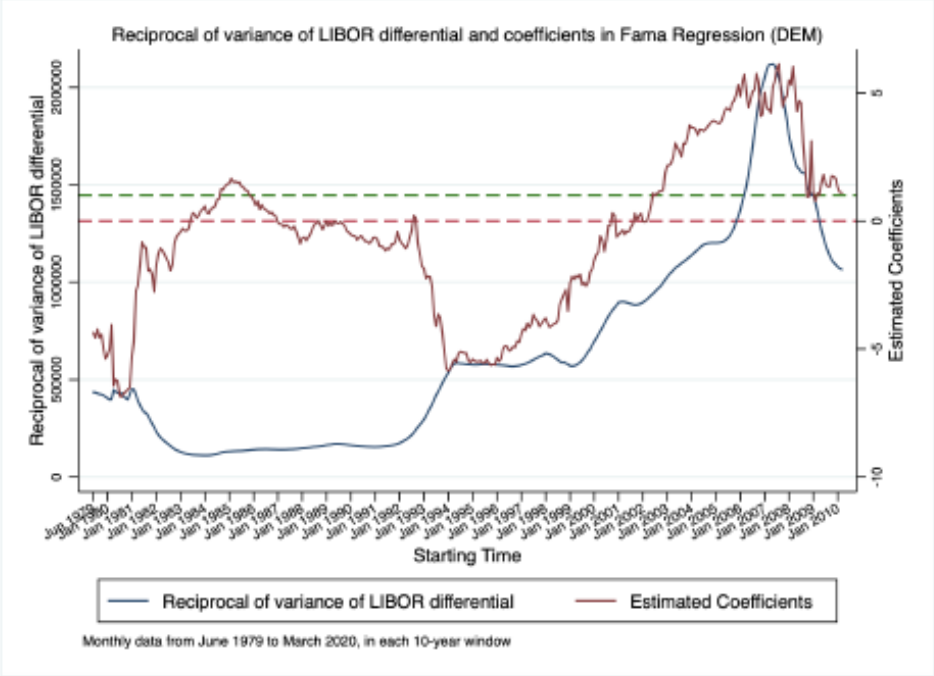


Figure 4: Correlation between Fama coefficients and variance reciprocal: DEM, 10-year rolling

