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The Instability of the Bilson-Fama Forward Rate Anomaly

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ABSTRACT

The paper examines the Bilson-Fama regression for discrete points of structural change. We find greater instability than previous studies and a forward rate bias that is more often insignificant or positive than negative as widely reported. We also find considerably more evidence of a time-varying risk premium. Systematic forecasting errors also play a key role, but the correlations are unstable and switch sign across many of the subperiods. The results present a challenge for the view that currency markets are systematically irrational.

Keywords: Forward premium puzzle, structural change of predictive regressions, exchange rate risk premium, systematic forecast errors, rational forecasting

JEL Codes: F31, G14. G15

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1 Introduction

Scores of studies over the past four decades find that forward exchange rates are biased predictors of spot exchange rates. The finding is based on a linear regression of the one-period-ahead change in the spot rate on the forward premium. Bilson (1981) and Fama (1984) (BF) and many subsequent studies report a slope coefficient (hereafter β) that is less than unity and, in many advanced economies, negative.[1] A negative β implies that "one can make predictable profits by betting against the forward rate" (Obstfeld and Rogoff, 1996, p. 589). Studies of carry trade strategies, which exploit a negatively biased β (from unity), support the predictable profits view (see Burnside et al. 2007, 2011).

The literature focuses largely on two competing explanations of the predictable profits: a time-varying risk premium required by rational investors or systematic forecasting errors committed by less-than-fully rational individuals. Early risk premium studies were unable to plausibly explain a negative β, giving credence to behavioral models that rely on less than fully rational forecasting.[2] But recent studies show that rational risk premium models with nonstandard preferences can account for the anomaly.[3] Engel (2016) suggests that the newer models' ability to explain asset pricing puzzles in other markets lends weight to the anomaly's risk premium explanation. But survey measures of exchange rate expectations imply that little of the puzzle can be explained by a time-varying risk premium; most of the action comes from systematic forecasting errors (Froot and Frankel, 1989, Bacchetta et al., 2009, and Chinn and Frankel, 2020).

In this paper, we find that risk and forecasting errors both underpin forward rate biasedness, although how they do presents a challenge to models of both phenomena. We first test the BF regression for discrete points of structural change and find more instability than previously documented. The results indicate that linear estimates provide spurious evidence of pre-

Thinking (INET) and the University of New Hampshire for financial support.

[1]For review articles, see Froot and Thaler (1990), Lewis (1995), Sarno (2005), and Engel (1996, 2014).

[2]See Mark and Wu (1998), Gourinchas and Tornell (2004), Burnside et al. (2011), Moran and Nono (2018). For a model of delayed portfolio adjustment, see Bacchetta and Van Wincoop (2010). For market microstructure explanations, see Carlson, Dahl and Osler (2008) and Burnside, Eichenbaum and Rebelo (2009).

[3]See Verdelhan (2010), and Colacito and Croce (2011, 2013). See also Farhr and Gabaix (2015) and Gourio et al. (2013) for disaster risk models.

dictable profits. We also consider a widely used survey dataset on market participants' currency forecasts. Our analysis shows that the inference we draw about the importance of risk and rationality hinges on whether the analysis incorporates the anomaly's instability.

To be sure, the literature contains considerable evidence of the BF regression's instability. Recent studies include Zigraiova et al.'s (2021) meta-analysis, which finds that β estimates increase in value as a study's publication year increases. Chinn and Frankel (2020), Cheung and Wang (2022), and Bussiere et al. (2022) find that the 2008 global financial crisis was associated with structural change of a striking form: forward rate biasedness shifted from negative to positive for most countries.[4]

However, the existing evidence is incomplete. Most studies impose one or more discrete break points exogenously or restrict the number, timing, and magnitude of change points via a two-state Markov-switching model or other nonlinear specification.[5] By contrast, we use structural change tests that leave the number, timing, and magnitude of break points largely unrestricted. The analysis allows for the possibility of more structural change than most other studies.

We examine six major currency markets and find more structural change than previously documented. Like other recent studies, we find that the bias in β is positive in subperiods following the global financial crisis. But, the shifts in β above and below unity, and above and below zero, occur throughout the samples. Our piece-wise linear approximation reveals a β that is less than unity (and sometimes negative) during some subperiods and equal to or greater than unity during other subperiods in all six currency markets examined.[6] Strikingly, the estimated bias is more often

[4]For additional evidence of the BF regression's instability, see Bekaert and Hodrick (1993), Lewis (1995), Mark and Wu (1998), Frydman and Goldberg (2007), Choi and Zivot (2007), Hatemi-Ja and Roca (2012), and Goldberg et al. (2020). For instability of predictive regressions in stock or bond markets, see Pesaran and Timmerman (1995), Bossaerts and Hillion (2015), Ang and Bekaert (2002, 2007), Timmermann (2008), Pettenuzzo and Timmermann (2011), and Farmer et al. (2023).

[5]Bekaert and Hodrick (1993) and MacDonald and Nagayasu (2015) estimate a Markov-switching model. Clarida et al. (2009) and Moore and Roche (2012) isolate subperiods of high and low volatility. Baillie and Kilic (2006) and Baillie and Cho (2014) estimate a two-state, logistic smooth transition regression. Zhu (2002) allows for time variation in β using a Kalman filter. Sakoulis et al. (2010) use a partial-break Bai and Perron (1998) procedure that limits structural change to the mean of the forward premium process.

[6]Other studies that find subperiods in which $\beta > 1$ and $\beta < 1$ include Bansal (1997),

insignificantly different than unity than significantly negative as is widely thought. The results are similar to those found in equity markets, where popular forecasting models also experience slope coefficients that change sign and produce protracted subperiods of insignificance (see Goyal and Welch, 2008, and Pettenuzzo and Timmermann, 2011).

Clearly, predicting returns in currency and other asset markets is more difficult than suggested by the many linear regression studies. Carry trade research suggests that the forward rate nonetheless possesses predictive power. For example, Burnside et al. (2007, 2011) find that the strategy generates significant predictable profits over their sample periods. Our piece-wise linear results may help explain this profitability as our β estimates are more often below than above unity in most markets. But our results also imply that carry trade returns are time dependent and unpredictable.[7] Hsu et al (2020, p. 1) reaches the same conclusion: "strategies chosen as profitable in one period are generally not profitable in an ensuing out-of-sample sample period, especially after correcting for data-snooping, and even after allowing for learning and stop-loss strategies."

Our structural change findings present a challenge to risk-premium and behavioral models. What needs to be explained is not a negative β, but the pattern of negative, zero, and positive forward rate biases across subperiods of floating exchange rates. We explore this question using survey data on exchange rate expectations.[8]

Most survey data studies ignore the anomaly's instability.[9] The linear estimates show that most if not all the forward rate bias arises from systematic forecast errors. Recent studies include a break for the global financial crisis and continue to report little evidence that risk and rationality drive outcomes (see Chinn and Frankel, 2020, and Bussiere et al., 2022).

By contrast, we find considerably more evidence of a time-varying risk

Zhu (2002), Frydman and Goldberg (2007), Clarida et al. (2009), Lothian and Wu (2011), and Baillie and Cho (2014), and Goldberg et al. (2020).

[7]See Melvin and Taylor (2009), Brunnermeier et al. (2008), and Baillie and Cho (2014) for additional evidence of this time dependency and unpredictability.

[8]Farmer et al. (2021) examine the pattern of *ex ante r*eturn predictability in equity markets. The researchers consider four risk premium models and a behavioral specification in which market participants systematically underreact to news about cash flows. The behavioral model is the only specification that can account for the pattern of return predictability.

[9]See for example Froot and Frankel (1989), Frankel and Chinn (1993), Chinn and Frankel (2002), Bacchetta et al. (2009).

premium once we allow for the BF regression's instability over the full sample. Our results show that risk accounts for 50 percent or more of the estimated bias in roughly a third of the subperiods across markets. Strikingly, we find a significant *mean* risk premium in more than half of the subperiods, the value of which switches sign across multiple subperiods. This instability provides additional evidence of a time-varying risk premium.

Systematic forecasting errors also play an important role in explaining the pattern of negative and positive subperiod biases in all six markets. But the correlations are highly unstable and often switch sign from one subperiod to the next. We also find a highly unstable mean forecasting error that also switches sign frequently across subperiods. The results are difficult to reconcile with models in which market participants mispredict news systematically in the same way.

The remainder of the paper is structured as follows. Section 2 considers existing evidence on the BF regression's instability. Section 3 sets out our structural change testing methodology. It also reports piece-wise linear estimates of the BF regression. In section 4, we use survey data to examine the relative importance of risk and forecasting errors in explaining the subperiod forward rate biases. We find that allowing for structural change leads to very different conclusions than full sample estimates. Section 5 concludes the paper.

2 Existing Evidence on Instability

In this section, we consider existing evidence on the BF regression's instability. The evidence comes from studies that estimate Markov switching or other nonlinear models, as well as those that impose break points exogenously. The evidence also entails β estimates that have been reported by studies using different sample periods over the past four decades. We focus on key studies whose findings are representative of most other studies, rather than provide a comprehensive review of the literature. Our review suggests that the nonlinear studies miss the extent and nature of the anomaly's instability. We argue that this difficulty is traceable to the frequency and novelty of the historical developments that trigger instability in the returns process. The nature of these developments implies that less restrictive test procedures are needed to characterize the anomaly's instability and draw inference from survey data about the importance of risk and rationality.

2.1 Full-Sample Estimates

The BF regression is specified using log returns:

$$\Delta s_{t+1} = \alpha + \beta fp_t + \varepsilon_{t+1} \tag{1}$$

where s_{t+1} is the log of the spot exchange rate at time $t+1$ (the price of foreign currency in terms of domestic currency), $fp_t = f_t - s_t$ is the time-t forward premium on foreign currency (where f_t denotes the log of the forward exchange rate), ε_{t+1} is an error term, and Δ is a first-difference operator. The assumptions of risk aversion and the rational expectations hypothesis (REH) imply that the forward exchange rate is an unbiased predictor of future exchange rates. In terms of the BF regression, unbiasedness implies that $\alpha = 0$, $\beta = 1$, and ε_{t+1} is random and orthogonal to fp_t.

Researchers usually focus on estimates of β (hereafter $\hat{\beta}$) in part because the slope coefficient determines the predictive ability of the forward rate. A $\beta < 1$ implies that the forward premium tends to *overpredict* future changes in the spot exchange rate, which we refer to as a negative forward rate bias. A $\beta < 0$ implies a tendency not only to overpredict (i.e., a negative bias), but to predict the wrong direction of change of the spot rate.

Most of the evidence of negative biasedness comes from full-sample linear regressions. We thus report linear BF regression estimates before examining the literature's key instability findings (see Table 1). Our data set entails 40+ years of monthly observations on spot and forward U.S. dollar exchange rates for six major currency markets: the Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), Eurozone euro (EUR), British pound (GBP), and Japanese yen (JPY).[10]

Like other recent studies with 40+ years of data, we find weaker evidence of negative βs than earlier studies. Five of our six slope estimates

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[10]Data for the DEM, GBP, and JPY markets come from Data Resources Inc. (DRIFACS) for 1973M6-2000M1 and from Thompson-Reuters Datastream for 2000M2-2018M2. The dollar value of the EUR before 1999M1 is derived from the dollar value of the German mark. Data for the AUD, CAD, and CHF come from Thompson-Reuters Datastream and run from 1975M1-2018M2. Spot and forward rate data are bid-asked averages.

are negative (except for the Japanese yen), but insignificantly different from zero. However, as with earlier research, the results continue to imply negative forward rate biasedness; the $\hat{\beta}$s are significantly less than unity except for the JPY. The α estimates in Table 1, like most other studies, are small and largely insignificant.

Full sample linear regressions provide a gauge of whether asset returns are predictable on average, across potentially very different economic states. Depending on the frequency and nature of the instability, they may provide a poor basis for gauging the extent and nature of forward rate biasedness or for understanding the roles of risk and forecast errors in such outcomes.