Figure 16: Fama Slope Coefficient and Inverse of Variance of $i_t - i_t^*$: FRF

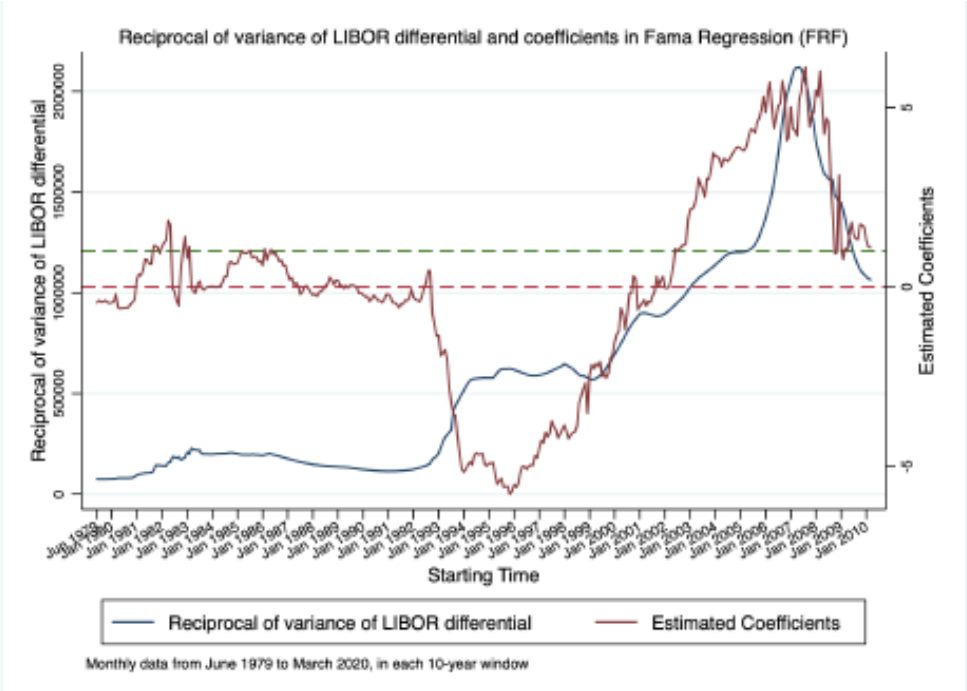


Figure 17: Fama Slope Coefficient and Inverse of Variance of $i_t - i_t^*$: GBP

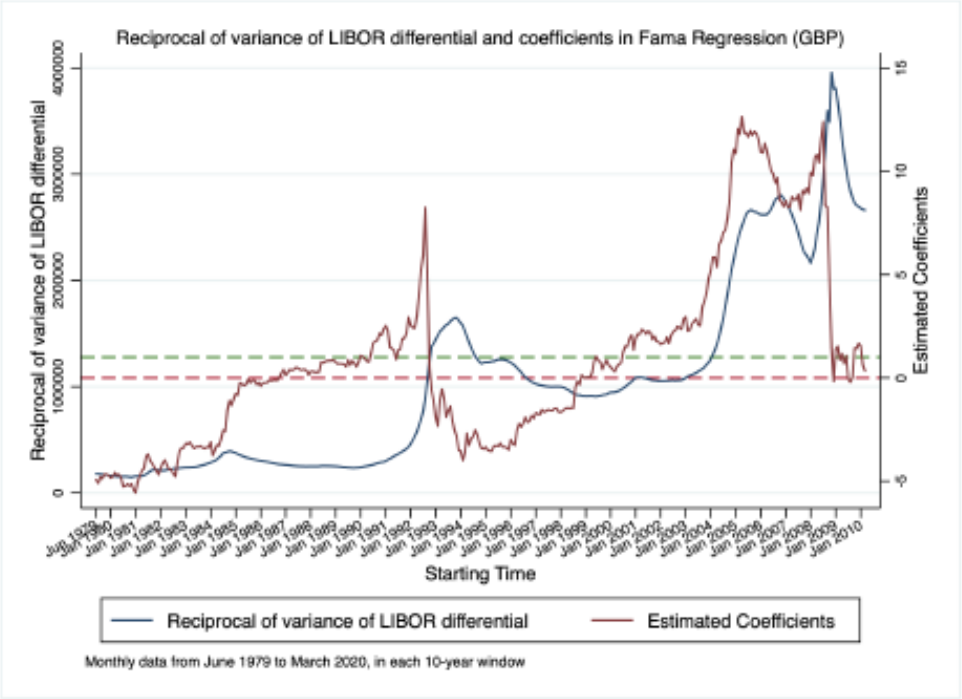


Figure 18: Fama Slope Coefficient and Inverse of Variance of $i_t - i_t^*$: ITL

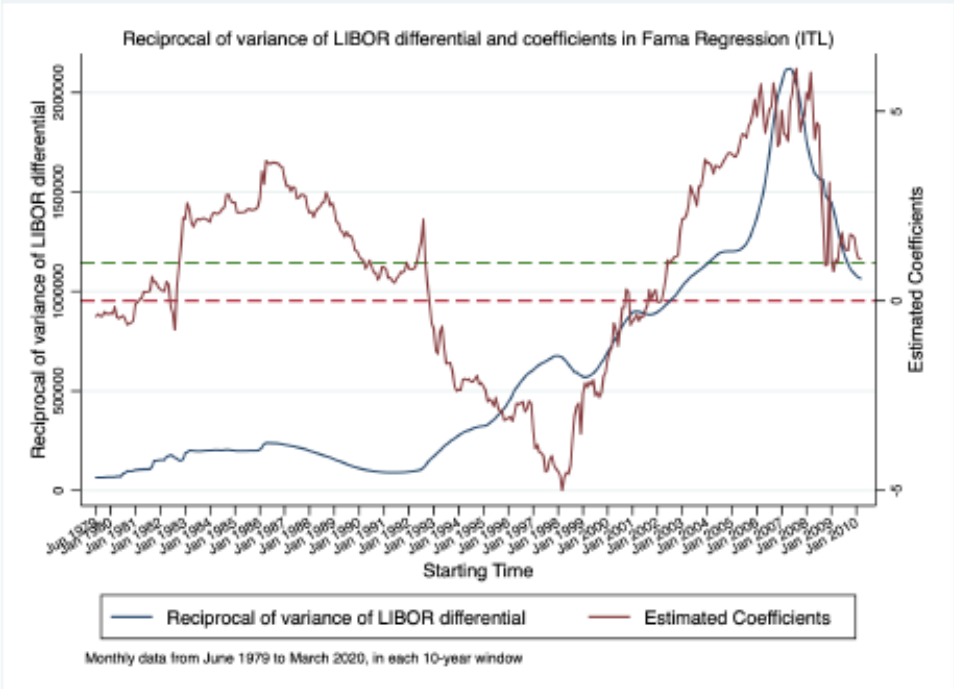


Figure 19: Fama Slope Coefficient and Inverse of Variance of $i_t - i_t^*$: JPY

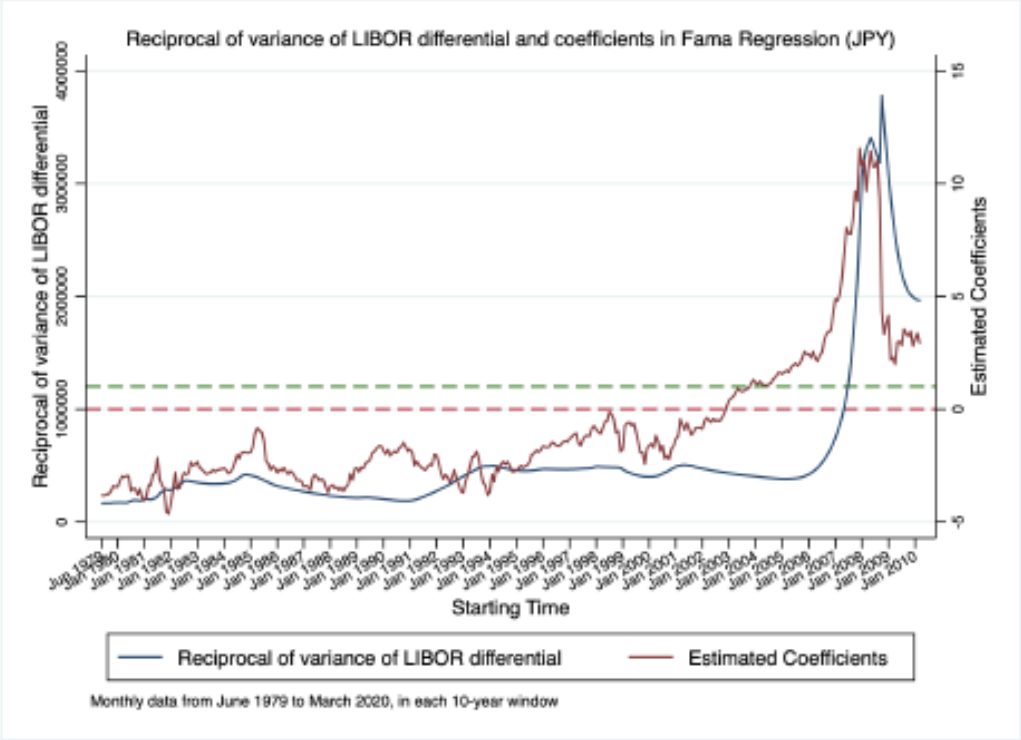


Figure 20: Fama Slope Coefficient and Inverse of Variance of $i_t - i_t^*$: NOK

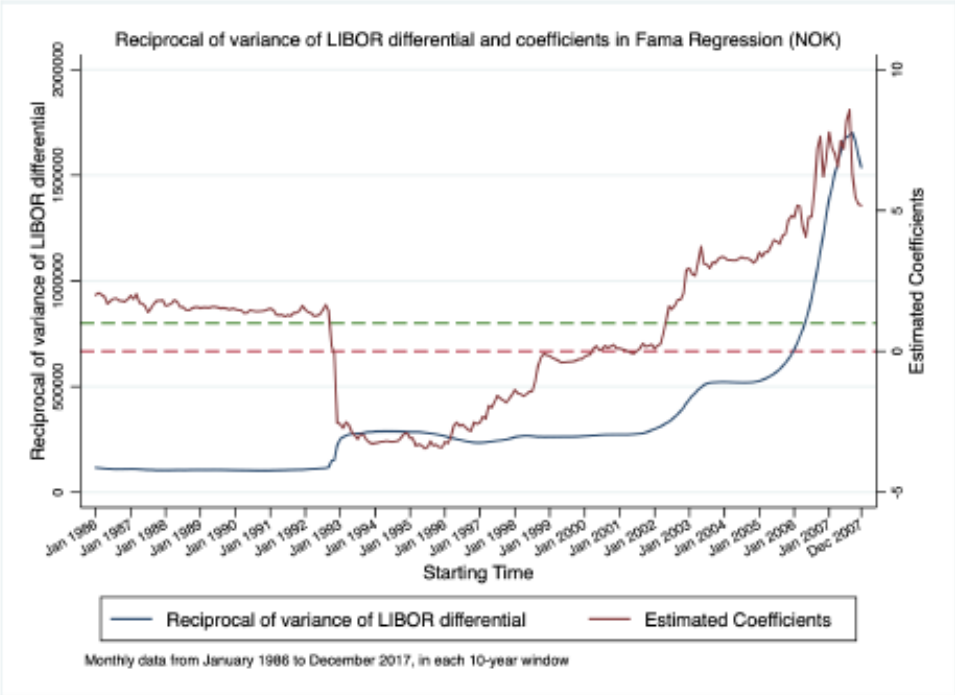


Figure 21: Fama Slope Coefficient and Inverse of Variance of $i_t - i_t^*$: NZD

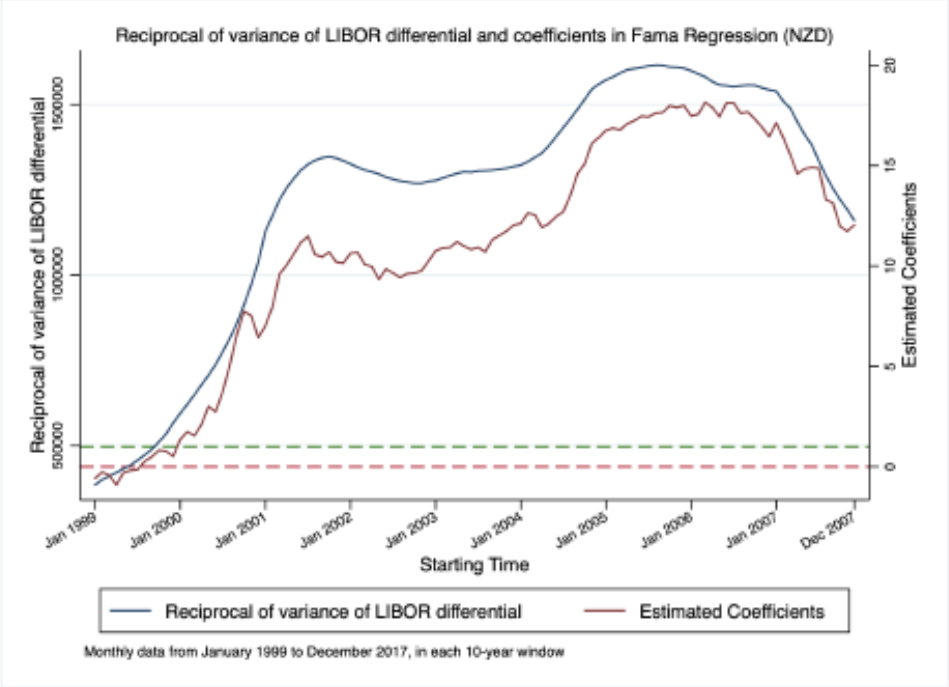


Figure 22: Fama Slope Coefficient and Inverse of Variance of $i_t - i_t^*$: SEK

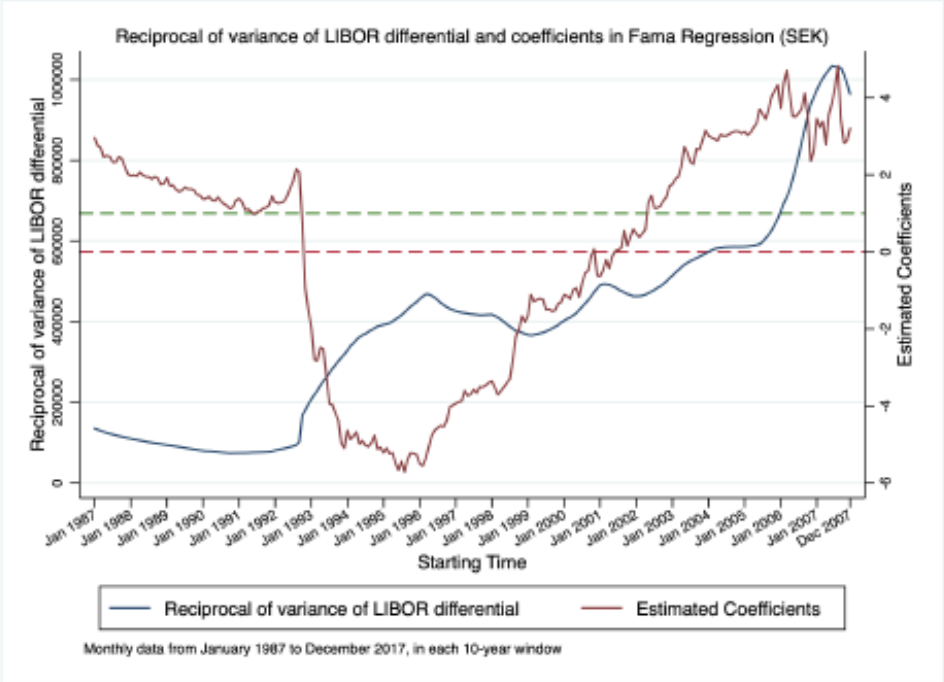


Figure 23: Interest Rates of the U.S. and Other Countries

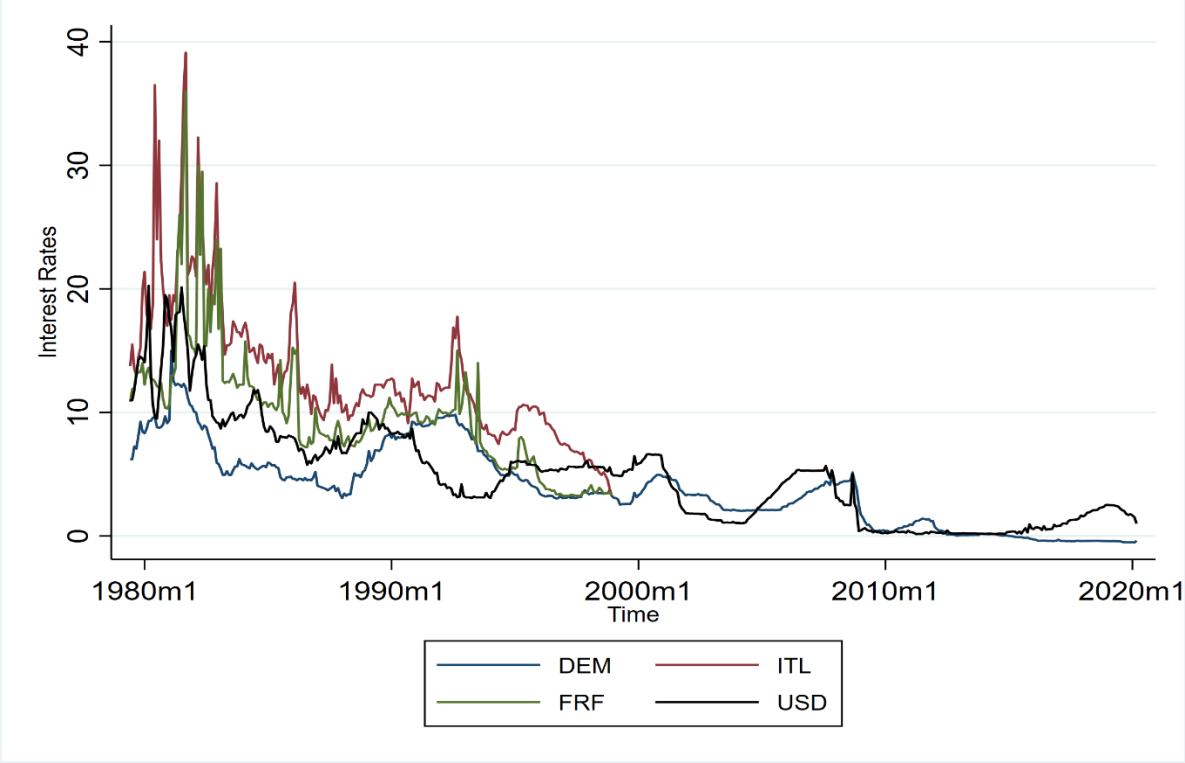


Figure 24: Interest Rates of the U.S. and Other Countries

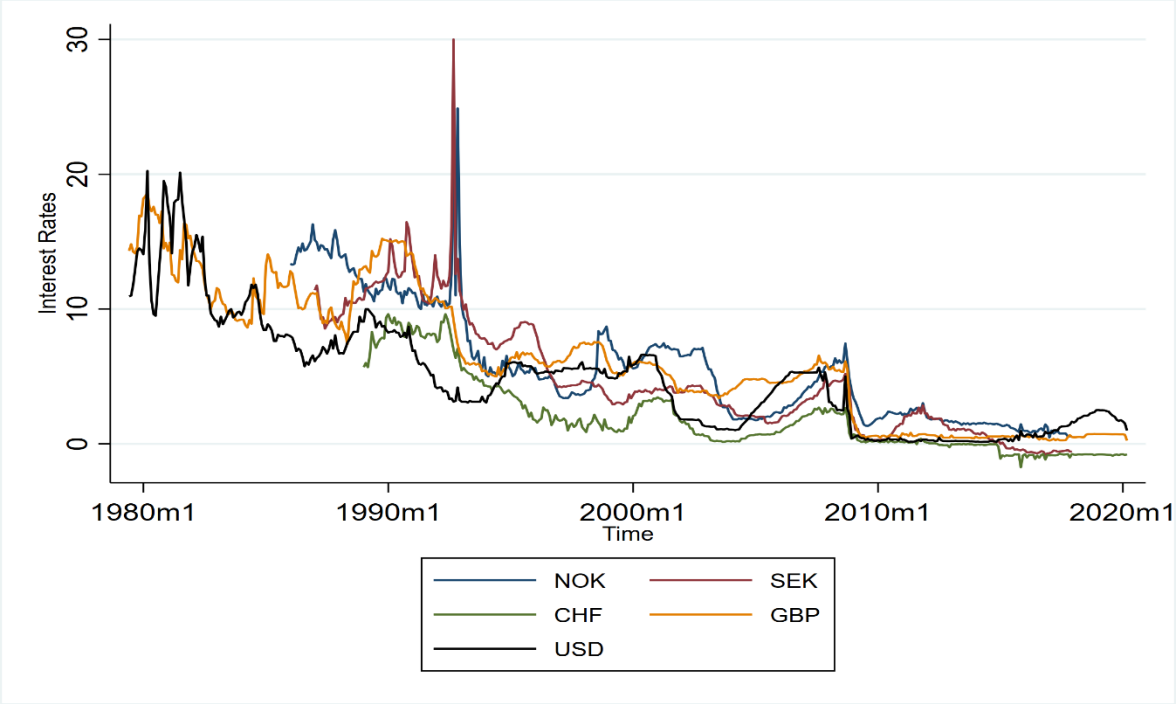


Figure 25: Interest Rates of the U.S. and Other Countries

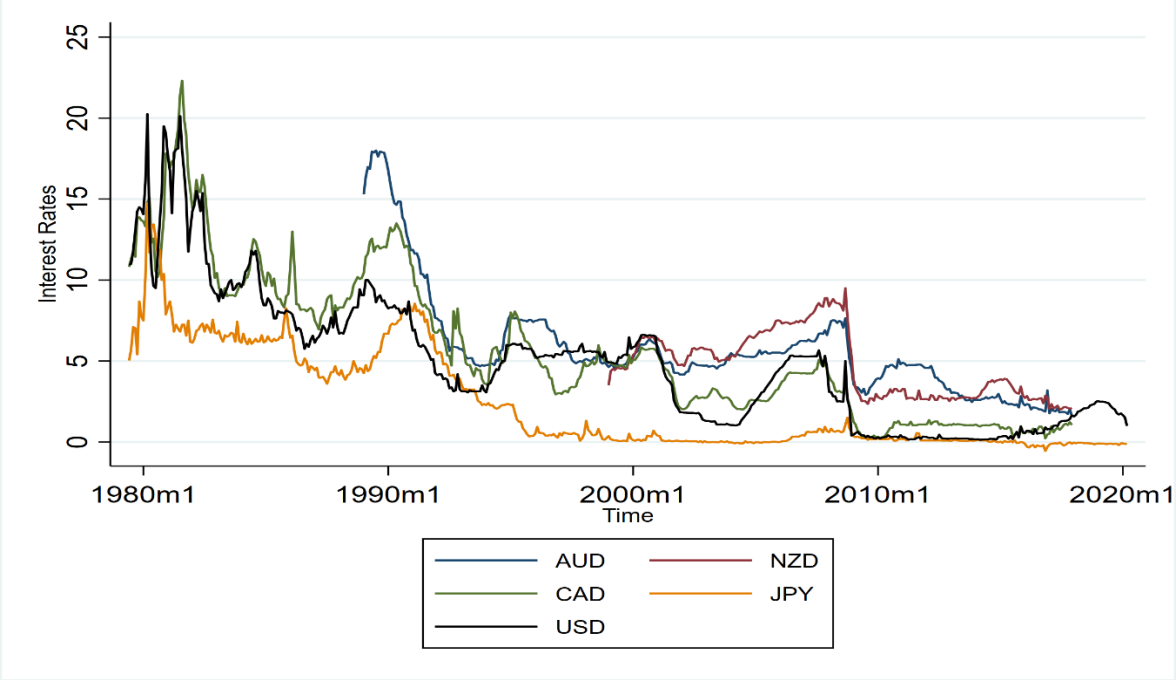


Figure 26: Slope Coefficient of Equation (6), 10-year Rolling Regressions: CAD

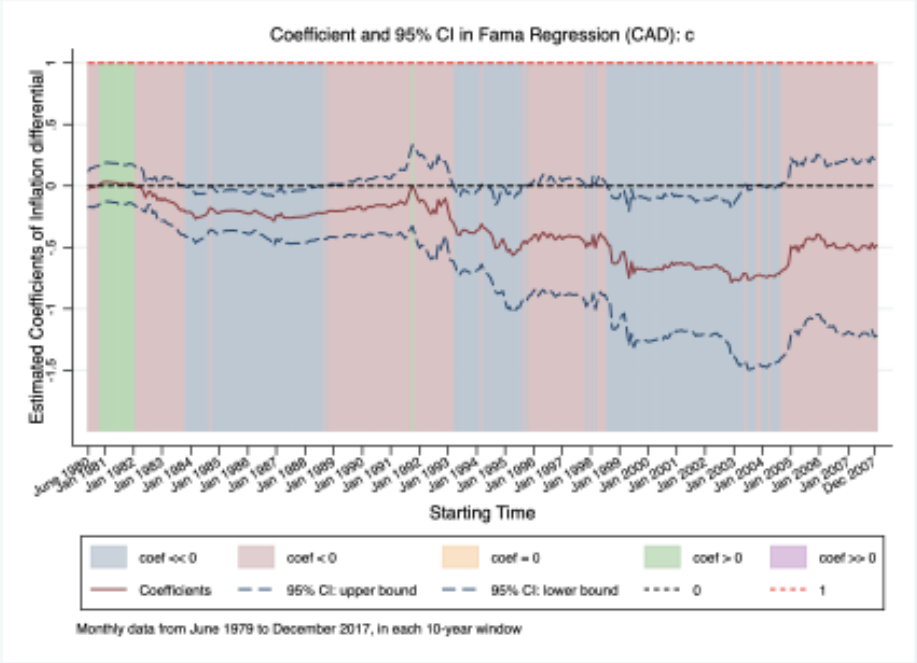


Figure 27: Slope Coefficient of Equation (6), 10-year Rolling Regressions: CHF

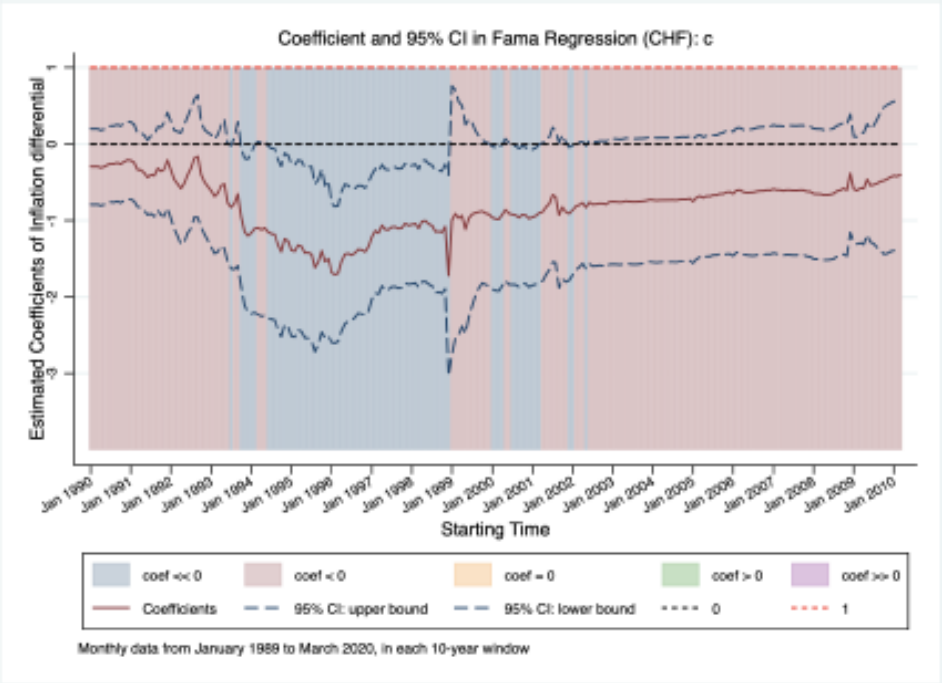


Figure 28: Slope Coefficient of Equation (6), 10-year Rolling Regressions: DEM

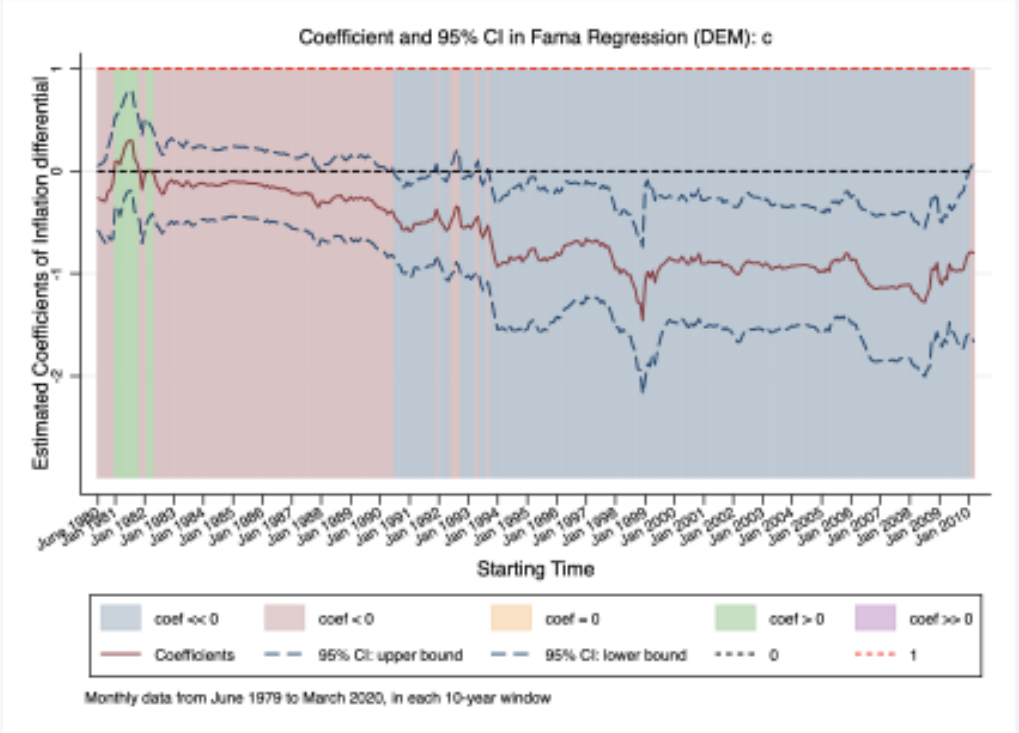


Figure 29: Slope Coefficient of Equation (6), 10-year Rolling Regressions: FRF

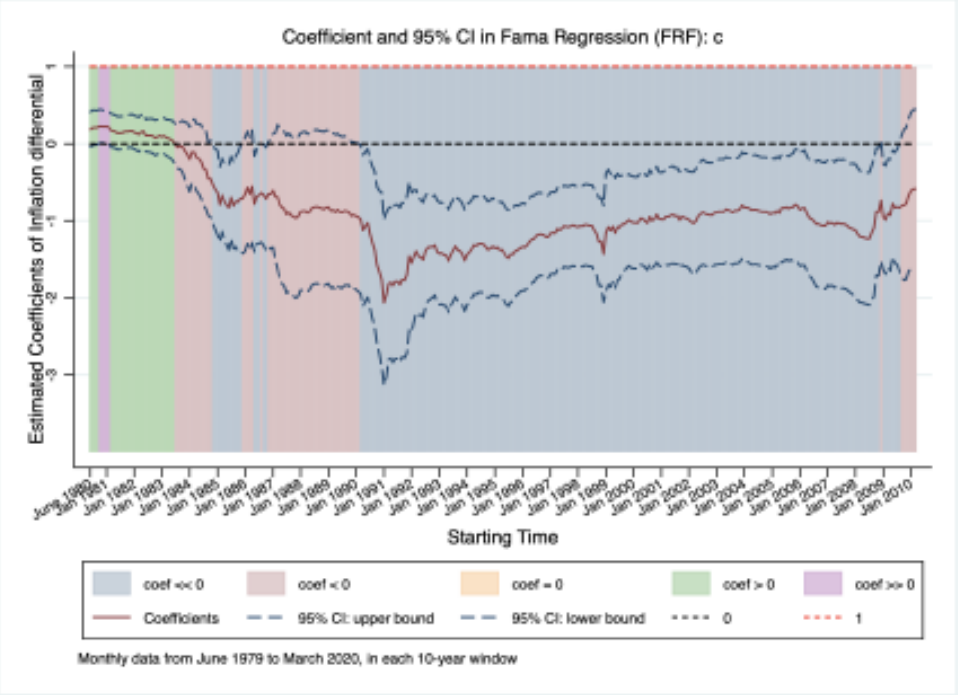


Figure 30: Slope Coefficient of Equation (6), 10-year Rolling Regressions: GBP

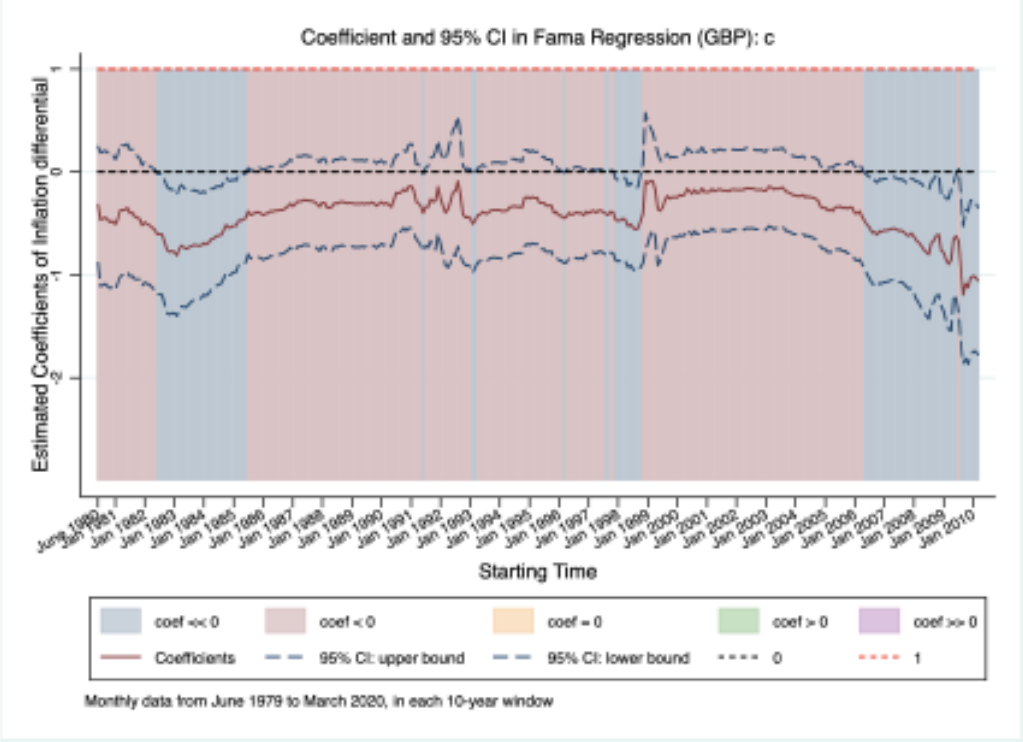