Indeed, linear BF regressions in long samples provide poor characterizations of returns. They are marked by extremely low R^2 values (see Table 1) and residual diagnostic tests (see Table A1 in the Appendix) that show ARCH and/or heteroskedasticity problems. The linear BF regression thus accounts for little to none of the variation of returns in every market. Researchers address the heteroskedasticity by adjusting standard errors (HAC), which we also do. However, such adjustment is insufficient when the underlying problem is structural change.

In Section 3, we find that the adequacy of the BF regression improves after allowing for structural change. To help motivate this analysis, we consider existing evidence of β's instability, The evidence comes from studies that employ endogenous structural change tests as well as exogenous subperiod tests. We consider first the endogenous test studies.

2.2 Endogenous Test Studies

Bekaert and Hodrick (1993) were among the first to formally test the BF regression's stability. They employ a two-state Markov-switching model and an exogenous subperiod analysis. The study examines the German mark (DEM), British pound (GBP), and Japanese yen (JPY) markets vis-a-vis the U.S. dollar in a sample of weekly data that runs from January 1975 through December 1989 (which we denote by 1975W1-1989W52).

The Markov-switching results show a negative $\hat{\beta}$ for both regimes that is significantly less than unity (or marginally so) in all three markets. MacDonald and Nagayasu (2015) also estimate a two-state Markov switching model for a monthly JPY sample that runs from May 1993 through April 2012 (which we denote by 1993M5-2012M4). The researchers also report negative $\hat{\beta}$s for both regimes that are significantly less than unity. Both studies find several break points in their samples. The $\beta < 1$ finding in both regimes is important; it implies that the carry trade strategy of betting against the forward rate would be profitable on average regardless of the structural change.

The logistic smooth transition regression (LSTR) studies of Ballie and Kilic (2006) and Baillie and Cho (2014) tell a different story. Both studies report a lower regime in which $\beta < 1$ and an upper regime in which $\beta = 1$ for most markets examined. They find that markets are most often in the upper regime, implying that the carry trade is most often unprofitable on average. Ballie and Kilic (2006, p. 45) point out however that "estimation issues lead to considerable uncertainty with the estimated transition functions and hence imprecise definitions of regimes." The poor fit and uncertainty suggest that the assumption of two basic regimes may be problematic.

2.3 Exogenous Subperiod Tests and Estimates

Exogenous test studies, together with the β estimates that have been reported over four decades, suggest that the Markov-switching and LSTR studies both miss the full character of the anomaly's instability. The four decades of exogenous estimates imply that β's instability is more frequent than the endogenous test studies suggest. They also indicate that β takes on values below and above unity.

Table 2 reports subperiod $\hat{\beta}$s from key studies in each decade for the six major currency markets, along with our own OLS estimates for decade-based subperiods.[11] Consider first estimates for the 1970s and 1980s.

2.3.1 The 1970s and 1980s

Bilson (1981) was the first published study to consider the BF regression. He reports negative $\hat{\beta}$s for four of the five currencies in the table, although none of the estimates are significantly less than unity. Bekaert and Hodrick (1993) and Mark and Wu (1998) consider 1970s subsamples. Although their subsamples start six months before or after Bilson's, they find $\hat{\beta}$s that are greater than unity for two of the three markets examined. Our own subperiod results show positive $\hat{\beta}$s for the DEM, JPY, and CAD, none

[11] A blank in the last six columns indicates that the study does not consider the currency.

of which are significantly different from unity. The evidence in the table shows considerable instability even within the 1970s and $\hat{\beta}$s that are often positive and largely consistent with forward rate unbiasedness.

The picture changes markedly when observations from the 1980s are included in the sample. Bekaert and Hodrick's (1993) full sample estimates show significantly negative $\hat{\beta}$s and a rejection of $\beta = 1$ for all three markets examined. Exogenous structural change tests show strong evidence of a break in the beginning of 1980.

The other studies in the table report similar results. Our 1980s subperiod results also show negative estimates and a rejection of forward rate unbiasedness in five of six markets. Estimates that include the 1970s and 1980s (which we call "inclusive") reveal just how sensitive the results are to the time period selected; unbiasedness is rejected for only one market (the GBP) when the samples include observations from the 1970s and 1980s. The evidence is suggestive not only of structural change within and across the two decades, but of shifts in β from positive to negative values.

2.3.2 The 1990s-2010s

Studies that include observations from the 1990s continue to report negative $\hat{\beta}$s and rejections of forward rate unbiasedness. However, our subperiod estimates suggest that the 1980s may be driving the results; three of the currencies (the DEM, GBP, and JPY) have a positive $\hat{\beta}$ for the 1990s subperiod; only two estimates (the DEM and GBP) are inconsistent with $\beta = 1$. The inclusive estimates tell a similar story; only one currency (the GBP) is characterized by a significantly negative $\hat{\beta}$.

Studies with observations from the 2000s also indicate structural change within and across decades. Bacchetta et al. (2009) and Wang and Wang (2009), whose samples omit observations from the 1970s and stop short of the global financial crisis, provide strong evidence of a negative β in most markets. But Engel (2016), whose samples include post-crisis observations, reports $\hat{\beta}$s that are all greater than unity. Three of the estimates imply that $\beta > 1$ and thus a positive forward rate bias (those for the GBP, JPY, and CD). Our subperiod and recursive results show negative $\hat{\beta}$s in most markets, but they are largely consistent with forward rate unbiasedness.

Studies published in the 2010s provide additional evidence that the instability involves βs greater than unity. The studies' full sample estimates continue to show negative and positive $\hat{\beta}$s, but the evidence against forward rate unbiasedness is weaker than reported by 1980s and 1990s studies. The three studies covered in Table 3 consider post-crisis subperiods and all find $\hat{\beta}$s that are greater than unity, with some significantly so. Our subperiod estimates for the 2010s deliver similar results; we find $\hat{\beta} > 1$ in four markets, with three significantly so (those for the GBP, JPY, and CAD).[12] The inclusive results show that when the 2010s are included, the full sample estimates are largely consistent with forward rate unbiasedness.

2.4 Rolling Window Estimates

The character of the instability within and across the decades is also seen with rolling window regressions. Figure 1 plots β estimates using a five-year window that is rolled through the sample one observation at a time for all six markets, along with 95 percent confidence bands.

The time plots show considerable variation in $\hat{\beta}$, with negative and positive values that are sometimes above unity in all markets. Confidence bands are wide and imply estimates that are largely insignificant from both zero and unity. But there are pockets of significance.

Consider the 1970s and 1980s. The three markets for which we have data back to 1973 show positive $\hat{\beta}$s for pockets at the end of the 1970s or beginning of the 1980s; for the JPY, the estimates are significantly greater than unity. The AUD and CAD markets are also characterized by positive (and insignificant) $\hat{\beta}$s for pockets in the 1970s, although this is difficult to see because of the large $\hat{\beta}$s after 2008. The 1980s, by contrast, particularly after 1985, show pockets of significantly negative $\hat{\beta}$s for four of six markets (CHF, JPY, CAD, and GBP).

The 1990s and the 2000s prior to the financial crisis also show pockets of significantly negative $\hat{\beta}$s in all markets. However, the GBP market shows a pocket of $\hat{\beta}$s that are significantly greater than unity at the end of 1990s. The 2010s show big shifts in $\hat{\beta}$ between large negative and large positive values. Four of the markets (AUD, CAD, EUR, and JPY) are characterized by pockets in which $\hat{\beta}$ is significantly greater (or marginally so) than unity.

[12] Chinn and Frankel (2020) and Bussierre et al (2020) also report $\hat{\beta}$s consistent with a $\beta > 1$ in some markets when the samples begin in July 2007.

2.5 Instability and the Nature of Historical Developments

Taken as a whole, the exogenous subperiod and rolling-window estimates show a forward rate whose predictive power is 1) highly sensitive to the time period examined; and 2) characterized by negative bias in some subperiods and no or positive bias in other subperiods. The evidence suggests that the Markov-switching and LSTR studies give an incomplete account of the extent and nature of the instability. A reason for the difficulty may be due to the novelty of the historical developments that trigger structural change.

The process that underpins asset returns is complex, one in which the relationships with predictor variables are likely to change multiple times in long samples. Many studies report that the structural change is often associated with changes in policy, institutions, or other significant economic developments.[13] Why some developments ultimately trigger structural change while others do not is an open question. However, the frequency and novelty of important developments suggests that shifts in β (and α) likely occur in every decade and involve distinct values.

To clarify this point, we express the BF regression's slope coefficient in terms of conditional moments involving the market's risk premium and forecast error

$$\beta_t = 1 - \beta_t^{rp} - \beta_t^{fe} \tag{2}$$

$$\beta_t^{rp} = -\frac{cov_t\left(E_t^{\mathrm{M}}\left(\Delta s_{t+1}\right), fp_t\right) + var_t\left(fp_t\right)}{var_t\left(fp_t\right)} = -\frac{cov_t\left(rp_t, fp_t\right)}{var_t\left(fp_t\right)} \tag{3}$$

$$\beta_t^{fe} = -\frac{cov_t\left(\eta_{t+1}, fp_t\right)}{var_t\left(fp_t\right)} \tag{4}$$

where $cov_t(\cdot)$ and $var_t(\cdot)$ denote the conditional covariance and variance, respectively, and rp_t, $E_t^{\mathrm{M}}(\Delta s_{t+1})$, and η_{t+1} are the market's risk premium, time-t conditional expectation of the one-period-ahead change in the exchange rate, and the $t+1$ forecast error, respectively. The market's risk premium and forecast error are given by

[13]In currency markets, see Goldberg and Frydman (1996a,b), Melvin and Taylor (2009), Bai and Mollick (2010), Beckmann et al. (2011), Ahmad et al. (2012), Baillie and Cho (2014), Chinn and Frankel (2020), and Bussiere et al. (2018). In equity marlets, see Pettenuzzo and Timmermann (2011) and Dangl and Halling (2012). In credit markets, see Bulkley and Girodani (2011) and Ang and Timmerman (2012).

$$rp_t = E_t^{\mathrm{M}}(\Delta s_{t+1}) - fp_t \tag{5}$$

$$\eta_{t+1} = \Delta s_{t+1} - E_t^{\mathrm{M}}(\Delta s_{t+1}) \tag{6}$$

Equations (2)-(4) show that shifts in β_t can arise through any one of three channels: structural change in the fp_t process or how fp_t covaries with $E_t^{\mathrm{M}}(\Delta s_{t+1})$ or η_{t+1}.

Consider first the fp_t process, which is tightly connected to the process underpinning domestic and foreign interest rates through covered interest parity. The interest rate process is impacted by a wide range of historical developments, including shifts in monetary and fiscal policy, changes in political and economic institutions, election outcomes, financial crises, and war. As such, these developments can trigger shifts in $var_t(fp_t)$.

They may also impact how market participants form forecasts of returns and risk, which would in general lead to shifts in how fp_t covaries with the market risk premium and forecast error. For example, consider the conduct of U.S. monetary policy, which often has an outsized impact on currency markets. Since the 1970s, we have seen shifts along several dimensions, from an interest rate rule in the 1970s under Burns and Miller to a money growth rule and back to an interest rate rule under Volcker in the 1980s, from implicit inflation rate targeting under Greenspan in the 1990s and mid-2000s to explicit inflation rate targeting under Bernanke, Yellen, and Powell since the mid-2000s, first with no or little forward guidance to extensive forward guidance, from a proactive strategy based on theory to a reactive strategy based on current data.

Such shifts in monetary policy have the capacity to trigger structural change in the process governing world interest rates. They also likely influence how market participants forecast currency returns and risk. When and how market participants revise their forecasting strategies depends on how they interpret the broader economic context within which revisions occur. The context for the Volcker era alone included a second oil price shock, two U.S. Presidential elections, deep recessions in developed countries, the launching of the European Monetary System, and the Plaza and Louvre accords to name just a few important contextual developments.

Significant developments occur throughout every decade and have the capacity to trigger structural change in the BF regression. As such, studies that allow for a few break points, either by imposing them exogenously or by estimating a two-regime model, may underestimate the frequency of structural change in long samples.