Figure 31: Slope Coefficient of Equation (6), 10-year Rolling Regressions: ITL

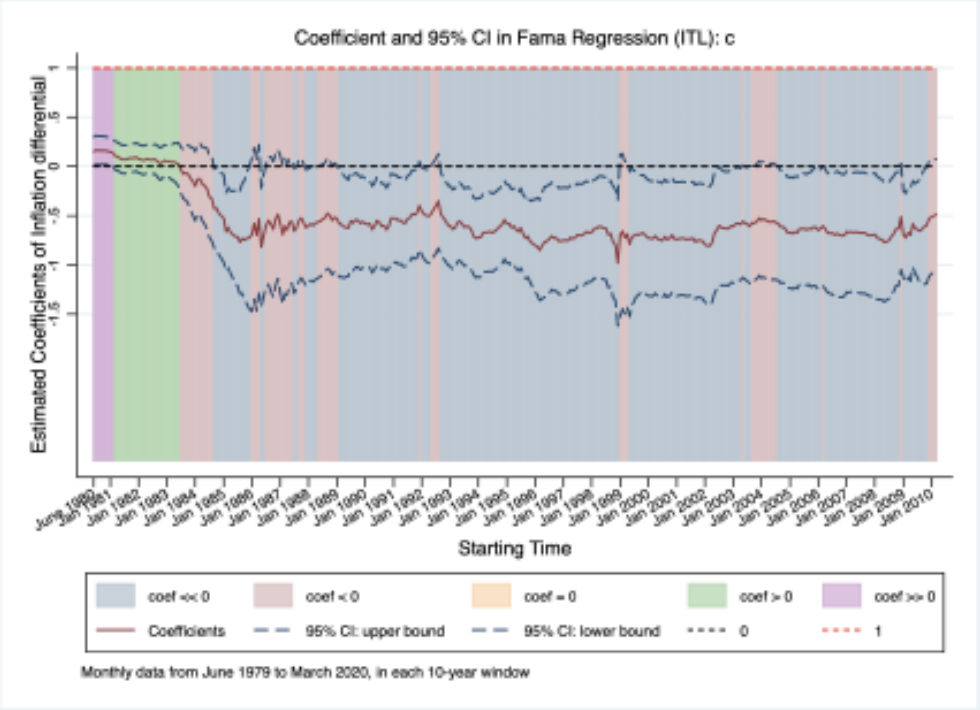


Figure 32: Slope Coefficient of Equation (6), 10-year Rolling Regressions: JPY

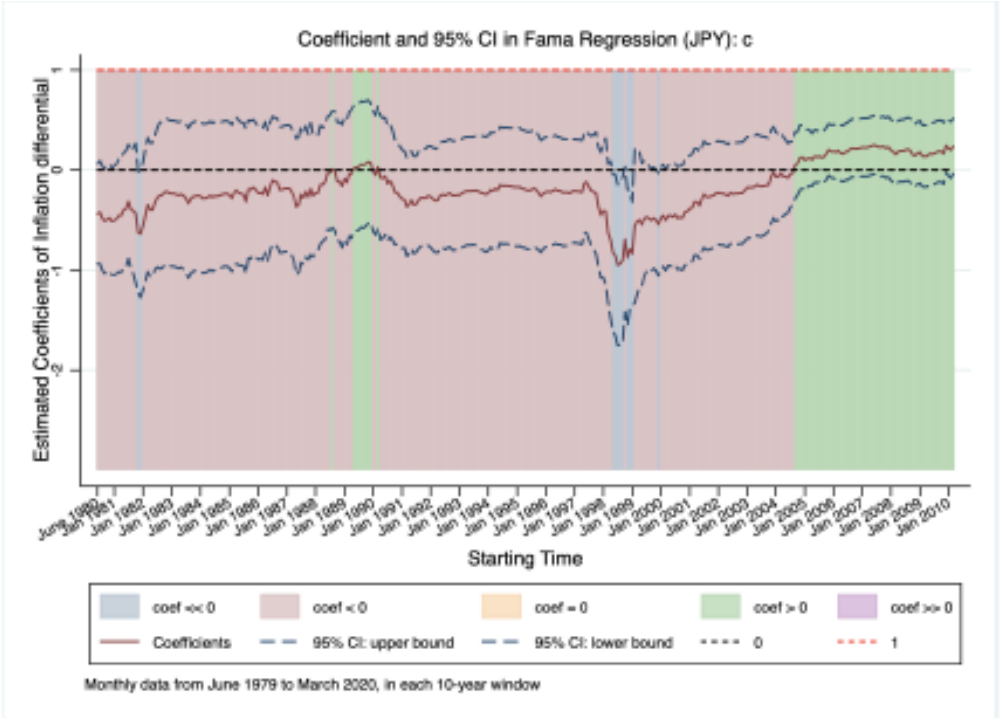


Figure 33: Slope Coefficient of Equation (6), 10-year Rolling Regressions: NOK

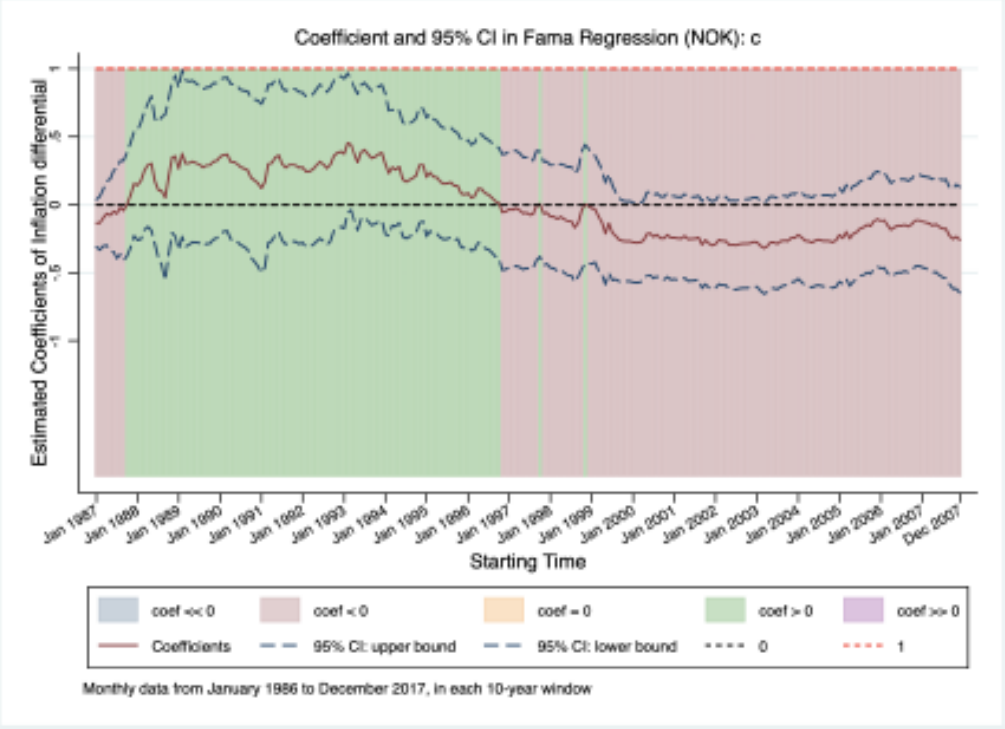


Figure 34: Slope Coefficient of Equation (6), 10-year Rolling Regressions: SEK

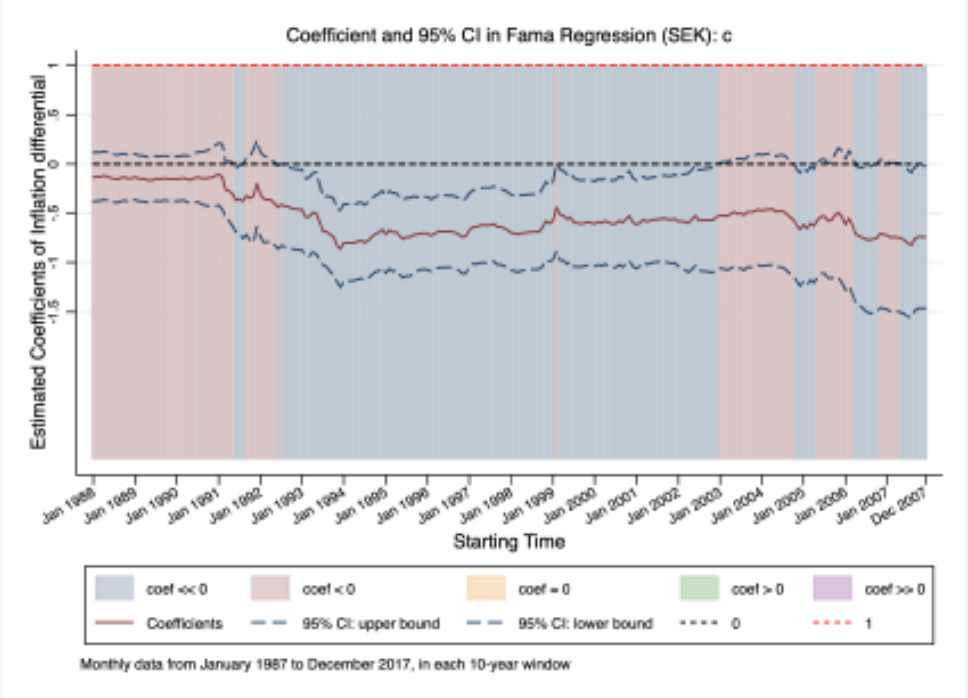


Figure 35: 10-year Rolling Medium-Run Regressions: AUD

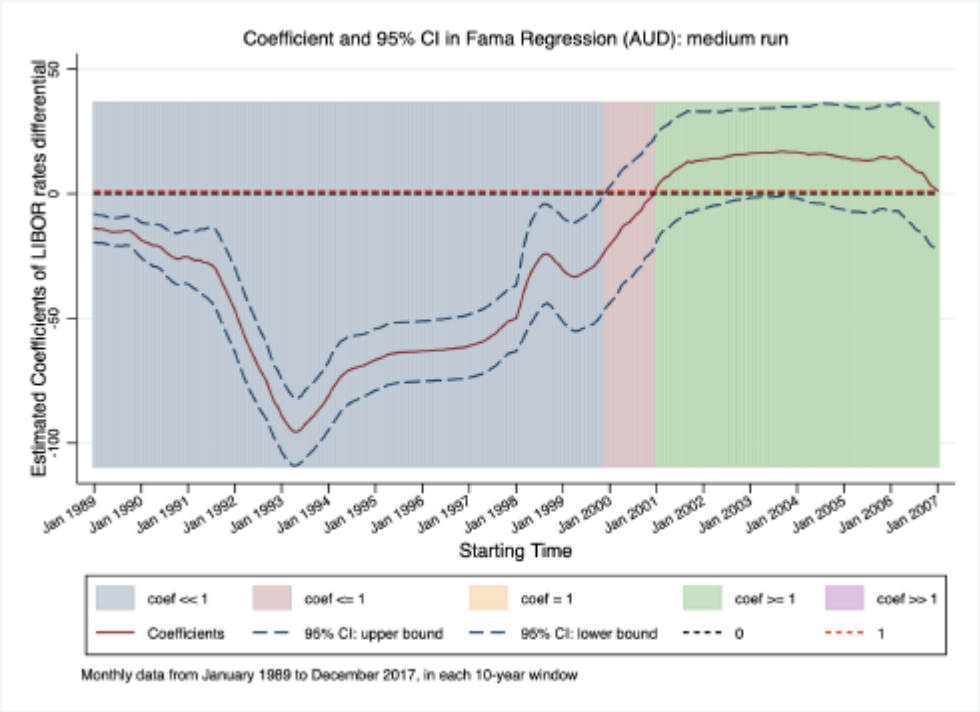


Figure 36: 10-year Rolling Medium-Run Regressions: CAD

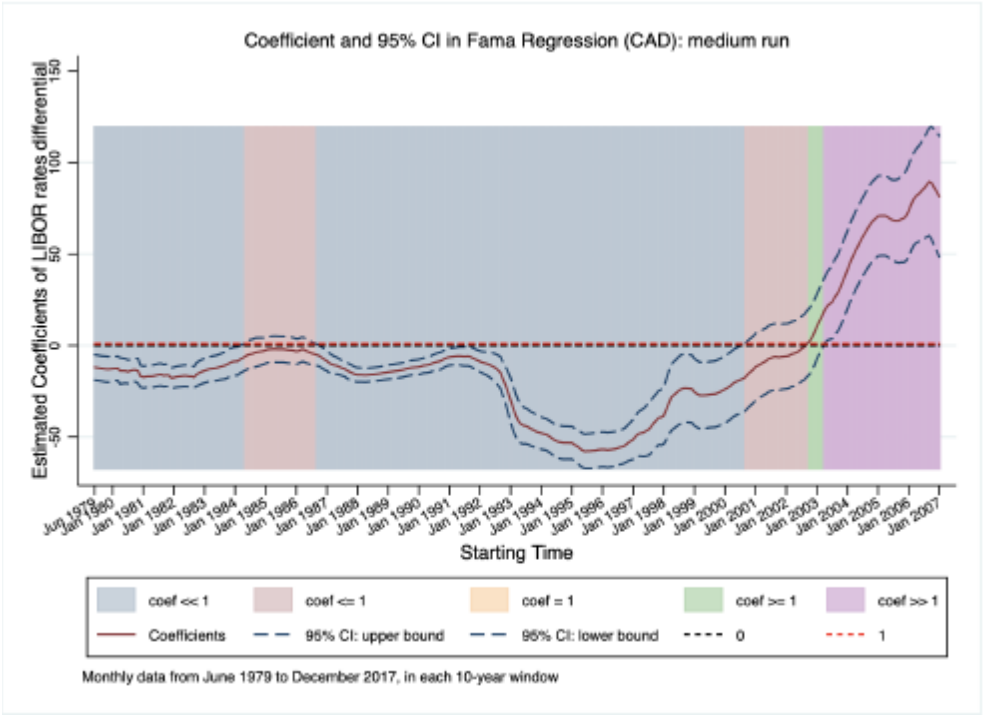


Figure 37: 10-year Rolling Medium-Run Regressions: CHF

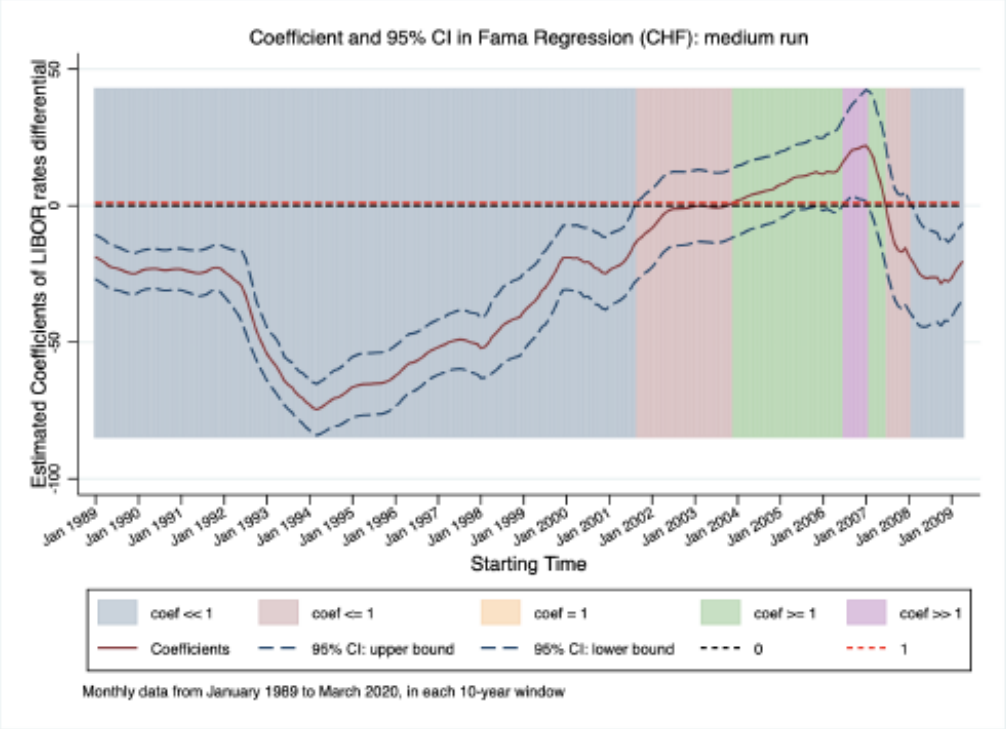


Figure 38: 10-year Rolling Medium-Run Regressions: DEM

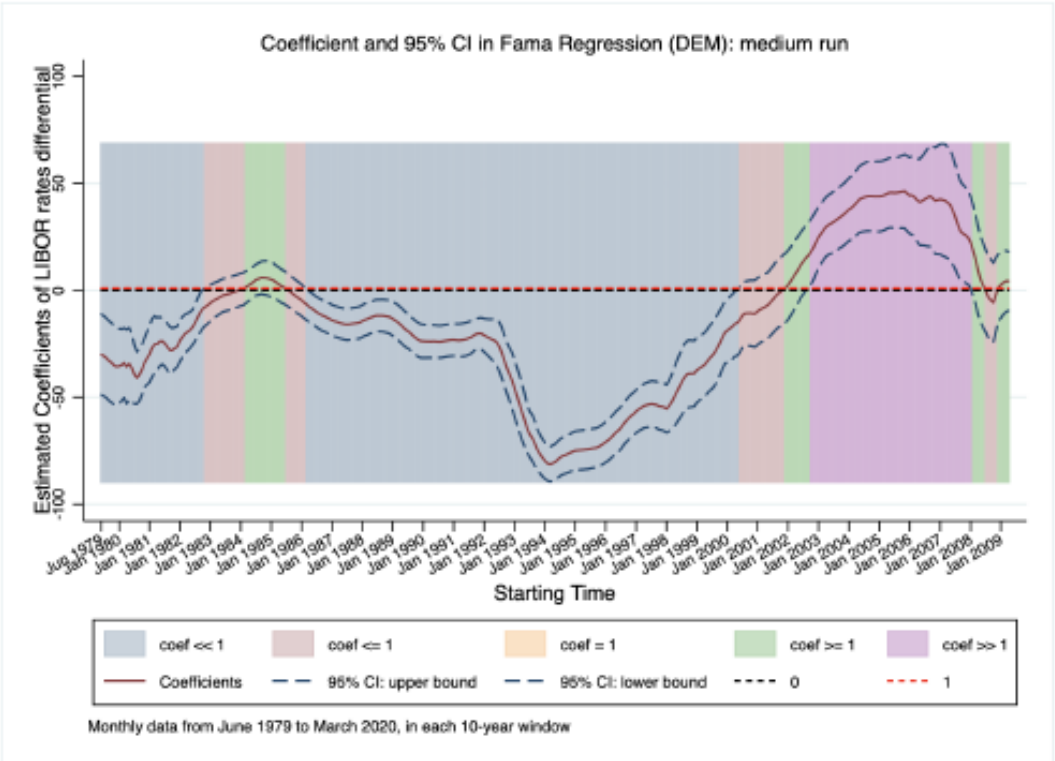


Figure 39: 10-year Rolling Medium-Run Regressions: FRF