Existing endogenous test studies may also mischaracterize the nature of the structural change. The difficulty arises because economic developments are inherently novel to some extent. There have been seven different Federal Reserve chairs since the 1970s. But the conduct of monetary policy under each chair was not merely a repetition of the conduct that preceded it. Moreover, the precise impact of policy and institutional changes on the processes governing interest rates and currency returns depends in turn on other important economic developments that are also novel to some extent. The novelty suggests that the BF regression's instability is unlikely to be characterized well by shifts between only two distinct slope coefficients. Indeed, we would expect that a distinct β_t would in general be needed to characterize each new subperiod in the data.

3 Characterizing the Anomaly's Instability

In this section, we test the BF regression for discrete points of structural change. We use the results to identify subperiods of parameter constancy and estimate the BF regression in the separate subperiods for each market. The estimates provide a piece-wise linear characterization of the anomaly's instability.

The literature on testing for structural change in macroeconomics and finance is vast, containing many different approaches and modeling choices. The novelty of the historical developments that underpin the anomaly's instability implies a need for test procedures that leave largely open the frequency, timing, and magnitude of possible break points. To be sure, different test statistics would in general deliver different results in terms of the number and locations of break points. However, it is important to approximate enough of the largest break points in order to draw meaningful inference about forward rate biasedness and its sources from survey data.

To this end, we employ Bai and Perron's (BP) (1998, 2003a,b) methodology and test endogenously for the number and locations of breaks rather than imposing them exogenously. BP's methodology provides several test procedures. We use the global supF statistic, which enables us to identify the approximate locations of the largest significant break points in the data.[14]

Researchers typically set the BP test's trimming level to 15 percent, which caps the number of possible break points to five. The frequency of the developments that trigger instability and the existing empirical record imply that this cap would likely miss the extent of the instability in our long samples of 40+ years. We thus set the test's trimming level to 5 percent, which enables us to check for structural change over a wider portion of the samples. The lower trimming level relaxes the break-point cap and allows us to test for the possibility of ten breaks.

3.1 Break Point Results

The break point results are reported in Table 3 and Figure 2. The solid vertical lines in the figures indicate points of structural change and show visually the number and location of the break points. The results reveal a greater prevalence of structural change than reported by the Markov-switching and other studies. We find four markets (AUD, CHF, GBP, and JPY) with 10 breaks and two markets (CAD and EUR) with nine breaks.

The location of the break points make sense and thus give confidence that the BP procedure delivers a reasonable approximation of the instability. Like other studies (see footnote 13 for references), we find many break points that are proximate to major historical developments, including the early 1980's monetary policy shifts, the 1987 Louvre Accord, and the 2008 global financial crisis. Also like other studies, we find many break points that are associated with large price reversals in every market (Kaminsky 1993, Bekaert and Hodrick 1993, Frydman and Goldberg 2007, and Sakoulis et al. 2010).

The soundness of the BP results is also seen by the BF regression's improved fit in the separate subperiods of parameter constancy. We report subperiod estimates in Table 3 and residual diagnostic tests in Table A1 in the Appendix. The last column in Table 3 shows that the majority of the subperiod R^2 values are considerably higher than the full-sample values.

[14] We also considered BP's double-max and sequential tests; however, the tests show fewer break points in several markets. In an earlier draft of the paper, we employed a sequential procedure based on Brown et al.'s (1975) CUSQ test and a recursive F-test. The procedure delivers a comparable number of break points with some that are proximate to those detected by the BP procedure. Despite the different break points, the corresponding piece-wise linear estimates also showed negative, positive, and no subperiod biasedness. These results are available on request.

The test statistics in Table A1 show, with a few exceptions, that the subperiod residuals are better behaved compared with the full-sample residuals.

3.2 Piece-Wise Linear Estimates

Table 4 reports subperiod BF regression estimates. The estimates show that every market is characterized by multiple subperiods in which $\beta < 1$ and multiple subperiods in which $\beta > 1$ (the JPY has one such subperiod). The number of $\hat{\beta}$s that are significantly less than unity (or marginally so) across all markets (20 in total) is larger than the number above unity (14 in total). In terms of the length of time, the difference is larger; 70 percent of the time in which $\hat{\beta}$ is significantly different than unity (or marginally so) it takes on values below this threshold. This finding may help explain why the Markov switching and LSTR studies find no subperiods with $\beta > 1$.

Table 4 also shows that many of the subperiod $\hat{\beta}$s are insignificantly different from unity in every market. The no-bias null cannot be rejected in half or more of the subperiods for the AUD, EUR, and JPY markets. In the other markets, the proportion ranges from 27 percent (GBP) to 45 percent (CHF).

The piece-wise linear estimates also show multiple subperiods characterized by a nonzero mean return ($\alpha \neq 0$) in every market. We find significant $\hat{\alpha}$s in roughly 40 percent of subperiods across all markets. The CAD and JPY markets have the lowest proportions (roughly 20 percent), whereas the GBP and CHF markets have the highest proportion (roughly 45 percent for both). The results are consistent with an α that is mostly zero, but that also takes on positive and negative values across the subperiods.

Taken as a whole, the results in Table 4 provide a fuller account of the BF regression's instability than other studies. We find that β is less than unity (and in some cases negative) during some stretches of time and equal to or greater than unity during others in every market. The instability is also characterized by shifts in α that involve positive and negative values. Interestingly, subperiods that are characterized by a $\hat{\beta} < 1$ ($\hat{\beta} > 1$) also tend to be characterized by a positive (negative) $\hat{\alpha}$. This pattern would help explain why carry trade strategies (which exploit periods with $\beta < 1$ and $\alpha = 0$) lose profitability for prolonged stretches of time.

3.3 *Ex Ante Predictability?*

This section's piece-wise linear characterizations of returns say little about the forward rate's *ex ante* predictive power other than prediction is more difficult than suggested by the many existing linear and nonlinear studies. Hsu et al. (2020) provide evidence of this difficulty, reporting that carry trades that are found to be profitable in one subperiod are generally not profitable out of sample. To earn excess returns on average from betting against the forward rate (and more generally from BF regression estimates), one would need to predict the structural change *ex ante*.

In a limited investigation, we explore whether a two-state Markov-switching specification and several moving window models give such predictive power. We compare the out-of-sample root mean square forecasting error of the models to that of a random walk. We also measure performance based on predicting the algebraic sign of returns out of sample. The results show that the models possess little to no *ex ante* predictive power in all six markets.[15]

A more comprehensive analysis with more highly nonlinear specifications might deliver stronger evidence of *ex ante* predictability. However, Stillwagon and Sullivan's (2020) results, which are based on Markov-switching models with greater nonlinearity, are not encouraging. The models are unable to outperform the random walk in out-of-sample forecasting even with up to nine states and multiple regressors, including the forward premium. Research in equity markets also suggests that the forward rate's predictive power would be unlikely to improve much, if at all. Studies consider a broad range of time-varying parameter models and a large set of predictor variables and report little or no predictability. Farmer et al's. (2021, p. 1) results are emblematic and show "short periods with significant predictability ('pockets') [that] are interspersed with long periods with little or no evidence of return predictability".[16]

The upshot of our and others' out-of-sample investigations is that linear regressions deliver misleading inference about return predictability and provide a poor basis for understanding the importance of risk and rationality in markets. This conclusion is born out by our analysis of the survey data.

[15]The results are available on request.

[16]See also Pesaran and Timmermann (1995), Goyal and Welch (2008), and Timmermann (2008).

4 Explaining Forward Rate Biasedness

In this section, we use survey data to examine the roles of risk and forecasting errors in underpinning forward rate biasedness. The linear regressions of Froot and Frankel (1989) and the many other studies show a negative β in most markets. The studies also find that little of the negative bias can be explained by a time-varying risk premium. Instead, most if not all the estimated bias is found to stem from systematic forecast errors.

The piece-wise linear estimates in Table 4, however, imply that what needs to be explained is not a negative β, but the pattern of negative, zero, and positive subperiod biases that characterize currency markets. Allowing for this nonlinearity leads to very different conclusions about the relative importance of risk and forecasting errors and whether markets are rational.

4.1 Survey Data

We follow much of the literature and use survey data from FX4casts.[17] The data entail monthly observations on the median point forecast of the three-month-ahead exchange rate. Surveys take place in the last full week of the month, except for November and December, when they are conducted in the third full week of the month because of holidays. Our sample runs from August 1986 through February 2018 for all six currency markets.

FX4casts's surveys possess three design features that add measurement error to the data. First, participants are asked each month for their point forecast, but not for the spot exchange rate that they used in forming that forecast. Second, FX4casts allows participants to submit their forecasts over a two-day window (the Monday and Tuesday) of survey week.[18] Consequently, any spot exchange rate that researchers use to proxy the market's predicted change–$E_t^{\mathrm{M}}(s_{t+1} - s_t)$–will in general differ from the individual spot rates participants used in forming their forecasts. To compound the problem, FX4casts delays its sampling of the spot and forward

[17] See Frankel and Chinn (1993), Chinn and Frankel (2002, 2020), Bacchetta et al. (2009), Furnagiev and Stillwagon (2019), and Bussiere et al. (2022). FX4casts is also called Consensus Forecasts and was formerly known as Currency Forecasters' Digest.

[18] Prior to January 2011, FX4casts used a three day window, from Thursday through Monday's close. FX4casts published their survey on the following Thursday, which is when it also sampled the spot and forward exchange rates.

exchange rates to the close on the Thursday of survey week, which is a full two days after the survey window closes.

To reduce the measurement error, we sample the spot and forward exchange rates midway through the survey's two day window each month (on Monday's close), instead of using FX4casts's sampling.[19] In measuring the market's forecast error, we use the one-month-ahead spot rate, which avoids problems with overlapping observations. Our monthly observations of spot and forward rates are again bid-asked averages.

There is considerable skepticism about survey measures of market participants' forecasts, in part because they are noisy. They are also sensitive to framing and language (Cochrane, 2011). Greenwood and Shleifer (2014) consider these concerns by examining the time series behavior of six different survey measures of equity return expectations. The measures are found to be highly correlated with each other and with investor trading, indicating that they are useful proxies despite potential noise or framing problems.[20]

Regardless of one's view of survey proxies, however, we find that the story they furnish about risk and rationality changes markedly when the problem of instability is incorporated into the analysis. Frydman and Stillwagon (2018) report a similar finding in equity markets. They consider a survey dataset examined by Greenwood and Shleifer (2014) and find behavior that is consistent with rational forecasting, but only after allowing for structural change.

4.2 Full Sample Estimates

Survey data proxies for rp_t and η_{t+1} enable us to estimate β_t^{rp} and β_t^{fe} in equations (3) and (4), respectively. Our analysis uses the following two regressions

$$rp_{j,t} = \alpha_j^{rp} + \beta_j^{rp} fp_t + \varepsilon_{j,t}^{rp} \quad \text{for } j = 1, 2, .. \tag{7}$$

$$\eta_{j,t+1} = \alpha_j^{fr} + \beta_j^{fe} fp_t + \varepsilon_{j,t}^{fe} \quad \text{for } j = 1, 2, .. \tag{8}$$

[19] Email correspondence with FX4casts revealed that prior to 2011 (see footnote 18), most survey participants submitted their forecasts on the Friday and Monday during the three day survey window. We thus sample the spot and forward rates on the Friday close in the window prior to 2011.

[20] See also Bacchetta et al. (2009) for a discussion of the criticisms.

where the subscript j denotes a subperiod in the data. We also use equation (2), which allows us to decompose the estimated bias in β into the proportions due to a time-varying risk premium and systematic forecasting errors.

Table 5 provides estimates of the BF regression in equation (1) for the full survey-data sample (the bottom rows in the third and fourth columns).[21] It also reports estimates of equations (7) and (8) over the full survey-data sample and in each subperiod based on the break dates in Table 3 (in columns five through eight).

Consider first the full sample BF estimates in the bottom rows of the tables. Like other studies, the α estimates are all found to be insignificant. We also find a negative $\hat{\beta}$ in every market, although only one of the estimates is marginally significant (CAD) and we cannot reject forward rate unbiasedness ($\beta = 1$) in GBP and EUR markets.

The survey data regressions reveal a small (less than 1 percent), but significant monthly mean risk premium ($\alpha^{rp} \neq 0$) and a significant monthly mean forecast error ($\alpha^{fr} \neq 0$) in five of the six currency markets examined (the EUR is the exception for both). They also show significant estimates of β_t^{rp} and β_t^{fe} in four markets (the AUD, CAD, EUR, and JPY (for β_t^{rp}) and CHF (for β_t^{fe}), suggesting that a time-varying risk premium and systematic forecasting errors both underpin currency returns.

However, the proportions of the bias that can be attributed to the two sources (see the last two columns in Table 5) show that little to none can be ascribed to a time-varying risk premium in five of the six currency markets.[22] The exception is the JPY market, which shows that 59.1 percent of the estimated negative bias is attributable to a time-varying risk premium.

The full sample results taken as a whole suggest that market participants under- or overpredict the exchange rate change on average and forward rate biasedness is explained largely by systematic forecasting errors. A very different view emerges when structural change is taken into account.

[21]The first subperiod in each market is shorter than in Table 3 because of the shorter FX4casts samples.

[22]A negative value in the columns implies that the particular source adds to, rather than explains, the estimated bias.

4.3 Time Varying Risk Premium

The subperiod estimates in Table 5 show considerably more support for a time-varying risk premium. The evidence comes from both the α_j^{rp} and β_j^{rp} estimates.

Table 5 shows a significant $\hat{\alpha}_j^{rp}$ in 50 percent or more of the subperiods in five of the six markets (the CHF is the exception with 38 percent of the subperiods). The estimates show a monthly mean risk premium that is generally larger than the full-sample counterpart and often quite sizeable. The mean risk premium also varies substantially across the separate subperiods, with one or more sign reversals. The smallest variation occurs in the CAD market, with estimates ranging from -0.5 percent to 0.8 percent per month. In the other five markets, the range of variation is 3.5 percentage points or more. In the AUD market, the estimates range from -3.0 percent to 2.1 percent per month. A time-varying mean risk premium does not help explain forward rate biasedness. But it does provide clear evidence that risk considerations underpin currency returns.

Evidence for a time-varying risk premium is also seen in the β_j^{rp} estimates. Five of the six markets are characterized by a significant $\hat{\beta}_j^{rp}$ in 38 percent or more of the subperiods (the AUD is the exception at 11 percent). The estimates also vary substantially across the separate subperiods and undergo multiple sign reversals in every market.

Unlike with the full-sample results, we find that a time-varying risk premium helps explain the estimated forward rate bias in roughly 40 percent of the subperiods across the six markets. Table 5 shows that the results vary across the markets. We find that risk helps account for the bias in roughly 25 percent of the subperiods for the CAD and EUR markets. For the CHF, GBP, and JPY markets, risk helps in 50 percent or more of the subperiods. In many of these subperiods, risk explains more than half of the estimated bias. In terms of the proportion of observations for which risk matters, the results again vary across markets. For the EUR and CAD markets, risk explains 15 percent or more of the estimated bias for 12 and 17 percent of the observations, repsectively. For the AUD and GBP markets, the results are 42 and 78 percent of the observations, respectively. If we consider only subperiods for which $\hat{\beta}_j^{rp}$ is significant, risk helps explain the estimated bias in roughly half of those subperiods across the markets.

4.4 Systematic Forecasting Errors

The subperiod results in Table 5 show that market participants' forecasting is marked by systematic errors in many of the subperiods. They also show that this behavior is key in understanding forward rate biasedness.

We find that the market's forecasting error is characterized by a non-zero mean ($\alpha_j^{fe} \neq 0$) in many of the separate subperiods. The percentage of subperiods in which $\hat{\alpha}_j^{fe}$ is significant ranges from 25 percent for the CAD market to 50 percent for the GBP and JPY markets. As with the mean risk premium, the mean forecast error varies considerably across the subperiods and is generally much larger than the full-sample estimates. The smallest variation occurs in the CAD market, with estimates ranging from -1.9 percent to 0.7 percent per month. In the other five markets, the range of variation is 4 percentage points or more. In the GBP market, the estimates range from -3.8 percent to 4.3 percent per month. Each market is characterized by multiple sign reversals in $\hat{\alpha}_j^{fe}$ across the subperiods.

The market's forecasting error is also correlated with the forward premium in many of the separate subperiods. Table 5 shows that the proportion of significant $\hat{\beta}_j^{fe}$s varies across the markets. The CAD, CHF, and GBP markets are at the low end, with significance in 13 percent of the subperiods, whereas the EUR and JPY are at the high end with significance in 63% of the subperiods. The frequencies of significant $\hat{\beta}_j^{fe}$s and significant $\hat{\beta}_j^{rp}$s are comparable, lower in the CAD, CHF, and GBP markets and higher in the other markets.

However, systematic forecasting errors are more important than a time-varying risk premium in accounting for the estimated forward rate biases across markets. Table 5 shows that correlations with η_{t+1} explain *all* of the estimated bias in more than half of the separate subperiods across the six currency markets. In terms of the proportion of observations, the results also show a greater importance of systematic forecasting errors. We find that these errors explain at least half of the estimated bias for half or more of the observations in every market. If we consider only subperiods for which $\hat{\beta}_j^{fe}$ is significant, then systematic forecasting errors explain all the bias in roughly 70 percent of the subperiods across the six markets.

4.5 Evidence of Irrationality?

Researchers typically view significant patterns in forecasting errors as an indication of predictability and less-than-full rational behavior. Studies account for the predictability with models in which market participants systematically mispredict spot rates (Mark and Wu, 1998, Burnside et al., 2009), interest rates (Gourinchas and Tornell, 2004, and Moran and Nano, 2018, or inflation rates (Burnside et al, 2011). They report that this irrationality can explain a negative β.

However, the piece-wise linear estimates in Table 5 lead to a very different view of currency markets. They show a mean forecast error and a correlation between η_{t+1} and fp_t that are not only highly unstable, but that frequently switch sign. The sign changes imply that market participants underpredict exchange rate changes during some stretches of time and overpredict during others. The instability is consistent with rational markets in which "[a]pparent over-reaction to information is about as common as under-reaction, and post-event continuation of pre-event abnormal returns is about as frequent as post-event reversal" (Fama, 1998, p. 283). The instability is also consistent with the view that rational individuals react to novel historical developments and structural change by revising their forecasting strategies, which in the process create temporary and unstable patterns in forecast errors.

Behavioral models that predict a fixed bias with systematic forecasting errors are inconsistent with our piece-wise linear estimates. Perhaps these models can be adapted to account for the pattern of the β_t, β_t^{rp}, and β_t^{fe} estimates across subperiods of floating rates.[23] However, their ability to explain linear, full sample estimates should not be viewed as evidence that currency markets are less than fully rational.

5 Conclusion

The paper tested the BF regression for discrete points of structural change and found greater instability than previously documented. It used the

[23] Farmer et al. (2021) find that a model of systematic underreaction to cash flow news can acount for pockets of return predictability in equity markets. However, such systematic underreaction is difficult to reconcile with the sign reverals in $\hat{\alpha}_j^{fe}$ and $\hat{\beta}_j^{fe}$ reported in Table 5.

break point results to estimate a piece-wise linear characterization of returns in six major currency markets. The nonlinear characterization showed shifts in β above and below unity, and above and below zero, that occurred throughout our samples in all six markets examined. Strikingly, forward rate biasedness was found to be more often insignificant or positive than negative as widely reported.

The literature offers many models that can account for a negative β either as a result of a time-varying risk premium and rationality or because of systematic forecasting errors and irrationality. Studies using survey data on exchange rate expectations report little evidence that risk and rationality underpin forward rate biasedness. All of the action is attributed to systematic forecasting errors.

The paper's piece-wise linear BF estimates, however, show that what needs to be explained is not a negative β, but rather the pattern of negative, zero, and positive subperiod biases that characterize currency markets. We found that existing survey studies' conclusions about the importance of risk and rationality in currency markets were reversed after including instability into the analysis.

The paper's results showed considerably more evidence of a time-varying risk premium in the separate subperiods in all six currency markets. Systematic forecasting errors were also found to play a key role in explaining the subperiod biases in all the markets. However, the correlations were highly unstable and involved frequent sign changes. The results are consistent with rational market participants who revise their forecasting strategies as novel historical developments cause structural change and who overpredict currency movements during some subperiods and underpredict currency movements during others.

An open question is whether the literature's risk premium and behavioral models can account for the pattern of negative, zero, and positive forward rate biases across subperiods of floating rates. The empirical results reported in this paper indicate that models with a time-varying risk premium and temporary patterns in forecast errors will be needed.

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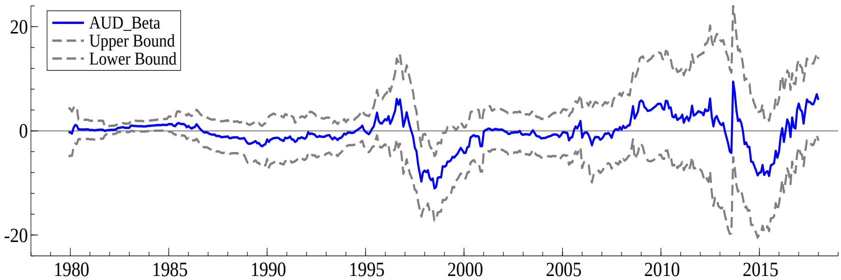
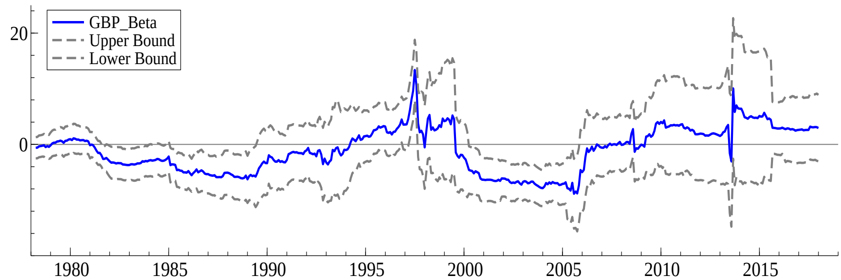
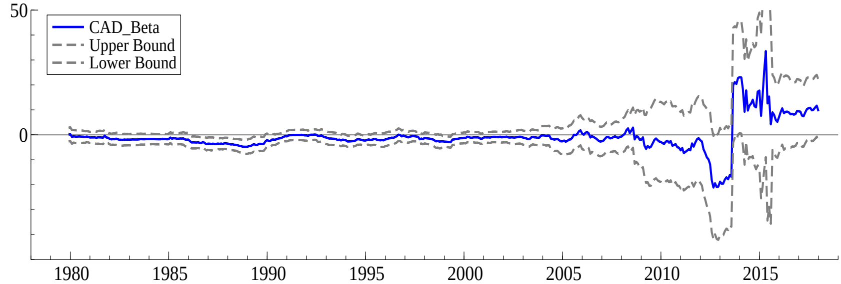