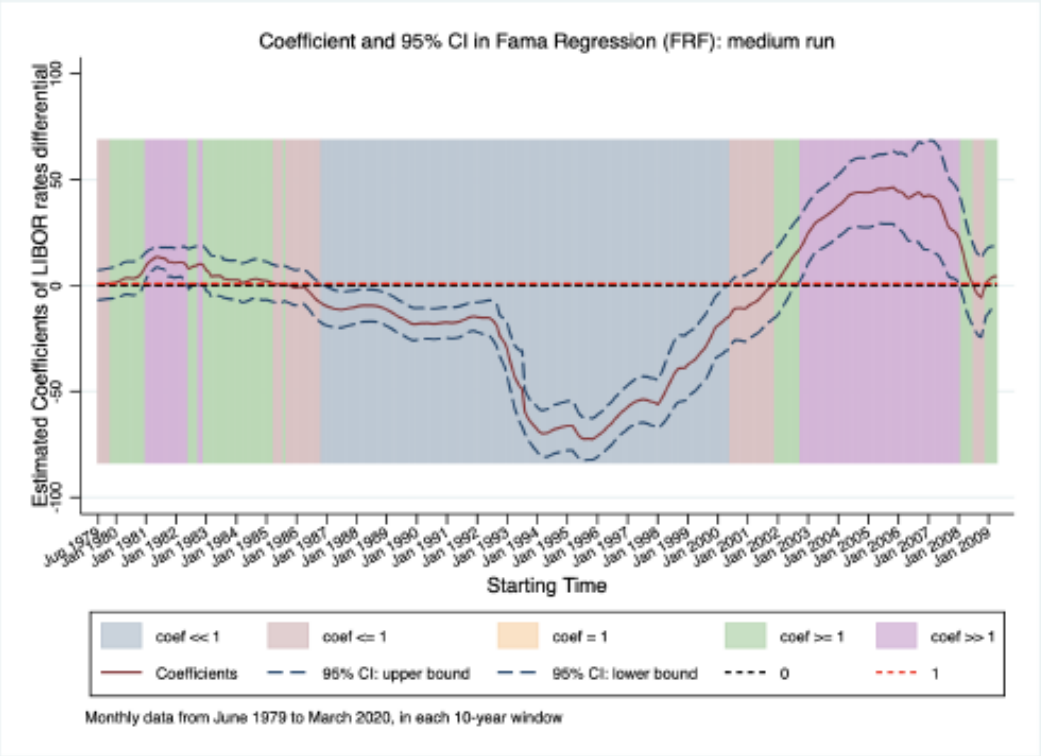


Figure 40: 10-year Rolling Medium-Run Regressions: GBP

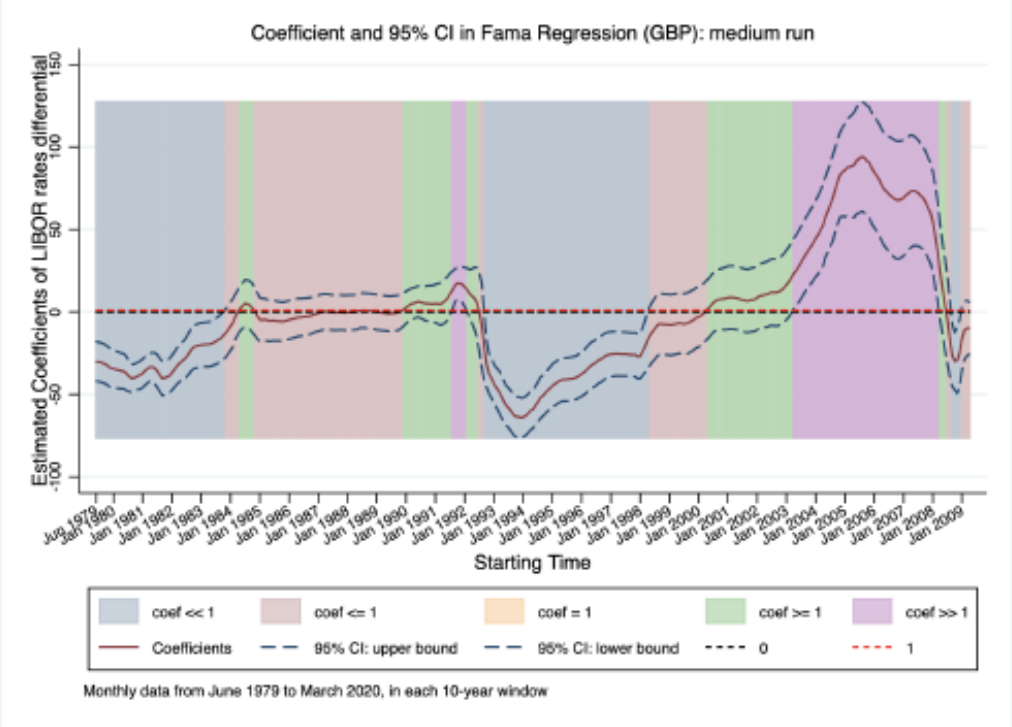


Figure 41: 10-year Rolling Medium-Run Regressions: ITL

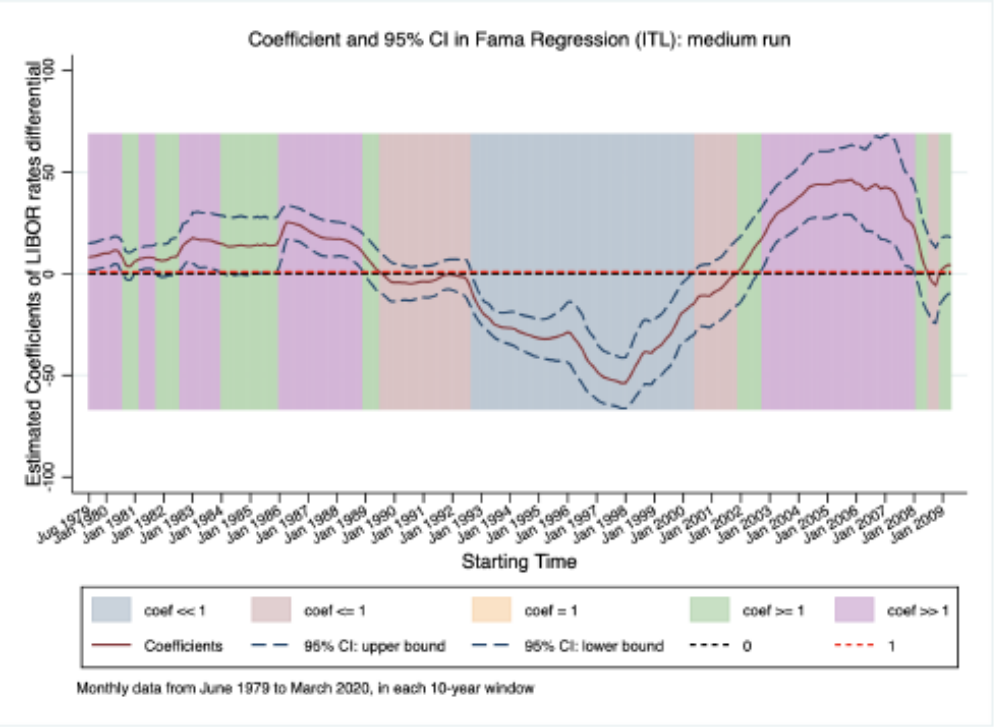


Figure 42: 10-year Rolling Medium-Run Regressions: JPY

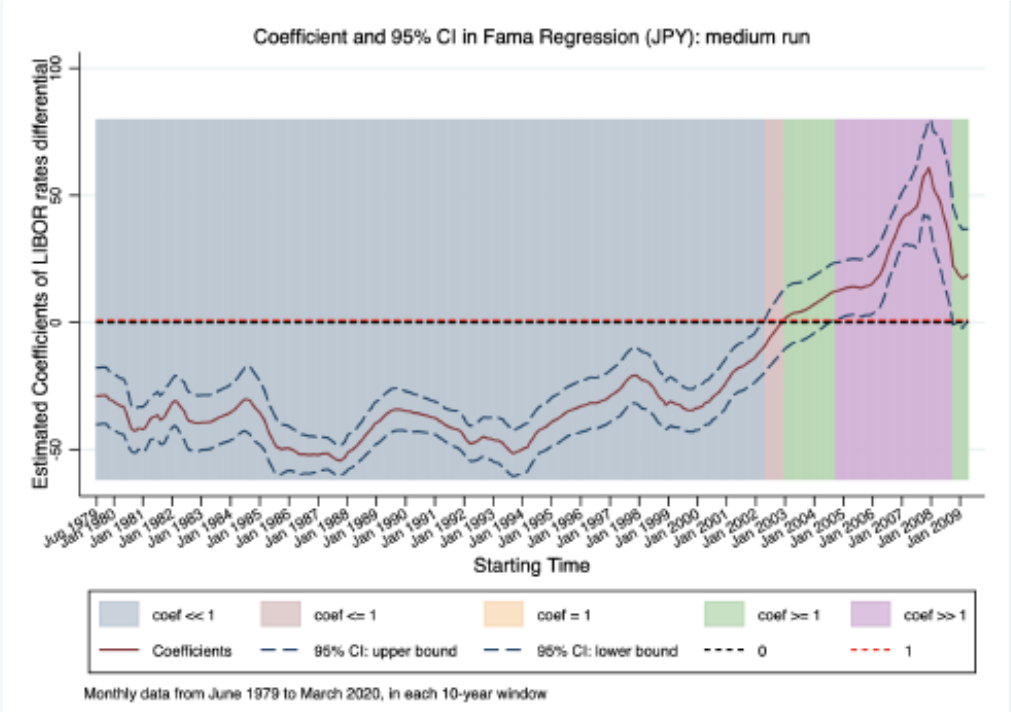


Figure 43: 10-year Rolling Medium-Run Regressions: NOK

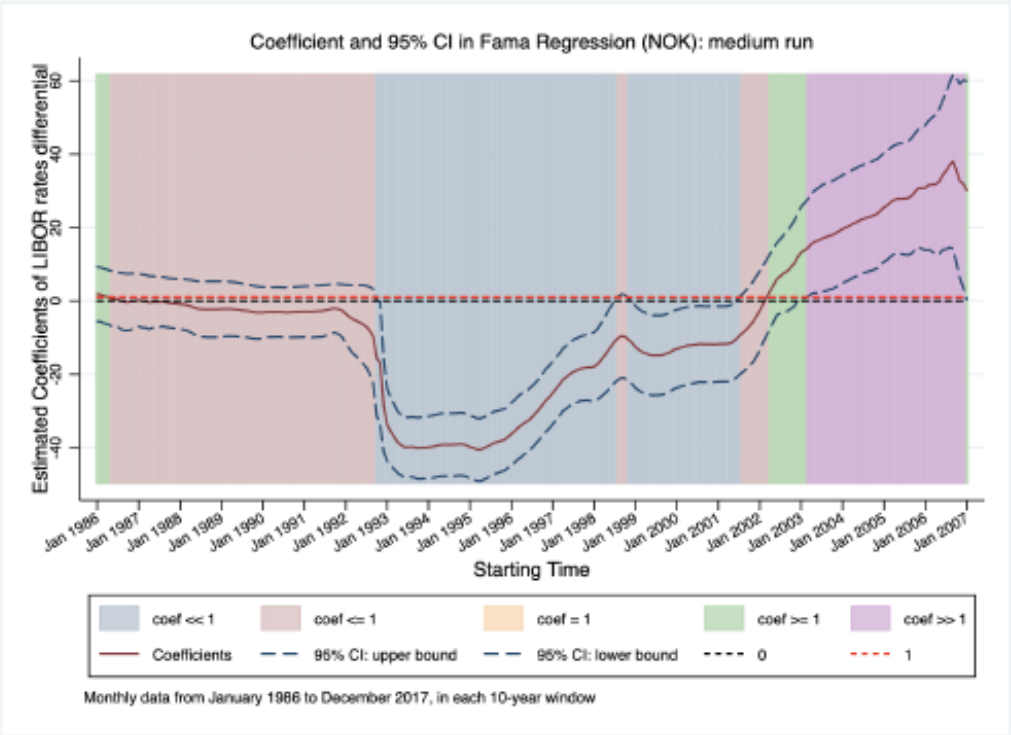


Figure 44: 10-year Rolling Medium-Run Regressions: NZD

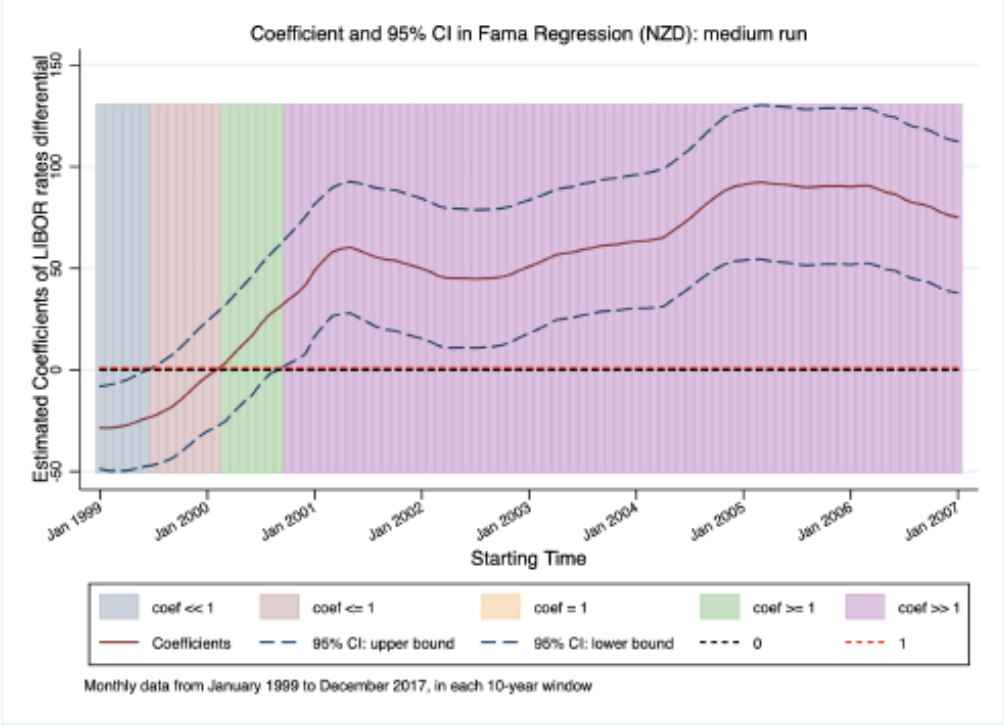


Figure 45: 10-year Rolling Medium-Run Regressions: SEK

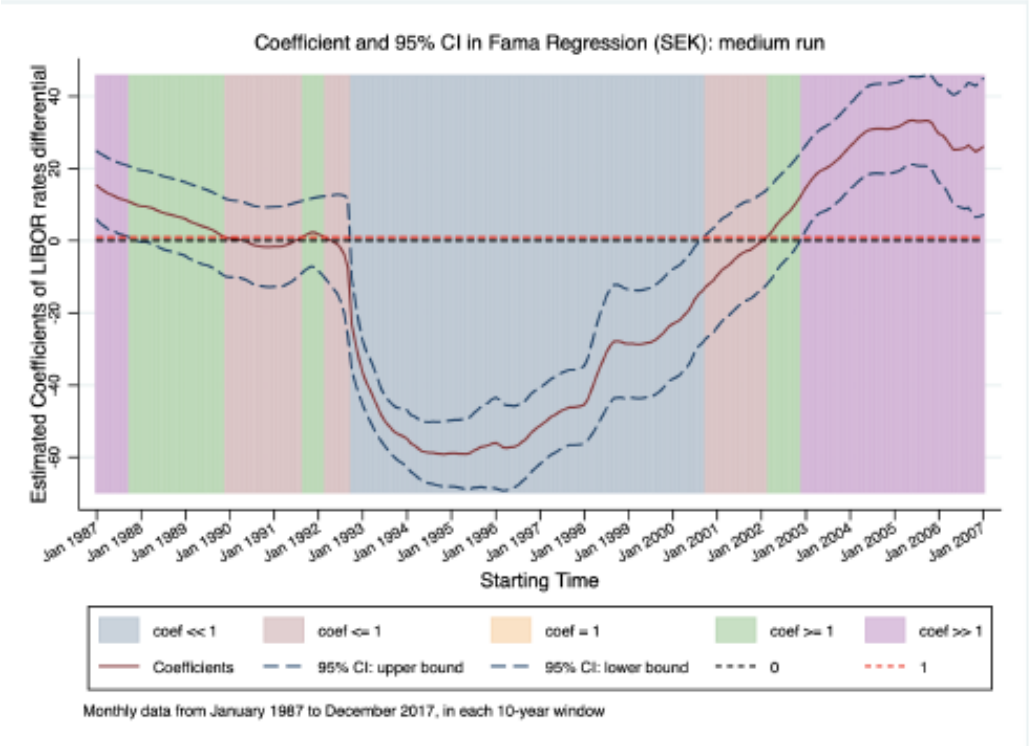


Figure 46: 10-year Rolling Medium-Run Regression, Inflation as Regressor: CAD

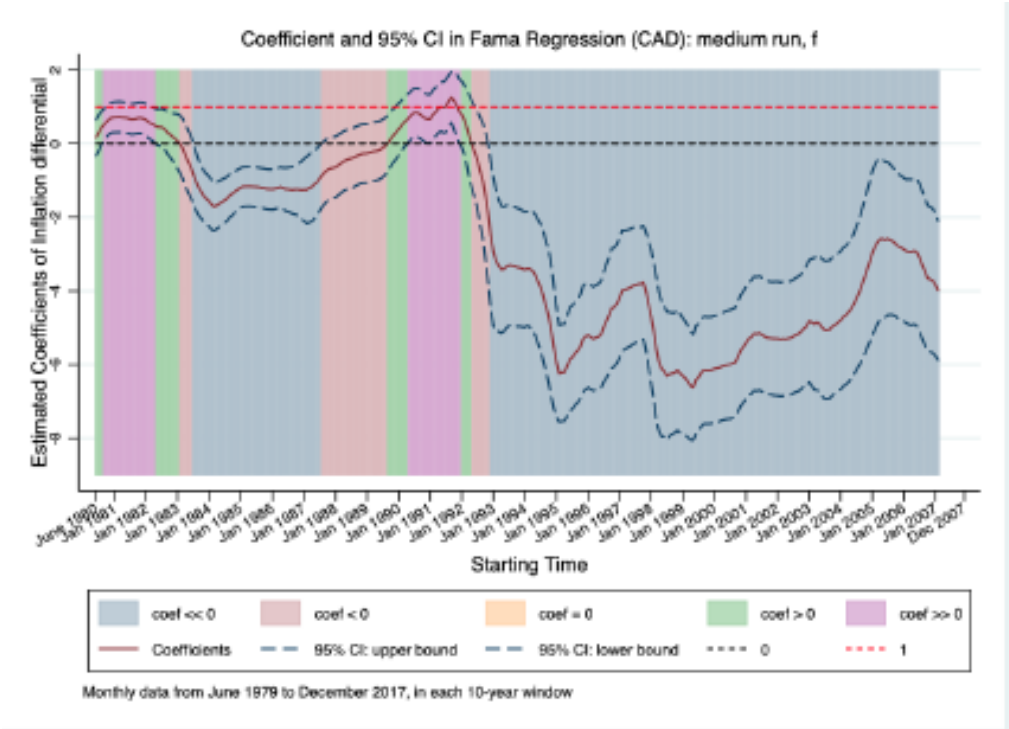


Figure 47: 10-year Rolling Medium-Run Regression, Inflation as Regressor: CHF

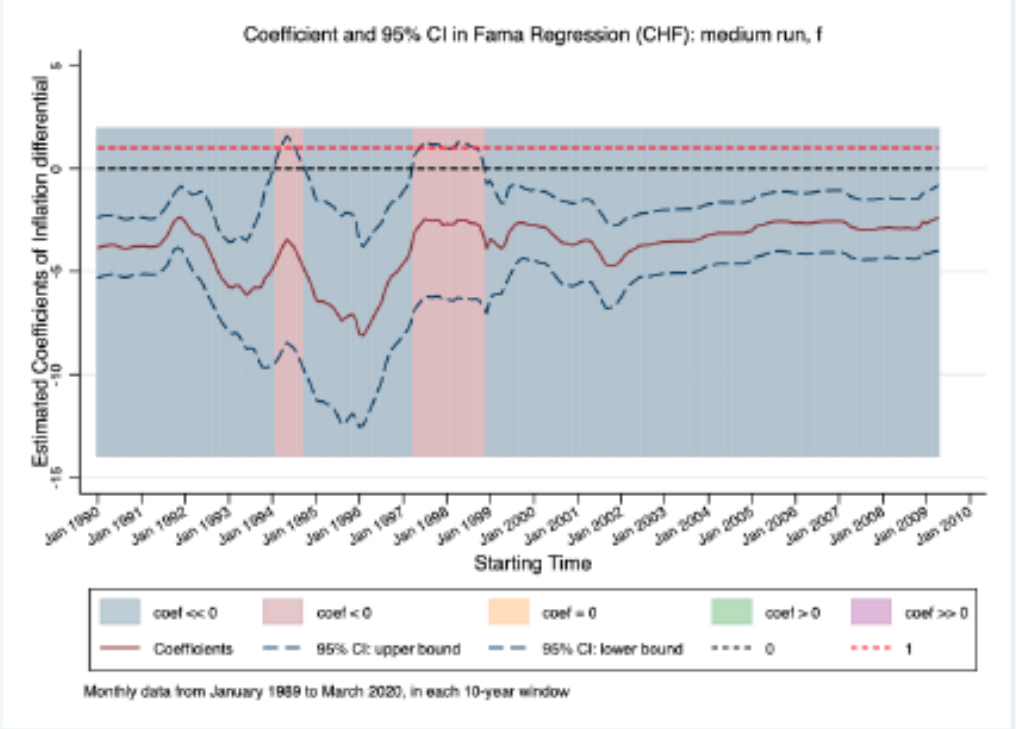


Figure 48: 10-year Rolling Medium-Run Regression, Inflation as Regressor: DEM

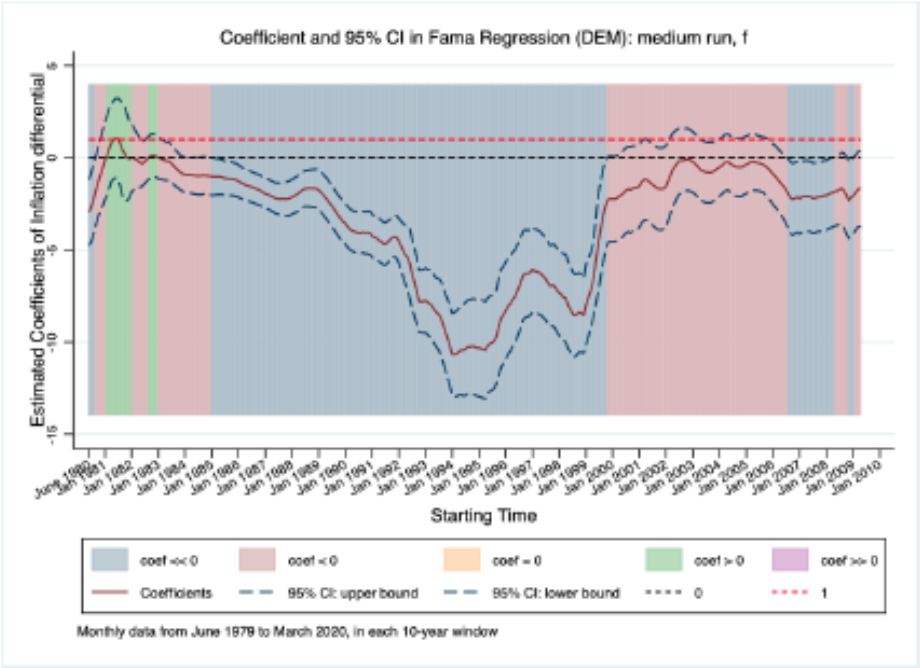


Figure 49: 10-year Rolling Medium-Run Regression, Inflation as Regressor: FRF

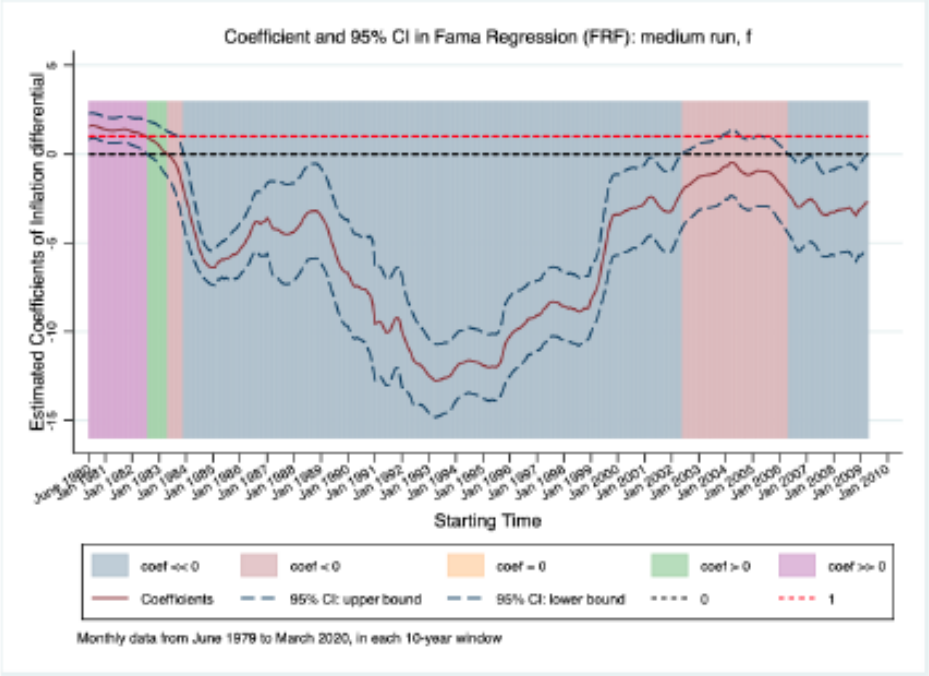


Figure 50: 10-year Rolling Medium-Run Regression, Inflation as Regressor: GBP

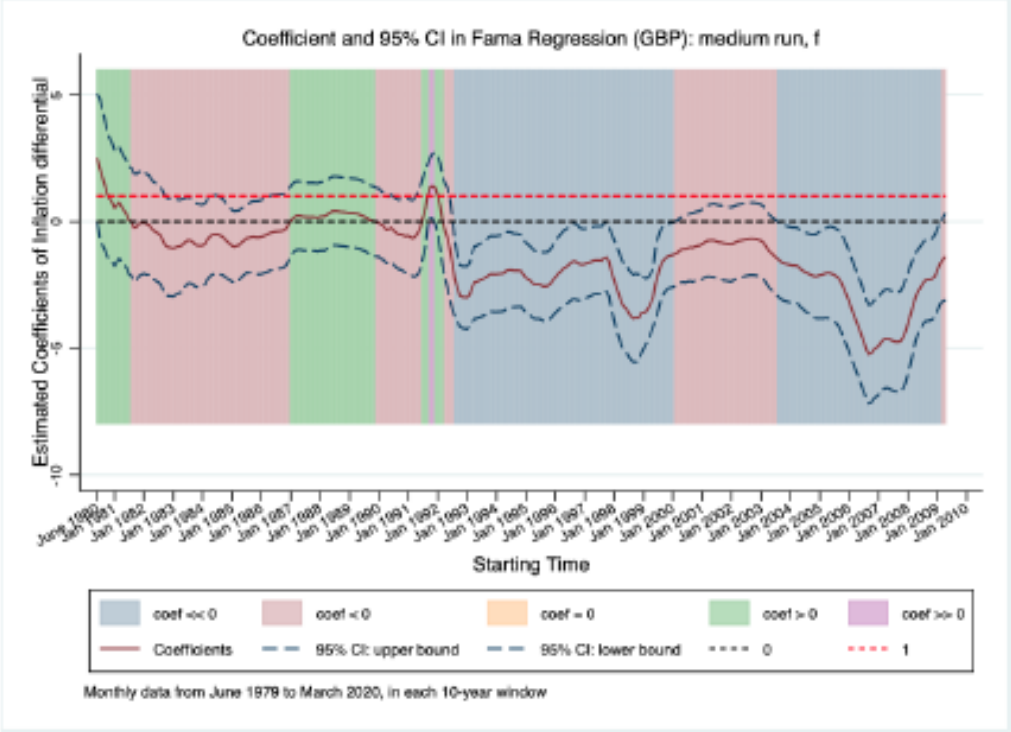


Figure 51: 10-year Rolling Medium-Run Regression, Inflation as Regressor: ITL

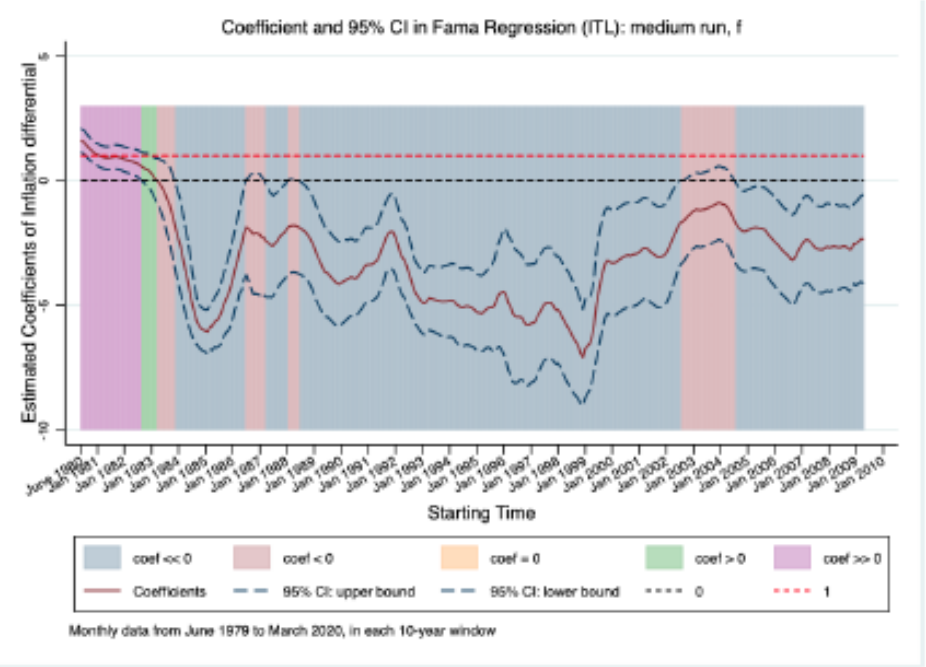


Figure 52: 10-year Rolling Medium-Run Regression, Inflation as Regrssor: JPY

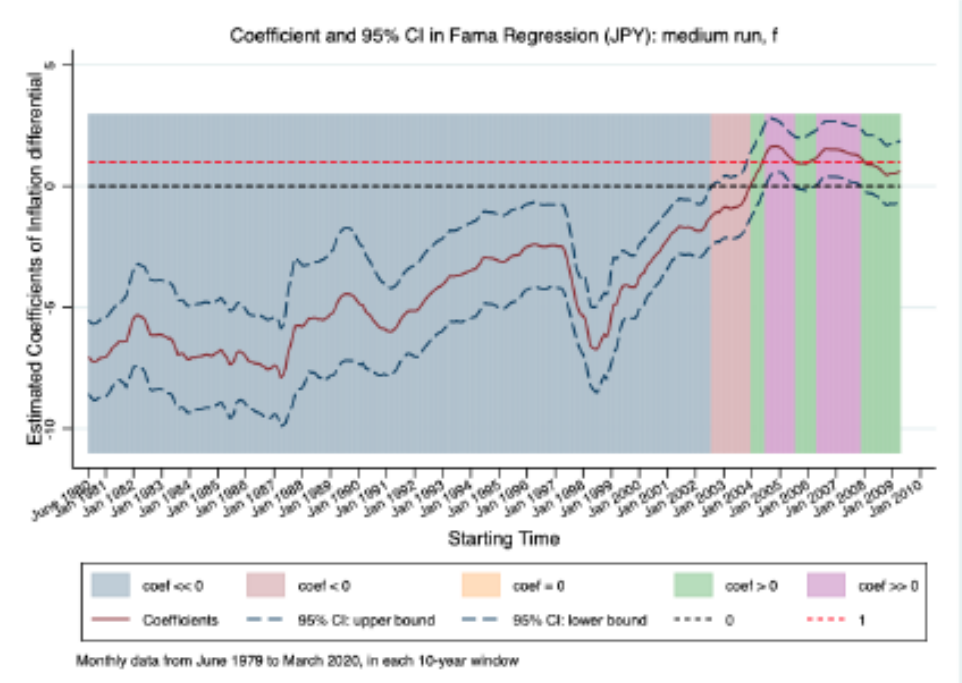


Figure 53: 10-year Rolling Medium-Run Regression, Inflation as Regrssor: NOK

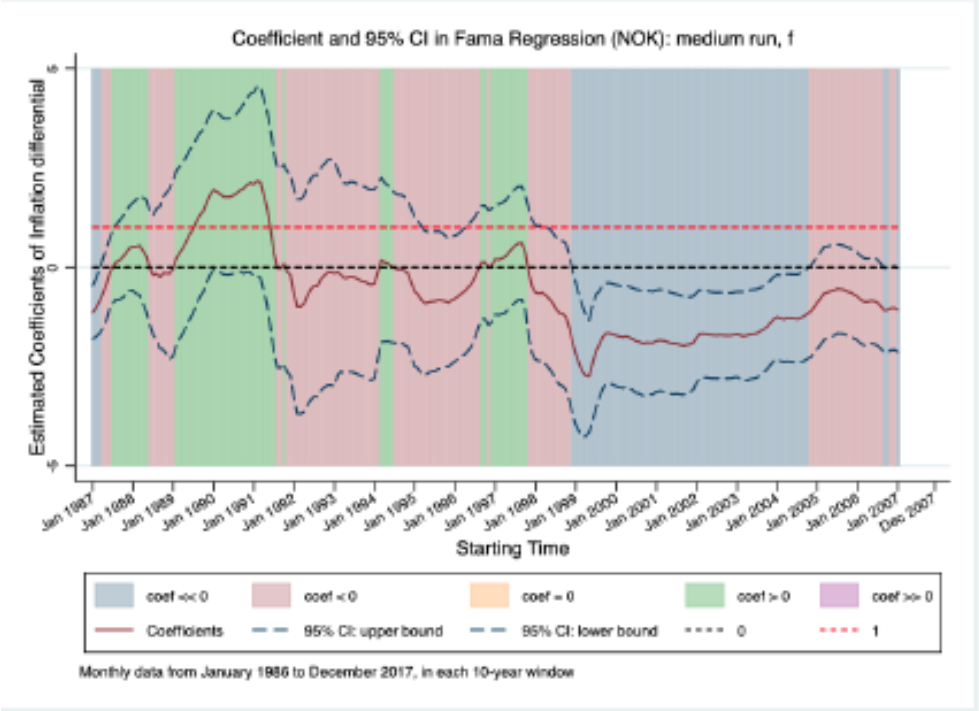


Figure 54: 10-year Rolling Medium-Run Regression, Inflation as Regressor: SEK

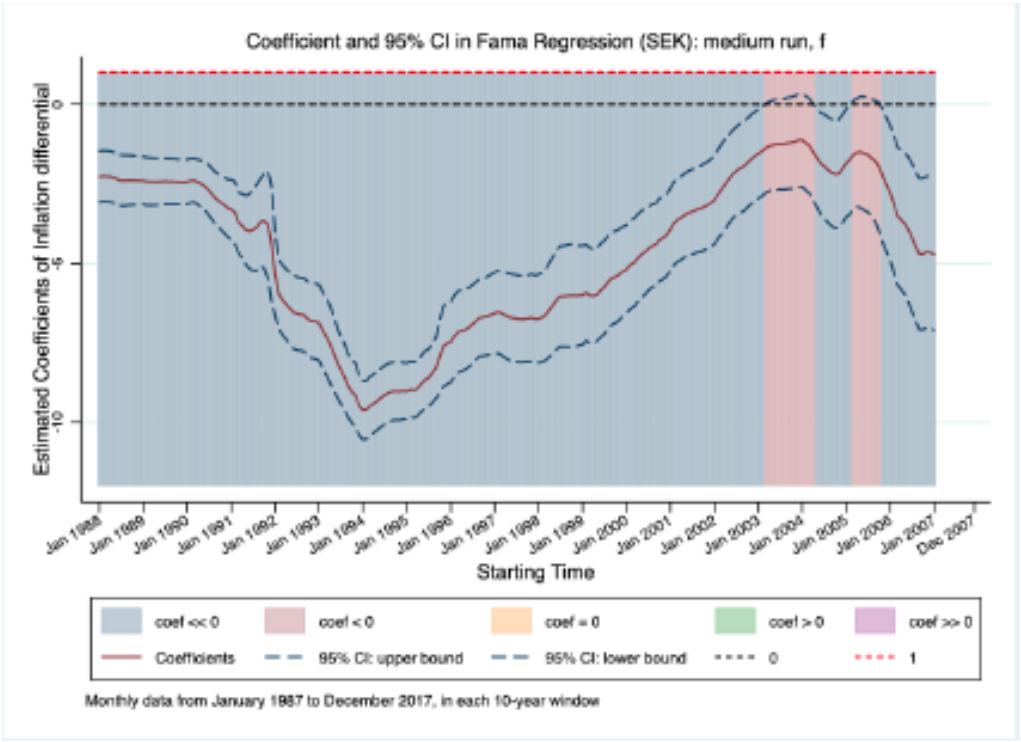


Figure 55: Reaction of Exchange Rate to Inflation Differential: CAD