(a) Australian Dollar

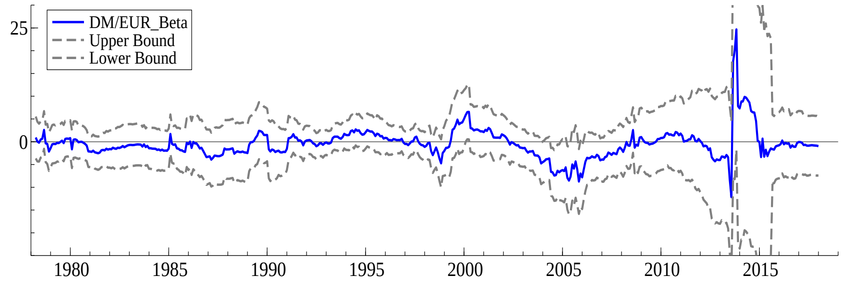


(b) British Pound

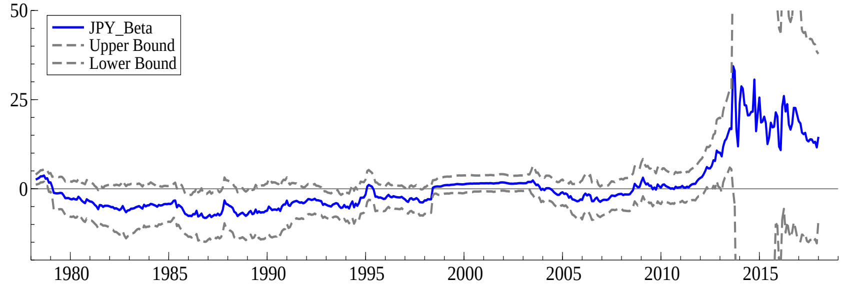


(c) Canadian Dollar

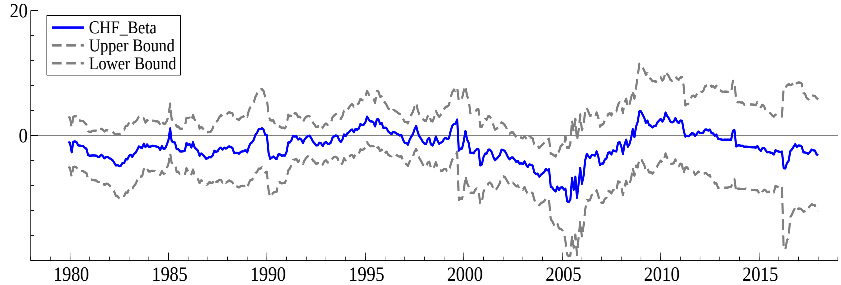
Figure 1: 5-Year Rolling Estimates of Beta



(d) Euro Area



(e) Japanese Yen

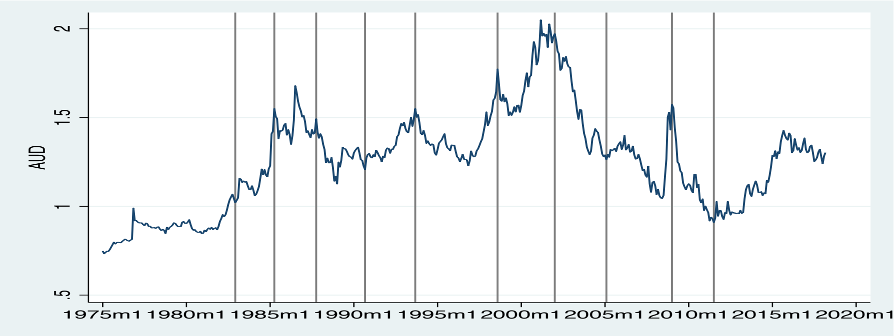


(f) Swiss Franc

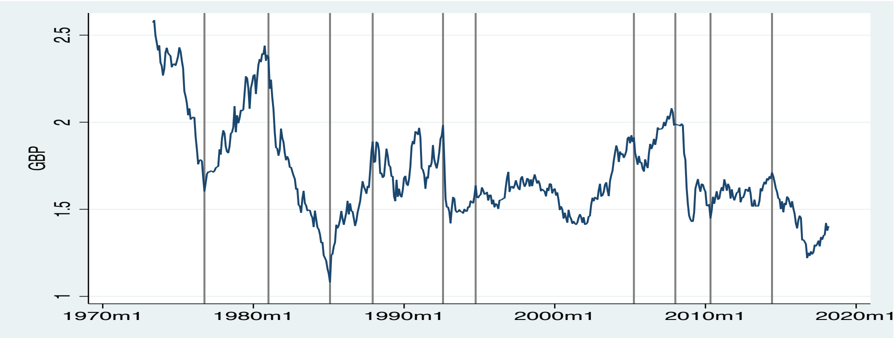
Figure 1: (*Continued*)

Description: The figure provides plots of β estimates (solid blue lines) using a five-year (60 observations) window that is rolled through the sample one observation at a time. The upper and lower gray dotted lines provide 95 percent confidence intervals.

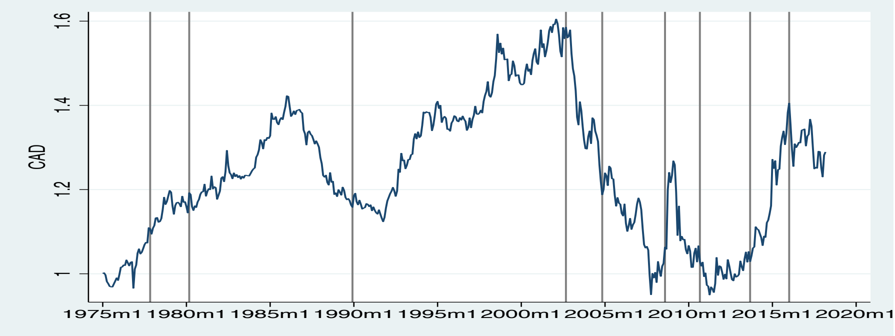
Interpretation: The figure shows considerable variation in β estimates, with negative and positive values that are sometimes above unity in all markets.



(a) Australian Dollar

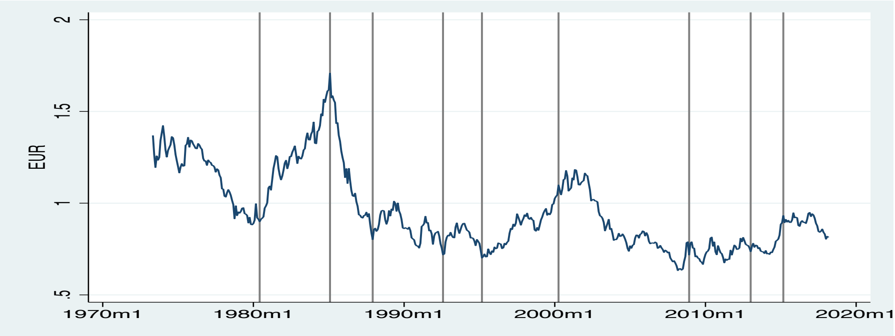


(b) British Pound

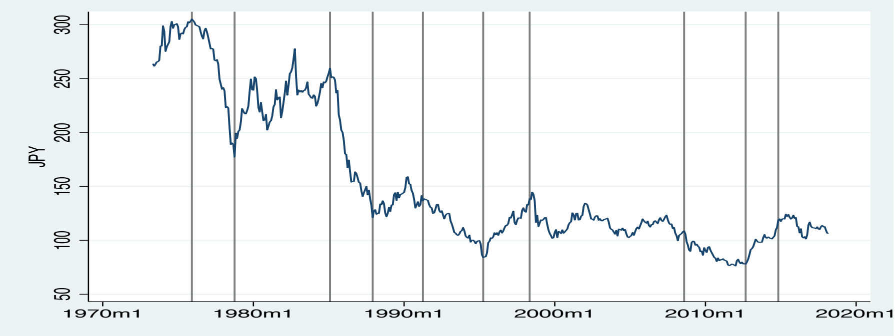


(c) Canadian Dollar

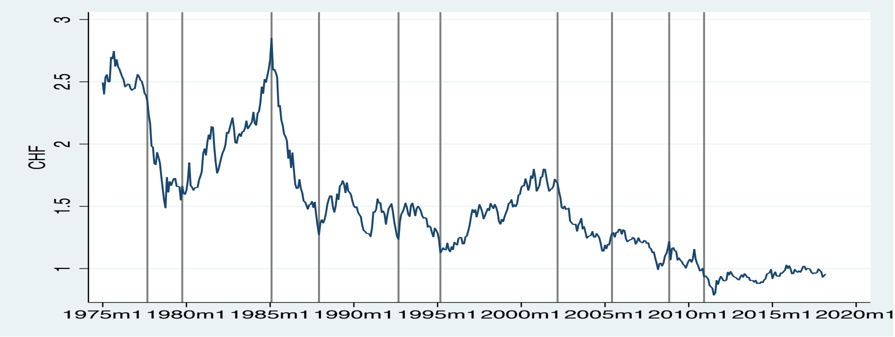
Figure 2: Bai-Perron Structural Change Results



(d) Euro Area



(e) Japanese Yen



(f) Swiss Franc

Figure 2: (*Continued*)

Description: The figure's solid vertical lines indicate points at which the BF regression experiences structural change based on the Bai Perron test procedure described in section 3. The solid blue lines are plots of the given spot exchange rate.

Interpretation: The figure shows a greater prevalence of structural change than reported by other studies. Many of the break points are proximate to major historical developments or large price reversals, giving confidence that the BP procedure delivers a reasonable approximation of the instability.

Table 1: Full Sample Estimates of the Bilson-Fama Regression

Sample	**Obs**	α	β	**Chi**^{2} $\beta = 1$	**R**^{2}
Australian Dollar (1975M1 - 2018M2)	518	0.001 (0.002)	−0.053 (0.392)	7.231 [0.007]***	0.0%
British Pound (1973M5 - 2018M2)	538	0.003* (0.002)	−1.163* (0.649)	11.103 [0.001]**	0.9%
Canadian Dollar (1975M1 - 2018M2)	518	0.001 (0.001)	−0.775 (0.536)	10.955 [0.001]***	0.3%
Euroarea (1973M5 - 2018M2)	538	−0.001 (0.002)	−0.239 (0.700)	3.133* [0.077]	0.0%
Japanese Yen (1973M5 - 2018M2)	538	−0.001 (0.002)	0.224 (0.690)	1.266 [0.261]	0.0%
Swiss Franc (1975M1 - 2018M2)	518	−0.003 (0.002)	−0.688 (0.635)	7.065*** [0.008]	0.3%

Description: The table provides full sample estimates of the BF regression in equation (1). A ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The numbers in parentheses are HAC standard errors. The Chi-squared tests use HAC standard errors. P-values for the test are shown in brackets.

Interpretation: The table reports weaker evidence of negative $\hat{\beta}$s than earlier studies, suggesting that more recent subperiods are characterized by higher slope coefficient values.

Table 2: Slope Estimates of Key Studies in the Literature

		No. of Currencies	Sample	Beta Estimate DM/EUR	GBP	JPY	CAD	CHF	AUD
1970s	Bekaert and Hodrick (1993)	3	1975W01-1980W01	1.04	1.62	**−1.04**			
	Bilson (1981)	9	1974M07−1980M01	−0.21	0.62	**−0.67**	**−0.80**	−0.18	
	Mark and Wu (1998)	3	1976M01−1979M12	−0.03	1.25	1.56			
	Decade/Inclusive	6	1973M05−1979M12	0.85	−0.04	1.631	0.13	−0.98	−0.22
1980s	Bekaert and Hodrick (1993)	3	1975W01−1989W12	−3.02*	−2.02*	−2.10*			
	Barnhart and Szakmary (1991)	4	1974M01−1988M10	−3.63*	−1.65*	**−0.59**	−2.02*		
	Fama (1984)	9	1973M08−1982M12	−1.32	−0.90*	**−0.29**	−0.87*	−1.14*	
	Decade	6	1980M01−1989M12	−2.65	**−3.79***	**−5.01***	**−2.24***	−2.69*	0.00
	Inclusive	6	1973M05−1989M12	−1.31	**−1.95***	0.344	**−1.50***	**−2.07**	−0.01
1990s	Engel (1996)	8	1976M01−1995M05	**−0.68**	−1.84*	−2.40*	−1.31*	**−1.34**	
	Chinn and Merideth (2005)	6	1980Q1−2000Q4	−0.81	−2.20*	−2.89*	**−0.48**		
	Bansal and Dalquist (2000)	28	1976M12−1998M05	**−0.56**	−1.55*	−2.21*	-1.04*	**−1.05**	−8.40*
	Decade	6	1990M01−1999M12	0.03	0.74	0.01	−0.78*	−0.50	−1.18*
	Inclusive	6	1973M05−1999M12	−0.05	**−1.35***	0.15	**−1.11***	**−0.62**	−0.12
2000s	Bacchetta et al. (2009)	6	1986M10−2004M07	−2.43*	**−1.34**	−3.88*	−1.97*	−2.76*	−2.49*
	Wang and Wang (2009)	6	1985M01−2004M12	−3.95*	−0.78	−2.30*	**−0.83**	−0.76	**−1.02**
	Burnside et al. (2011)	11	1983M10−2008M12	**−3.32**	**−2.08***	−0.51	**−1.05**	−0.63	**−0.73**
	Engel (2016)	6	1979M06−2009M10	2.09	**3.20**	**3.71**	**2.27**		
	Decade	6	2000M01−2009M12	−2.94	**−4.13***	−0.47	−1.76	−2.48	0.73
	Inclusive	6	1973M05−2009M12	**−0.33**	**−1.41***	0.05	**−0.88**	**−0.77**	−0.00
2010s	Chinn and Frankel (2020)	26	1999M01−2018M05	0.61	−0.50	**−1.14**	−0.12	**−1.12**	**−1.08**
	Bussierre et al (2020)	8	1999M01−2018M06	**−1.26**	−0.34	−0.16	1.53	**−1.73**	
	Berg and Mark (2019)	9	1973Q1−2014Q4		**−0.64**	**−0.17**	−0.64	**−1.02**	**−0.49**
	Decade	6	2010M01−2018M2	−0.21	**3.09***	**15.65***	**7.45**	**−2.30***	−1.03
	Inclusive	6	1973M05−2018M2	**−0.28**	**−1.17***	0.22	**−0.77**	**−0.70**	**−0.05**