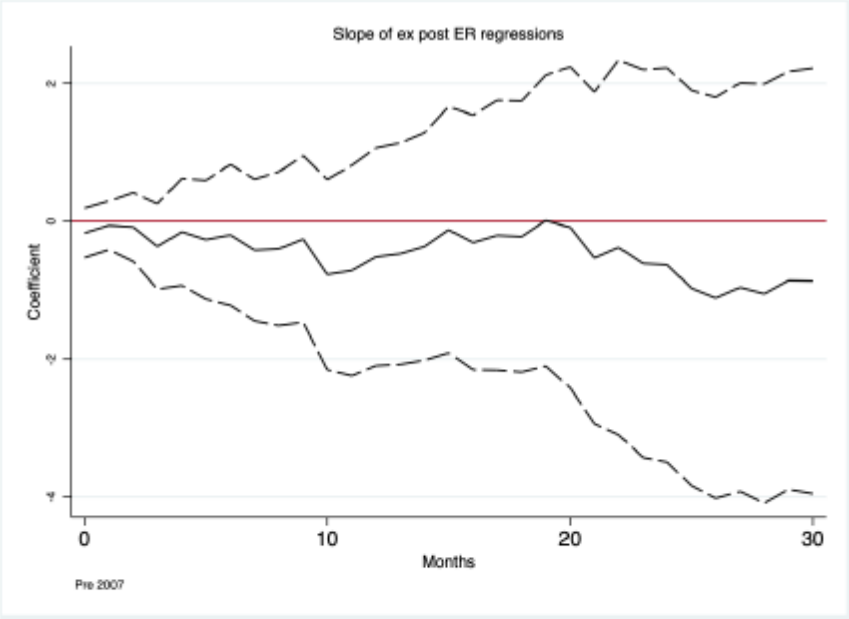


Figure 1: Pre-Crisis: CAD

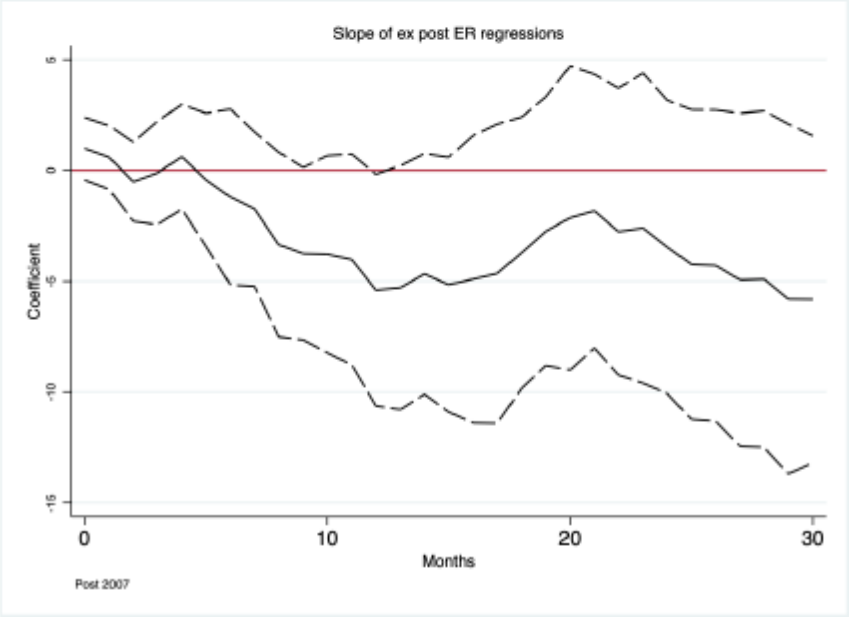


Figure 2: Post-Crisis: CAD

Figure 56: Reaction of Exchange Rate to Inflation Differential: CHF

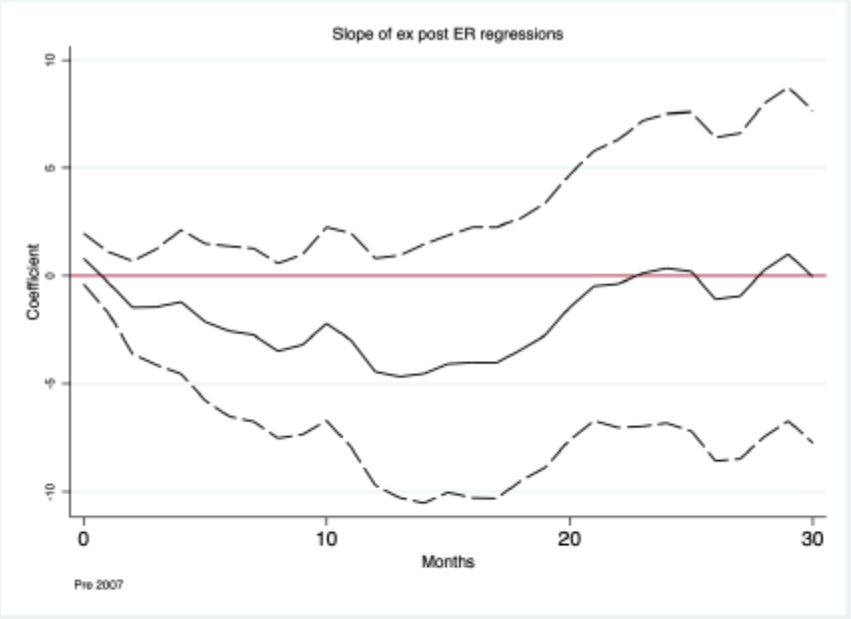


Figure 5: Pre-Crisis: CHF

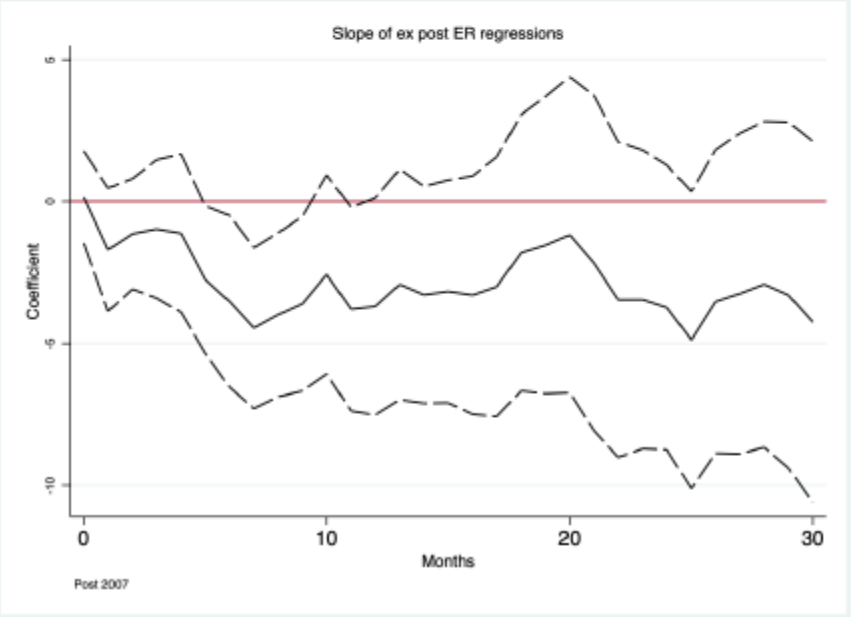


Figure 6: Post-Crisis: CHF

Figure 57: Reaction of Exchange Rate to Inflation Differential: DEM

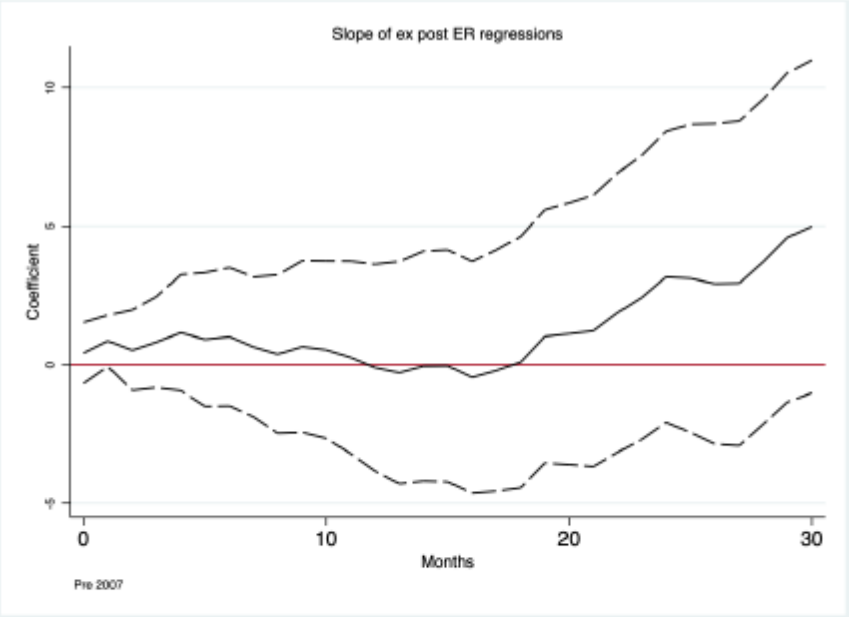


Figure 9: Pre-Crisis: DEM

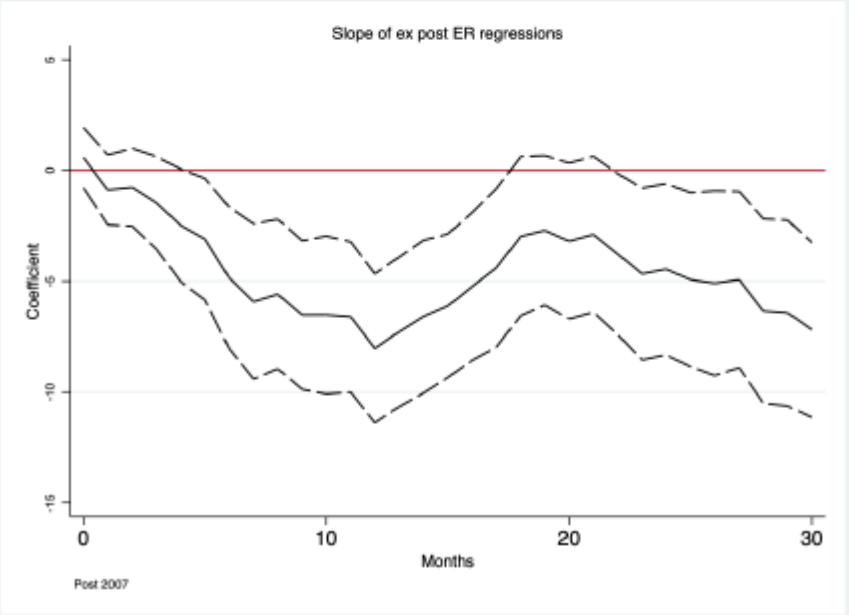


Figure 10: Post-Crisis: DEM

Figure 58: Reaction of Exchange Rate to Inflation Differential: FRF

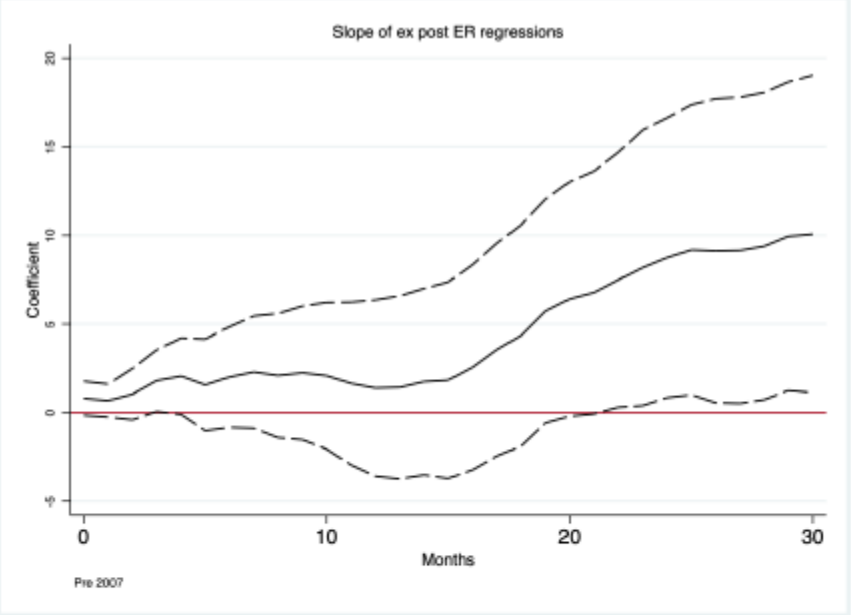


Figure 13: Pre-Crisis: FRF

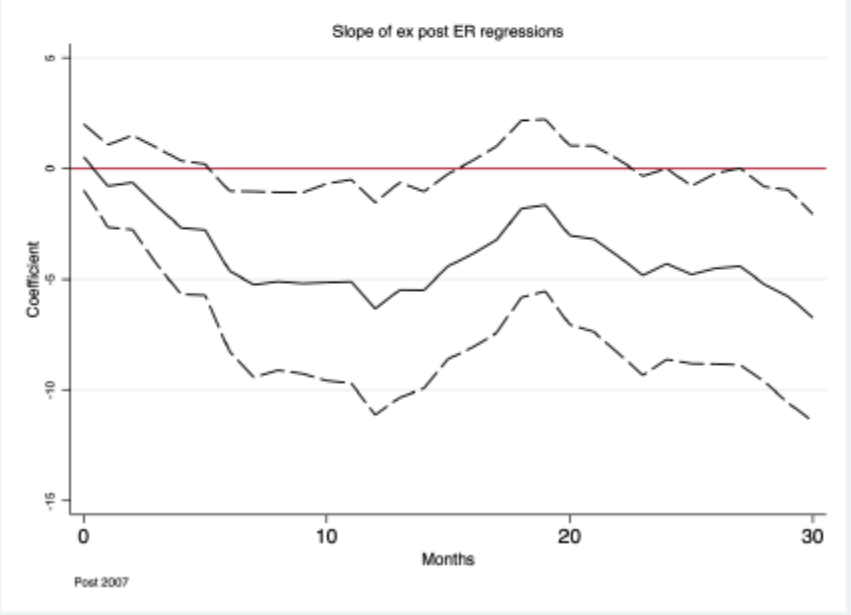


Figure 14: Post-Crisis: FRF

Figure 59: Reaction of Exchange Rate to Inflation Differential: GBP

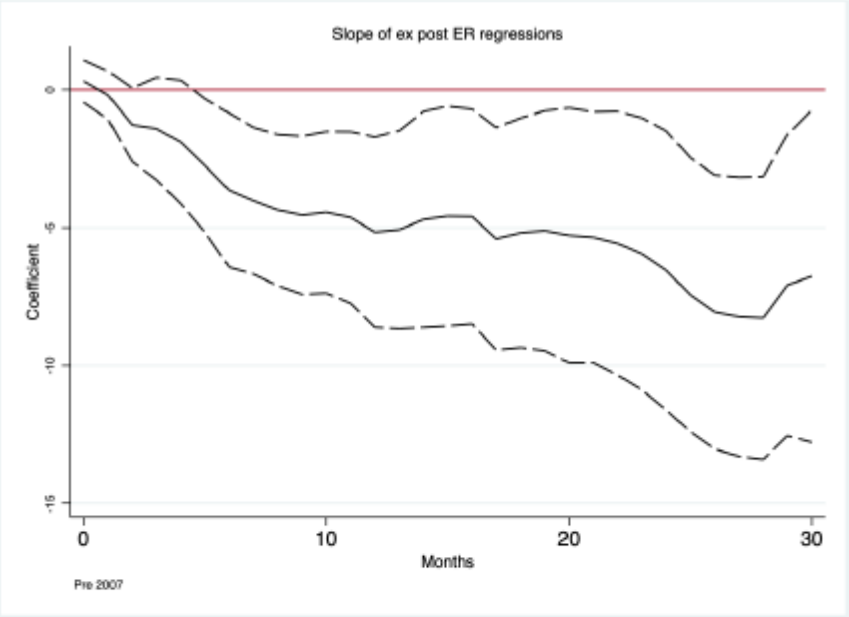


Figure 17: Pre-Crisis: GBP