Description: The table reports β estimates from key studies and for decade-based subperiods. Columns 3 and 4 indicate the number of currencies and sample period considered by the given study, respectively. A "*" denotes statistical significance from zero at the 5% level. Bolded values denote statistical significance from unity at the 5% level. The sample periods for the Australian dollar, Canadian dollar, and Swiss franc begin in 1975M01.

Interpretation: The table shows that four decades of key studies, when considered together, provide evidence of instability that involves negative and positive forward rate biases.

Table 3: Bai-Perron Break Dates

Sub Period	Break Points	Sub Periods of Parameter Stability	Number of Observations
(A) Australian Dollar			
1	1982M12	1975M01—1982M11	95
2	1985M04	1982M12—1985M03	28
3	1987M10	1985M04—1987M09	30
4	1990M09	1987M10—1990M08	35
5	1993M09	1990M09—1993M08	36
6	1998M08	1993M09—1998M07	59
7	2002M01	1998M08—2001M12	41
8	2005M02	2002M01—2005M01	37
9	2009M01	2005M02—2008M12	47
10	2011M07	2009M01—2011M06	30
11		2011M07—2018M02	80
(B) British Pound			
1	1976M10	1973M05—1976M09	41
2	1981M01	1976M10—1980M12	51
3	1985M02	1981M01—1985M01	49
4	1987M12	1985M02—1987M11	34
5	1992M08	1987M12—1992M07	56
6	1994M10	1992M08—1994M09	26
7	2005M04	1994M10—2005M03	126
8	2008M01	2005M04—2007M12	34
9	2010M05	2008M01—2010M04	28
10	2014M06	2010M05—2014M05	49
11		2014M06:2018M02	44
(C) Canadian Dollar			
1	1977M11	1975M01—1977M10	34
2	1980M03	1977M11—1980M02	28
3	1989M12	1980M03—1989M11	117
4	2002M09	1989M12—2002M08	153
5	2004M11	2002M09—2004M10	26
6	2008M08	2004M11—2008M07	45
7	2010M09	2008M08—2010M08	25
8	2013M09	2010M09—2013M08	36
9	2016M01	2013M09—2015M12	28
10		2016M01—2018M02	26

(*Continued*)

Table 3: (*Continued*)

Sub Period	**Break Points**	**Sub Periods of Parameter Stability**	**Number of Observations**
(D) Euroarea			
1	1980M06	1973M05—1980M05	85
2	1985M02	1980M06—1985M01	56
3	1987M12	1985M02—1987M11	34
4	1992M08	1987M12—1992M07	56
5	1995M03	1992M08—1995M02	31
6	2000M04	1995M03—2000M03	61
7	2008M12	2000M04—2008M11	104
8	2013M01	2008M12—2012M12	49
9	2015M03	2013M01—2015M02	26
10		2015M03—2018M02	36
(E) Japanese Yen			
1	1975M12	1973M05—1975M11	31
2	1978M10	1975M12—1978M09	34
3	1985M02	1978M10—1985M01	76
4	1987M12	1985M02—1987M11	34
5	1991M04	1987M12—1991M03	40
6	1995M04	1991M04—1995M03	48
7	1998M05	1995M04—1998M04	37
8	2008M08	1998M05—2008M07	123
9	2012M09	2008M08—2012M08	49
10	2014M11	2012M09—2014M10	26
11		2014M11:2018M02	40
(F) Swiss Franc			
1	1977M09	1975M01—1977M08	32
2	1979M10	1977M09—1979M09	25
3	1985M02	1979M10—1985M01	64
4	1987M12	1985M02—1987M11	34
5	1992M09	1987M12—1992M08	57
6	1995M03	1992M09—1995M02	30
7	2002M03	1995M03—2002M02	84
8	2005M06	2002M03—2005M05	39
9	2008M11	2005M06—2008M10	41
10	2010M12	2008M11—2010M11	25
11		2010M12—2018M02	87

Description: The table reports the results of BP structural change tests. Break dates in column 2 are based on BF's global supF test using a 5 percent trimming level.

Interpretation: The table shows a greater prevalence of structural change than reported by other studies. Many of the break points are proximate to major historical developments or large price reversals, giving confidence that the BP procedure delivers a reasonable approximation of the instability.

Table 4: Piece-Wise Linear Estimates of the Bilson-Fama Regression

(A) Australian Dollar

Sub Period	**Obs**	α	β	**Chi** ^{2} $\beta = 1$	R^2
Full	1975M1	0.00	**−0.05**	7.23***	0%
Sample	2018M2	(0.45)	(0.90)	[0.01]	
1	1975M1	0.00	0.54	1.14	1%
	1982M11	(0.21)	(0.22)	[0.29]	
2	1982M12	0.00	**5.94****	5.10**	16%
	1985M3	(0.85)	(0.01)	[0.02]	
3	1985M4	0.06***	**−8.39*****	25.22***	13%
	1987M9	(0.00)	(0.00)	[0.00]	
4	1987M10	−0.02	2.00	0.16	1%
	1990M8	(0.34)	(0.44)	[0.70]	
5	1990M9	0.01	0.48	0.02	0%
	1993M8	(0.60)	(0.90)	[0.89]	
6	1993M9	0.01***	**−11.69*****	16.35***	19%
	1998M7	(0.00)	(0.00)	[0.00]	
7	1998M8	0.00	1.42	0.06	1%
	2001M12	(0.76)	(0.43)	[0.81]	
8	2002M1	−0.06***	**17.61****	4.32**	13%
	2005M1	(0.01)	(0.03)	[0.04]	
9	2005M2	−0.01	7.98	2.11	5%
	2008M12	(0.32)	(0.10)	[0.15]	
10	2009M1	−0.06**	**13.6***	2.55	7%
	2011M6	(0.03)	(0.10)	[0.10]	
11	2011M7	0.00	2.92	0.62	1%
	2018M2	(0.91)	(0.23)	[0.43]	

(*Continued*)

Table 4: (*Continued*)

(B) British Pound

Sub Period	**Obs**	α	β	**Chi** ^{2} $\beta = 1$	R^2
Full	1973M5	0.00	**−1.16***	11.10***	1%
Sample	2018M2	(0.06)	(0.07)	[0.00]	
1	1973M5	0.02	−1.22	1.31	2%
	1976M9	(0.19)	(0.53)	[0.25]	
2	1976M10	−0.01	**−0.90**	6.46**	1%
	1980M12	(0.19)	(0.23)	[0.01]	
3	1981M1	0.02***	**−2.33**	4.26**	3%
	1985M1	(0.00)	(0.16)	[0.04]	
4	1985M2	−0.02*	0.07	0.17	0%
	1987M11	(0.10)	(0.97)	[0.69]	
5	1987M12	0.02**	**−5.59****	7.20***	6%
	1992M7	(0.04)	(0.03)	[0.01]	
6	1992M8	−0.04***	**20.99*****	13.00***	51%
	1994M9	(0.00)	(0.00)	[0.00]	
7	1994M10	0.01***	**−5.76*****	29.39***	10%
	2005M3	(0.00)	(0.00)	[0.00]	
8	2005M4	−0.01**	**17.36*****	15.67***	23%
	2007M12	(0.03)	(0.00)	[0.00]	
9	2008M1	0.01	−2.45	0.28	1%
	2010M4	(0.35)	(0.71)	[0.60]	
10	2010M5	−0.01	**6.07*****	10.82***	2%
	2014M5	(0.11)	(0.00)	[0.00]	
11	2014M6	0.01	**3.87*****	12.26***	3%
	2018M2	(0.18)	(0.00)	[0.00]	

(*Continued*)

Table 4: (*Continued*)

(C) Canadian Dollar

Sub Period	Obs	α	β	Chi [2] $\beta = 1$	R^2
Full Sample	1975M1 2018M2	0.00 (0.34)	**−0.77** (0.15)	10.96*** [0.00]	0%
1	1975M1 1977M10	0.00 (0.71)	0.77 (0.71)	0.01 [0.91]	0%
2	1977M11 1980M2	0.00 (0.79)	**−13.84***** (0.00)	35.23*** [0.00]	34%
3	1980M3 1989M11	0.00 (0.12)	**−2.16***** (0.00)	31.95*** [0.00]	6%
4	1989M12 2002M8	0.00** (0.08)	**−0.71** (0.18)	10.58*** [0.00]	1%
5	2002M9 2004M10	−0.02** (0.04)	10.67 (0.28)	0.99 [0.32]	5%
6	2004M11 2008M7	0.00 (0.25)	**12.92**** (0.07)	4.01** [0.05]	7%
7	2008M8 2010M8	−0.00 (0.85)	**−47.45**** (0.03)	6.01** [0.01]	19%
8	2010M9 2013M8	−0.02 (0.44)	27.76 (0.42)	0.61 [0.43]	1%
9	2013M9 2015M12	0.01** (0.05)	**8.72*** (0.05)	3.29** [0.07]	4%
10	2016M1 2018M2	−0.01 (0.25)	−47.37 (0.13)	2.58 [2.58]	7%

(*Continued*)

Table 4: (*Continued*)

(D) Euroarea

Sub Period	**Obs**	α	β	**Chi** ^{2} $\beta = 1$	R^2
Full	1973M5	-0.00	**−0.24**	3.13*	0%
Sample	2018M2	(0.43)	(0.73)	[0.08]	
1	1973M5	0.00	−0.53	0.79	0%
	1980M5	(0.64)	(0.76)	[0.37]	
2	1980M6	0.00	**−2.91**	3.45*	3%
	1985M1	(0.96)	(0.17)	[0.06]	
3	1985M2	−0.01	**6.98*****	8.78***	10%
	1987M11	(0.41)	(0.00)	[0.00]	
4	1987M12	−0.00	**−2.04**	3.69*	3%
	1992M7	(0.72)	(0.20)	[0.06]	
5	1992M8	−0.02	**7.94*****	7.48***	27%
	1995M2	(0.01)	(0.00)	[0.01]	
6	1995M3	0.02***	**6.51*****	6.94***	7%
	2000M3	(0.00)	(0.00)	[0.01]	
7	2000M4	−0.00	**−3.35**	3.71*	2%
	2008M11	(0.15)	(0.14)	[0.05]	
8	2008M12	−0.00	**26.87***	2.90*	6%
	2012M12	(0.68)	(0.08)	[0.09]	
9	2013M1	−0.00	**−114.00*****	9.33***	25%
	2015M2	(0.72)	(0.01	[0.00]	
10	2015M3	−0.01	**−1.98**	4.08**	1%
	2018M2	(0.21)	(0.19)	[0.04]	

(*Continued*)

Table 4: (*Continued*)

(E) Japanese Yen

Sub Period	**Obs**	α	β	**Chi** ^{2} $\beta = 1$	R^2
Full Sample	1973M5 2018M2	–0.00 (0.47)	0.22 (0.76)	1.27 [0.26]	0%
1	1973M5 1975M11	0.00 (0.55)	2.23*** (0.01)	2.30 [0.13]	22%
2	1975M12 1978M9	–0.01*** (0.00)	**7.13***** (0.00)	9.97*** [0.00]	13%
3	1978M10 1985M1	–0.01 (0.21)	**–5.01**** (0.01)	9.04*** [0.00]	5%
4	1985M2 1987M11	–0.02 (0.22)	2.83 (0.73)	0.05 [0.82]	1%
5	1987M12 1991M3	–0.01 (0.10)	**–6.86***** (0.00)	13.11*** [0.00]	12%
6	1991M4 1995M3	–0.01** (0.03)	**4.47**** (0.04)	2.77* [0.10]	8%
7	1995M4 1998M4	–0.01 (0.45)	**–4.16***** (0.00)	18.67*** [0.00]	3%
8	1998M5 2008M7	0.00 (0.30)	1.64*** (0.00)	1.76 [0.19]	3%
9	2008M8 2012M8	0.00 (0.99)	**15.43***** (0.00)	65.64*** [0.00]	14%
10	2012M9 2014M10	–0.03*** (0.00)	**–242.46***** (0.00)	28.76*** [0.00]	30%
11	2014M11 2018M2	0.00 (0.87)	11.09 (0.20)	1.42 [0.23]	2%

(*Continued*)

Table 4: (*Continued*)

(F) Swiss Franc

Sub Period	**Obs**	$\boldsymbol{\alpha}$	$\boldsymbol{\beta}$	**Chi** ^{2} $\boldsymbol{\beta = 1}$	$\mathbf{R^2}$
Full	1975M1	–0.00*	**–0.69**	7.07***	0%
Sample	2018M2	(0.08)	(0.28)	[0.01]	
1	1975M1	–0.01	–1.39	0.41	0%
	1977M8	(0.65)	(0.71)	[0.52]	
2	1977M9	–0.11***	**–13.38*** **	20.53***	20%
	1979M9	(0.00)	(0.00)	[0.00]	
3	1979M10	0.01	–0.32	0.35	0%
	1985M1	(0.62)	(0.89)	[0.55]	
4	1985M2	–0.01	**6.40** **	4.49**	8%
	1987M11	(0.48)	(0.08)	[0.03]	
5	1987M12	–0.00	**–2.70** *	5.53**	6%
	1992M8	(0.74)	(0.09)	[0.02]	
6	1992M9	–0.02***	**14.42** ***	14.33***	42%
	1995M2	(0.00)	(0.00)	[0.00]	
7	1995M3	–0.00	**–3.18**	3.40*	3%
	2002M2	(0.60)	(0.16)	[0.07]	
8	2002M3	–0.03***	**–29.06** ***	28.01***	18%
	2005M5	(0.00)	(0.00)	[0.00]	
9	2005M6	0.01	3.78	0.53	2%
	2008M10	(0.55)	(0.33)	[0.47]	
10	2008M11	0.02***	**76.76** ***	110.46***	41%
	2010M11	(0.01)	(0.00)	[0.00]	
11	2010M12	–0.00	**–2.64** **	11.31***	1%
	2018M2	(0.77)	(0.02)	[0.00]	

Description: The table provides full-sample and subperiod estimates of the BF regression. Subperiods are based on the Bai-Perron tests reported in Table 3. A ***, **, and * denote statistical significance relative to zero at the 1%, 5%, and 10% levels, respectively. Bolded beta coefficients denote significance from unity based on the Chi-squared test in column five. We use HAC standard errors. The values in the parentheses and brackets are p-values for the related tests.

Interpretation: The table reveals instability of a striking form: markets are characterized by multiple subperiods in which β is either less than or greater than unity and many subperiods in which α is not only nonzero, but changes signs across multiple time periods.

Table 5: Survey Data Estimates and Bias Decomposition

Sub Period	Dates	α_{BF}	β_{BF}	α_{RP}	β_{RP}	α_{FE}	β_{FE}	RP: % Bias Exp.	FE: % Bias Exp.
(A) Australian Dollar									
3	1986M8	−0.07	−4.19***	−0.02	0.98	0.00	−6.17**	−19%	119%
	1987M9	(0.15)	(0.01)	(0.14)	(0.55)	(0.98)	(0.01)		
4	1987M10	−0.00	−0.92	−0.03**	−2.53	0.03**	0.61	132%	−32%
	1990M8	(0.93)	(0.68)	(0.03)	(0.27)	(0.01)	(0.71)		
5	1990M9	−0.01*	−2.38	−0.00	3.17	−0.01	−6.56	−94%	194%
	1993M8	(0.09)	(0.33)	(0.94)	(0.30)	(0.42)	(0.11)		
6	1993M9	−0.01***	−11.00***	0.01***	−3.30	−0.02***	−8.70***	28%	73%
	1998M7	(0.00)	(0.00)	(0.00)	(0.14)	(0.00)	(0.01)		
7	1998M8	−0.00	2.5	0.01***	−0.39	−0.02**	1.84	−27%	127%
	2001M12	(0.46)	(0.53)	(0.00)	(0.70)	(0.04)	(0.60)		
8	2002M1	0.02	3.26	0.02**	1.02	0.00	1.25	45%	55%
	2005M1	(0.33)	(0.70)	(0.01)	(0.72)	(1.00)	(0.89)		
9	2005M2	0.01	7.71	0.01	−0.57	0.00	7.27	−8%	108%
	2008M12	(0.21)	(0.26)	(0.23)	(0.85)	(0.83)	(0.23)		
10	2009M1	0.06**	13.77*	0.02**	6.51**	0.04	6.26	51%	49%
	2011M6	(0.02)	(0.08)	(0.02)	(0.02)	(0.12)	(0.45)		
11	2011M7	0.00	4.41*	−0.01***	−1.82	0.02	5.23*	−53%	153%
	2018M1	(0.38)	(0.07)	(0.00)	(0.27)	(0.24)	(0.07)		
Full	1986M8	−0.00	−1.19	0.01***	2.97***	−0.01***	−5.16***	−135%	235%
Sample	2018M1	(0.37)	(0.10)	(0.00)	(0.00)	(0.01)	(0.00)		
(B) British Pound									
4	1986M8	0.02	2.01	0.02	4.82	0.00	−3.82	480%	−380%
	1987M11	(0.45)	(0.80)	(0.50)	(0.55)	(0.89)	(0.15)		
5	1987M12	−0.08	−4.43	0.02***	4.43**	−0.04***	−9.87***	−82%	182%
	1992M7	(0.13)	(0.10)	(0.01)	(0.05)	(0.00)	(0.00)		
6	1992M8	0.03***	17.42***	−0.02***	4.47	0.06***	11.95	27%	73%
	1994M9	(0.00)	(0.00)	(0.00)	(0.22)	(0.00)	(0.10)		
7	1994M10	−0.00	−3.35**	−0.01	−3.74	0.01	−0.62	86%	14%
	2005M3	(0.25)	(0.03)	(0.12)	(0.25)	(0.33)	(0.85)		
8	2005M4	0.01**	17.46***	0.01**	8.92***	0.00	7.52	54%	46%
	2007M12	(0.01)	(0.00)	(0.01)	(0.00)	(0.89)	(0.21)		
9	2008M1	−0.00	10.39	−0.01**	−2.75	0.01	12.14	−29%	129%
	2010M4	(0.86)	(0.23)	(0.02)	(0.58)	(0.66)	(0.17)		
10	2010M5	0.01	36.13	−0.00	16.79	0.01*	18.34	48%	52%
	2014M5	(0.20)	(0.28)	(0.40)	(0.25)	(0.10)	(0.59)		
11	2014M6	−0.00	−11.86	−0.01***	−3.73	0.01	−9.13	29%	71%
	2018M1	(0.32)	(0.56)	(0.01)	(0.59)	(0.06)	(0.53)		
Full	1986M8	0.00	−0.14	−0.01**	−0.03	0.00*	−1.11	3%	98%
Sample	2018M1	(0.9)	(0.91)	(0.02)	(0.99)	(0.06)	(0.45)		

(*Continued*)

Table 5: (*Continued*)

Sub Period	Dates	α_{BF}	β_{BF}	α_{RP}	β_{RP}	α_{FE}	β_{FE}	RP: % Bias Exp.	FE: % Bias Exp.
(C) Canadian Dollar									
3	1986M8	−0.00	−1.51	0.01**	−4.92***	−0.01	2.41	196%	−96%
	1989M11	(0.62)	(0.56)	(0.02)	(0.00)	(0.12)	(0.39)		
4	1989M12	0.00**	−0.83	−0.00***	2.30***	0.01***	−4.13***	−126%	226%
	2002M8	(0.02)	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)		
5	2002M9	−0.01	2.16	−0.01	−0.59	−0.01	1.75	−51%	151%
	2004M10	(0.35)	(0.86)	(0.20)	(0.89)	(0.78)	(0.90)		
6	2004M11	0.00	8.73	−0.01*	−3.31	0.01	11.04	−43%	143%
	2008M7	(0.78)	(0.14)	(0.10)	(0.41)	(0.27)	(0.11)		
7	2008M8	0.00	−33.48	−0.00	20.08**	0.00	−54.56	−58%	158%
	2010M8	(0.93)	(0.36)	(0.32)	(0.02)	(0.77)	(0.19)		
8	2010M9	-−0.02	24.51	0.00	−11.73	−0.02	35.24	−50%	150%
	2013M8	(0.35)	(0.35)	(0.56)	(0.34)	(0.37)	(0.31)		
9	2013M9	0.01**	0.45	0.00*	2.14	0.01	−2.69	−386%	486%
	2015M12	(0.03)	(0.96)	(0.09)	(0.61)	(0.26)	(0.81)		
10	2016M1	−0.01	1.50	0.00	33.30	−0.01	−32.80	6627%	-6527%
	2018M1	(0.41	(0.98)	(0.40	(0.14)	(0.37)	(0.65)		
Full	1986M8	0.00	−0.83	−0.00***	1.40**	0.00*	−3.23***	−77%	177%
Sample	2018M1	(0.90)	(0.23)	(0.00)	(0.01)	(0.06)	(0.00)		

(D) Euroarea									
3	1986M8	(0.00)	4.09	0.00	8.45	0.00	−5.36	274%	−174%
	1987M11	(0.82)	(0.69)	(0.76)	(0.18)	(0.95)	(0.28)		
4	1987M12	0.00	−2.20	0.01*	5.23***	−0.01	−8.43***	−164%	264%
	1992M7	(0.70)	(0.13)	(0.06)	(0.00)	(0.24)	(0.00)		
5	1992M8	0.02*	5.25***	−0.03***	0.66	0.04***	3.59	16%	85%
	1995M2	(0.04)	(0.01)	(0.00)	(0.69)	(0.00)	(0.20)		
6	1995M3	−0.01*	1.24	−0.01**	−0.69	0.00	0.93	−280%	380%
	2000M3	(0.10)	(0.58)	(0.04)	(0.62)	(0.63)	(0.63)		
7	2000M4	0.00	−1.87	0.01***	2.38*	−0.00	−5.25***	−83%	183%
	2008M11	(0.28)	(0.26)	(0.00)	(0.09)	(0.18)	(0.00)		
8	2008M12	0.00	6.29***	−0.00	−5.20**	0.00	10.49***	−99%	199%
	2012M12	(0.99)	(0.00)	(0.27)	(0.03)	(0.44)	(0.00)		
9	2013M1	−0.00	−79.15*	−0.02***	11.59	0.01***	−91.74**	−15%	115%
	2015M2	(0.65)	(0.09)	(0.00)	(0.60)	(0.00)	(0.01)		
10	2015M3	0.00	7.94***	−0.01**	−6.10**	0.01***	13.04***	−88%	188%
	2018M1	(0.61)	(0.01)	(0.04)	(0.02)	(0.00)	(0.00)		
Full	1986M8	0.00	−0.16	−0.00	3.01***	0.00	−4.17***	−258%	358%
Sample	2018M1	(0.65)	(0.83)	(0.25)	(0.01)	(0.19)	(0.00)		