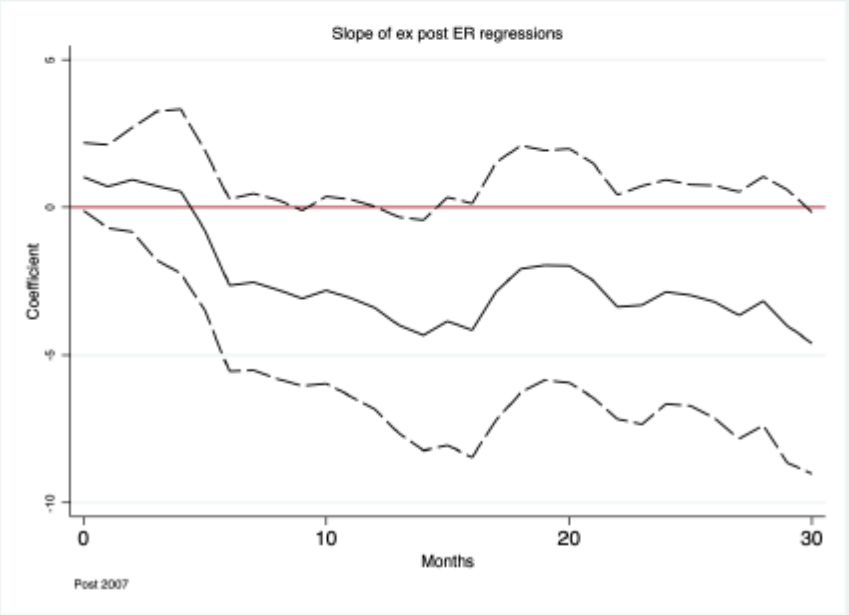


Figure 18: Post-Crisis: GBP

Figure 60: Reaction of Exchange Rate to Inflation Differential: ITL

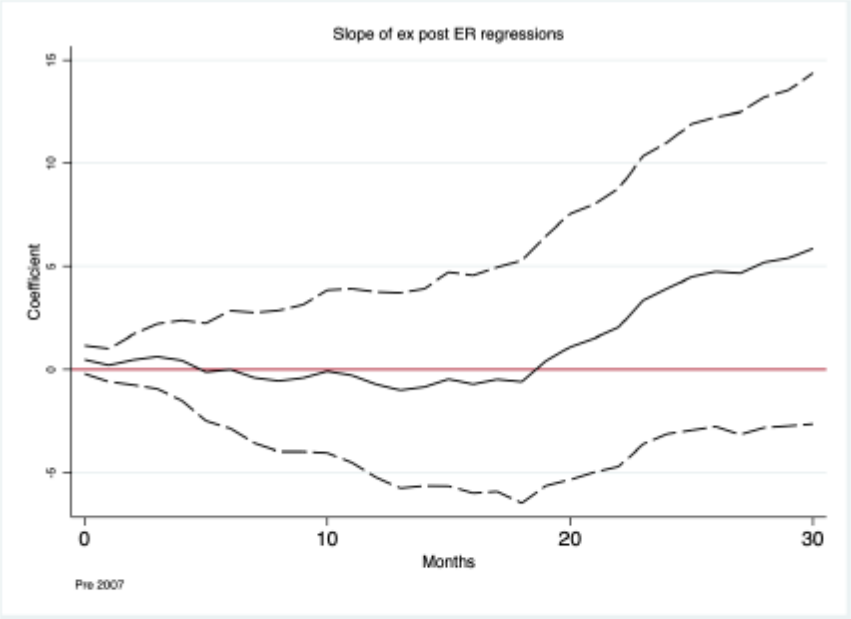


Figure 21: Pre-Crisis: ITL

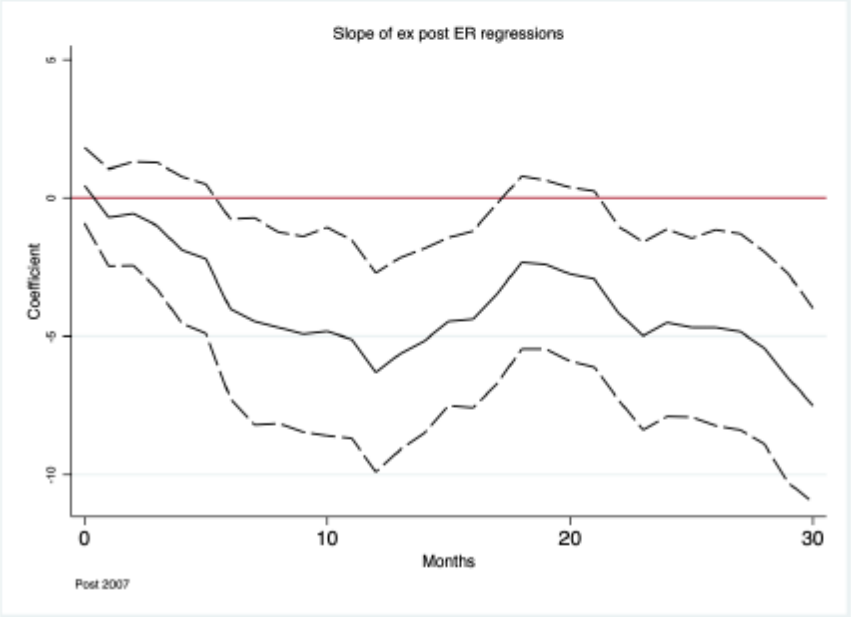


Figure 22: Post-Crisis: ITL

Figure 61: Reaction of Exchange Rate to Inflation Differential: JPY

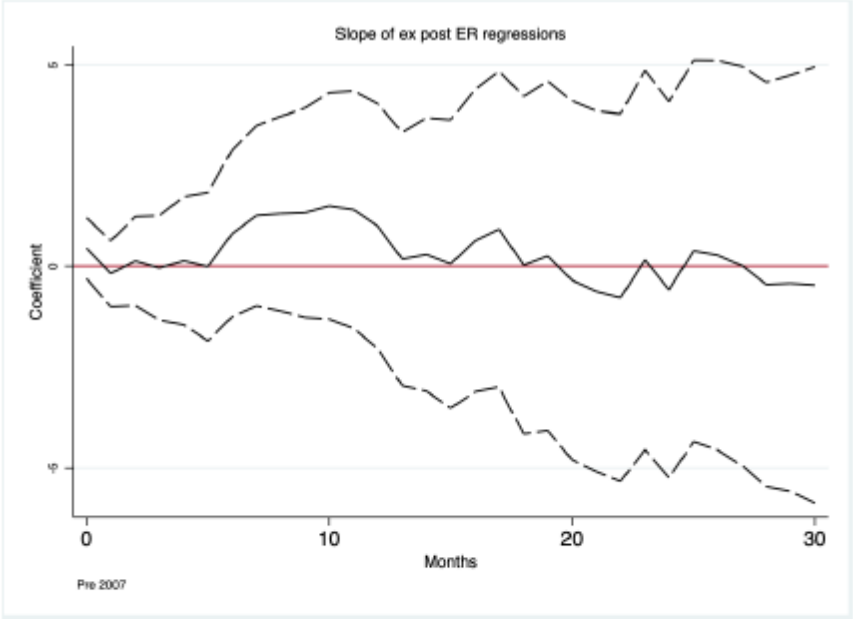


Figure 25: Pre-Crisis: JPY

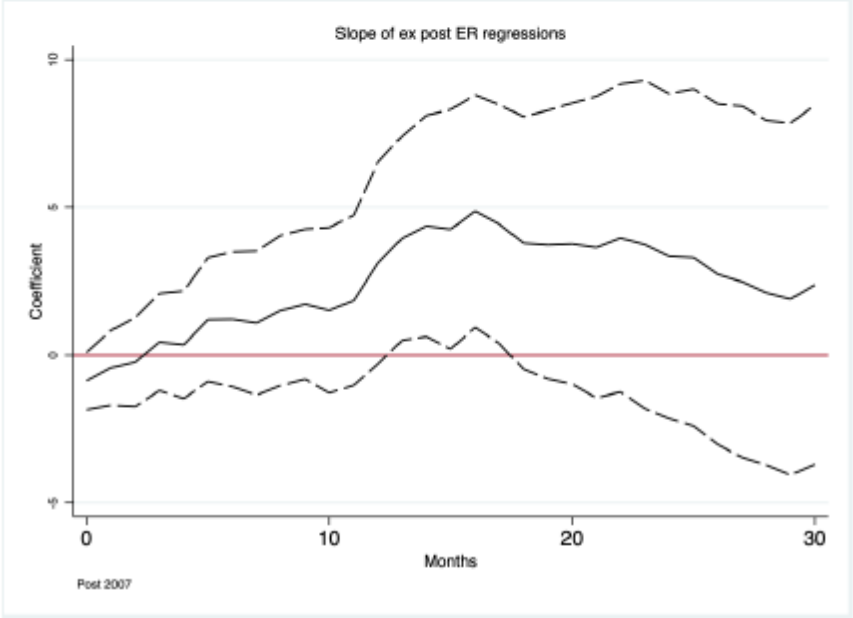


Figure 26: Post-Crisis: JPY

Figure 62: Reaction of Exchange Rate to Inflation Differential: NOK

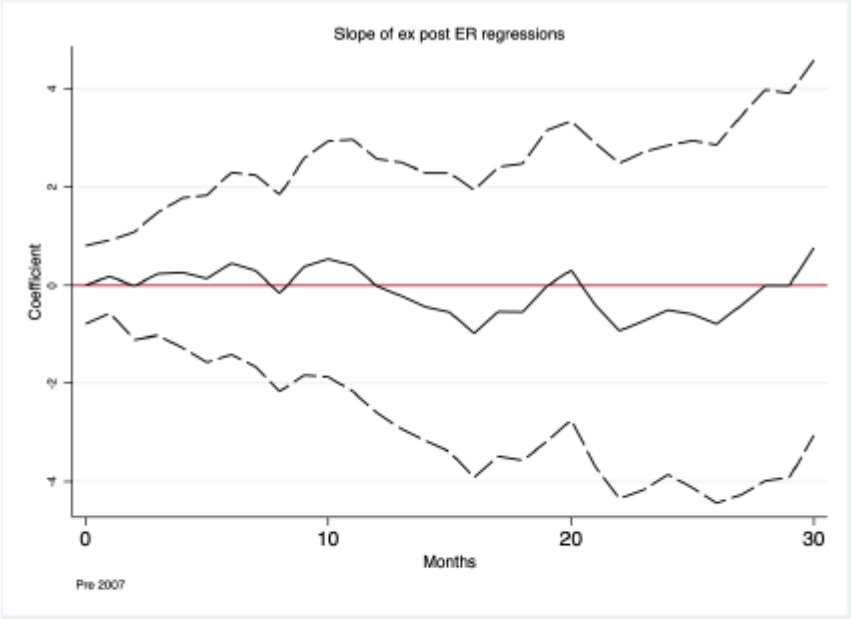


Figure 29: Pre-Crisis: NOK

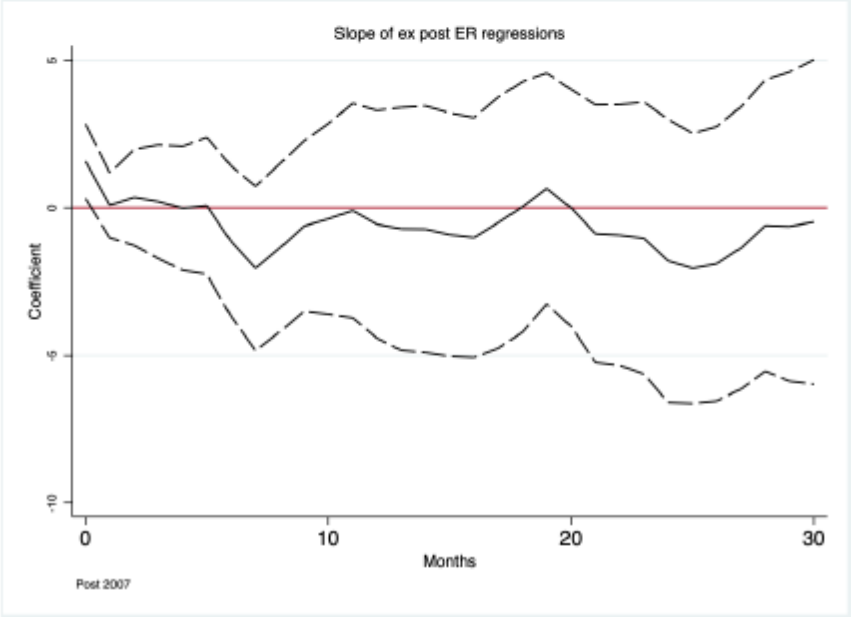


Figure 30: Post-Crisis: NOK

Figure 63: Reaction of Exchange Rate to Inflation Differential: SEK

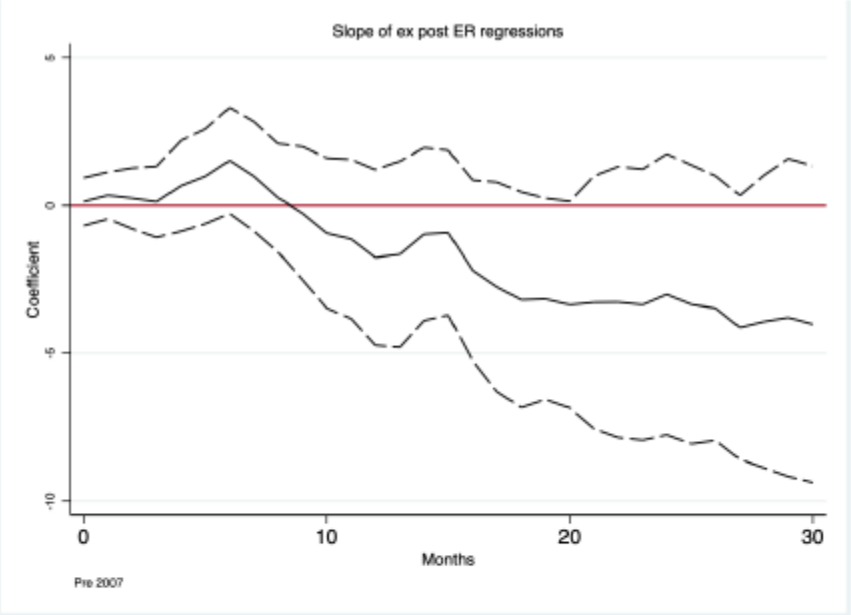


Figure 33: Pre-Crisis: SEK

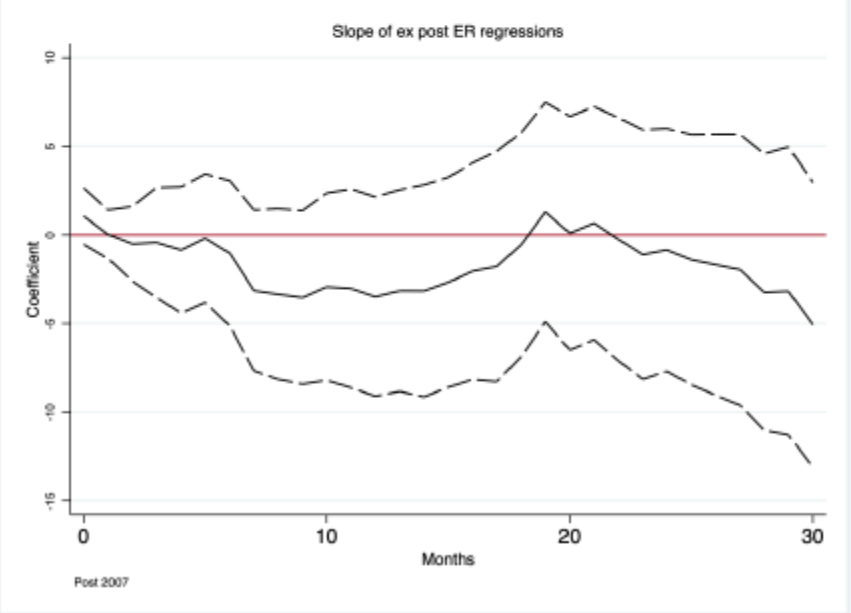


Figure 34: Post-Crisis: SEK