(*Continued*)

Table 5: (*Continued*)

Sub Period	Dates	α_{BF}	β_{BF}	α_{RP}	β_{RP}	α_{FE}	β_{FE}	RP: % Bias Exp.	FE: % Bias Exp.
(E) Japanese Yen									
4	1986M8	0.01	8.82	−0.01	5.74	0.02	2.08	73%	27%
	1987M11	(0.69)	(0.30)	(0.38)	(0.29)	(0.39)	(0.78)		
5	1987M12	−0.00	−2.44	−0.01	5.71**	0.00	−9.16***	−166%	266%
	1991M3	(0.74)	(0.40)	(0.41)	(0.02)	(0.83)	(0.01)		
6	1991M4	−0.01**	3.71	0.01***	−3.83***	−0.02***	6.54*	−142%	242%
	1995M3	(0.01)	(0.25)	(0.00)	(0.00)	(0.00)	(0.06)		
7	1995M4	0.01	−0.80***	0.03***	−0.41***	−0.02***	−1.38***	23%	77%
	1998M4	(0.13)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
8	1998M5	0.00	1.91**	0.01	−1.22	−0.00	2.13*	−134%	234%
	2008M7	(0.20)	(0.04)	(0.31)	(0.29)	(0.80)	(0.07)		
9	2008M8	0.00	19.14***	0.01***	10.58***	−0.01***	7.56*	58%	42%
	2012M8	(0.81)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
10	2012M9	0.00	−56.10	0.01	2.37	−0.01	−59.47	−4%	104%
	2014M10	(0.90)	(0.70)	(0.12)	(0.96)	(0.73)	(0.64)		
11	2014M11	−0.00	4.78	0.01***	3.97	−0.01***	−0.19	105%	−5%
	2018M1	(0.81)	(0.15)	(0.00)	(0.18)	(0.00)	(0.92)		
Full	1986M8	0.00	-0.36	0.01***	−0.80**	−0.01***	−0.56	59%	41%
Sample	2018M1	(0.39)	(0.57)	(0.00)	(0.04)	(0.00)	(0.39)		
(F) Swiss Franc									
4	1986M8	0.00	2.96	−0.00	7.07	−0.00	−5.11	361%	−261%
	1987M11	(0.88)	(0.85)	(0.91)	(0.45)	(0.86)	(0.51)		
5	1987M12	−0.00	−1.77	−0.00	3.96**	0.00	−6.74***	−144%	244%
	1992M8	(0.84)	(0.30)	(0.60)	(0.01)	(0.75)	(0.00)		
6	1992M9	−0.01	3.61**	0.03***	0.90*	−0.03***	1.71	35%	66%
	1995M2	(0.16)	(0.01)	(0.00)	(0.06)	(0.00)	(0.20)		
7	1995M3	−0.01**	−5.25***	−0.01	−6.86***	0.00	0.61	110%	−10%
	2002M2	(0.05)	(0.00)	(0.12)	(0.00)	(0.95)	(0.72)		
8	2002M3	−0.01	1.59	−0.02***	−7.74**	0.01	8.33	−1303%	1403%
	2005M5	(0.65)	(0.89)	(0.01)	(0.02)	(0.36)	(0.42)		
9	2005M6	0.01	4.36	−0.01	−0.82	0.02	4.18	−24%	124%
	2008M10	(0.58)	(0.40)	(0.37)	(0.80)	(0.22)	(0.34)		
10	2008M11	0.00	22.26**	0.01	14.26	−0.01	7.00	67%	33%
	2010M11	(0.97)	(0.02)	(0.29)	(0.58)	(0.47)	(0.80)		
11	2010M12	−0.00	−4.79	0.01***	2.23	−0.01***	−8.02	−39%	139%
	2018M1	(0.40)	(0.42)	(0.00)	(0.15)	(0.00)	(0.16)		
Full	1986M8	−0.00	−1.12	0.07**	1.64	−0.01***	−3.76***	−77%	177%
Sample	2018M1	(0.18)	(0.25)	(0.02)	(0.15)	(0.00)	(0.00)		

Description: The table reports subperiod and full sample estimates of the BF regression (columns 3 and 4) and risk premium (rp) and forecast error (fe) regressions in equations (5) and (6), respectively (columns 5-8). A ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Values shown in parentheses are p-values using HAC standard errors.

Interpretation: The table shows that inference from survey data about the importance of risk and rationality changes dramatically when the analysis accounts for the BF regression's instability.

Table A1: (*Piecewise linear Subperiod Mis-specification Tests*)

(A) Australian Dollar

	Full Sample	**Subperiods 1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
AR	0.78	0.69	1.58	0.14	0.54	0.16	0.96	0.43	0.79	0.89	0.22	0.80
	[0.61]	[0.63]	[0.22]	[0.93]	[0.66]	[0.93]	[0.44]	[0.74]	[0.51]	[0.48]	[0.88]	[0.55]
ARCH	2.34*	0.34	0.18	0.14	1.58	0.82	0.36	1.04	1.13	0.70	0.35	0.51
	[0.02]	[0.92]	[0.91]	[0.93]	[0.22]	[0.50]	[0.84]	[0.39]	[0.35]	[0.60]	[0.79]	[0.77]
Hetero.	1.74	0.13	1.11	0.87	0.60	3.63*	0.68	0.19	1.49	0.23	0.26	7.69**
	[0.18]	[0.88]	[0.34]	[0.43]	[0.55]	[0.038]	[0.51]	[0.83]	[0.24]	[0.79]	[0.77]	[0.00]

(B) British Pound

	Full Sample	**Subperiods 1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
AR	0.93	1.10	2.38	0.63	0.33	0.73	0.80	1.52	2.70	2.23	1.67	2.11
	[0.48]	[0.36]	[0.07]	[0.64]	[0.80]	[0.57]	[0.51]	[0.17]	[0.06]	[0.11]	[0.17]	[0.10]
ARCH	2.68**	1.62	1.54	0.40	1.03	0.34	1.04	0.72	1.59	0.25	0.53	0.86
	[0.01	[0.20]	[0.21]	[0.81]	[0.40]	[0.85]	[0.40]	[0.66]	[0.21]	[0.86]	[0.71]	[0.50]
Hetero.	1.87	1.13	1.64	0.13	0.45	0.52	1.39	0.78	0.00	2.25	0.28	0.16
	[0.16]	[0.33]	[0.20]	[0.88]	[0.64]	[0.56]	[0.27]	[0.46]	[0.99]	[0.13]	[0.75]	[0.85]

(C) Canadian Dollar

	Full Sample	**Subperiods 1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
AR	1.19	0.57	0.16	0.62	1.63	0.93	0.29	0.11	2.00	2.70	1.51
	[0.31]	[0.64]	[0.92]	[0.74]	[0.13]	[0.44]	[0.88]	[0.95]	[0.14]	[0.07]	[0.24]
ARCH	10.66**	0.77	1.67	0.60	1.13	0.34	2.91*	0.97	1.04	1.21	0.05
	[0.00]	[0.52]	[0.20]	[0.75]	[0.35]	[0.79]	[0.03]	[0.42]	[0.40]	[0.33]	[0.98]
Hetero.	2.25	1.63	0.26	0.60	0.35	0.91	1.38	0.42	0.37	0.11	0.60
	[0.11]	[0.21]	[0.77]	[0.55]	[0.71]	[0.42]	[0.26]	[0.66]	[0.69]	[0.90]	[0.56]

(*Continued*)

Table A1: (*Continued*)

(D) Euroarea

	Full Sample	**Subperiods 1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
AR	0.63	1.11	1.34	2.17	1.12	1.68	0.56	1.81	0.39	0.53	0.14
	[0.73]	[0.36]	[0.27]	[0.11]	[0.36]	[0.20]	[0.69]	[0.11]	[0.82]	[0.67]	[0.93]
ARCH	1.56	0.20	0.70	1.39	0.33	0.21	0.72	5.96**	1.10	1.87	0.94
	[0.15]	[0.94]	[0.59]	[0.27]	[0.85]	[0.89]	[0.58]	[0.00]	[0.37]	[0.17]	[0.43]
Hetero.	14.47**	0.16	0.10	0.60	0.20	1.07	0.13	3.06	0.50	0.20	0.35
	[0.00]	[0.85]	[0.90]	[0.55]	[0.82]	[0.36]	[0.88]	[0.05]	[0.61]	[0.82]	[0.71]

(E) Japanese Yen

	Full Sample	**Subperiods 1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
AR	1.22	0.12	7.31**	1.02	0.78	0.10	0.70	0.60	0.67	0.60	0.04	0.25
	[0.29]	[0.95]	[0.00]	[0.41]	[0.52]	[0.96]	[0.60]	[0.62]	[0.70]	[0.66]	[0.99]	[0.86]
ARCH	2.61*	0.10	3.74*	0.54	0.35	1.03	0.93	0.40	0.20	0.33	1.26	0.16
	[0.01]	[0.96]	[0.02]	[0.74]	[0.79]	[0.39]	[0.46]	[0.75]	[0.99]	[0.86]	[0.32]	[0.92]
Hetero.	2.72	2.47	8.61**	0.06	0.89	0.87	1.35	0.38	0.21	0.50	2.06	1.83
	[0.07]	[0.10]	[0.00]	[0.95]	[0.42]	[0.42]	[0.27]	[0.69]	[0.81]	[0.61]	[0.15]	[0.18]

(F) Swiss Franc

	Full Sample	**Subperiods 1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
AR	0.84	0.23	1.42	0.65	1.68	0.99	2.00	1.42	0.26	0.62	0.14	1.84
	[0.56]	[0.87]	[0.27]	[0.63]	[0.19]	[0.42]	[0.14]	[0.23]	[0.86]	[0.61]	[0.94]	[0.10]
ARCH	2.76**	0.26	0.31	1.44	0.65	0.80	0.61	0.27	0.44	2.03	0.47	0.92
	[0.01]	[0.85]	[0.81]	[0.23]	[0.59]	[0.53]	[0.62]	[0.93]	[0.73]	[0.13]	[0.71]	[0.49]
Hetero.	12.44**	0.53	0.64	7.15**	0.54	0.08	0.50	0.71	1.25	4.66*	0.60	0.18
	[0.00]	[0.59]	[0.54]	[0.00]	[0.59]	[0.93]	[0.61]	[0.50]	[0.30]	[0.02]	[0.56]	[0.84]

Description: The table reports on three different residual diagnostic tests conducted using OxMetrics' (PcGive) and its default settings. The AR row provides Lagrange-multiplier tests for the rth order residual autocorrelation under the null hypothesis of no autocorrelation. The ARCH row provides AutoRegressive Conditional Heteroscedasticity tests based on Engle (1982). The Hetero. row provides heteroscedasticity tests based on White (1980). For each sample, Oxmetrics determines the default lag length for the AR and ARCH tests based on the length of the individual subperiod. The full sample estimates use seven lags. In smaller subsamples (less than 65 months), three, or more often four, lags are used, whereas in longer subsamples the lag length increases to six or seven. See Doornik and Hendry (2013) for additional details on the tests conducted. The subperiod numbers correspond to the numbered subperiods in Table 5. A ** and * denote statistical significance at the 1% and 5% levels, respectively. Values in brackets are test statistic p-values. For all tests reported, a statistically significant result implies error misspecification.

Interpretation: The diagnostic test results show improved fit in the separate subperiods of parameter constancy and thus give support to the our structural change analysis.