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Rationality and the Meese and Rogoff Exchange-Rate-Disconnect Puzzle: Learning vs. Contingent Knowledge

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This paper is an abridged version of Frydman, Goldberg, and Sullivan (2013)

There is much anecdotal evidence in the popular media, backed up by survey research, that participants in currency markets pay close attention to fundamental economic variables in forming their forecasts of future exchange rates. It is obvious, for example, that market participants hang on every word that central bank officials utter, attuned to the slightest hint of a change in monetary policy. Similarly, in the aftermath of the global financial crisis that began in 2008, market participants saw the US dollar as a safe haven, and watched for any news that might indicate whether the crisis was deepening or dissipating.

Because participants' forecasts drive their behavior in currency (and other financial) markets, we would expect fundamental variables to have considerable influence on exchange-rate fluctuations. And yet, over the past three decades, empirical researchers, operating with models that rely on the rational expectations hypothesis (REH), have uncovered little formal evidence that fundamentals matter for exchange-rate movements.

Meese and Rogoff (1983) is perhaps the most often cited study. They compared the out-of-sample forecasting performance of the most popular REH models of the 1970s with the performance of a simple random-walk model and found that none of these models' predictions would enable a forecaster to do any better than she would if she merely flipped a fair coin.[1] Most researchers concluded that fundamentals play no role for currency fluctuations. Although a few recent studies report some improvement, the consensus is that "not only have a subsequent twenty years of data and research failed to overturn the Meese-Rogoff result, they have cemented it" (Rogoff, 2001, p. 1).[2]

Behavioral-finance economists have interpreted these results as evidence of REH's failure to account for how market participants actually make decisions. But, rather than concluding that REH does not adequately represent rational forecasting, they argued that market participants are irrational - largely driven by psychological biases, emotions, and momentum trading.[3]

[1] A real forecasting exercise would, of course, need to project the values of the fundamental variables for the future dates of the forecasts. But, to keep their study's focus on whether their in-sample estimates of the REH models could account for the influence of fundamentals out of sample, they used the actual future values of the fundamentals to obtain exchange-rate predictions.

[2] For overviews of this literature, see Frankel and Rose (1995), Cheung, Chinn and Pascual (2005), and Frydman and Goldberg (2007).

[3] For examples of behavioral models of exchange rates, see Mark and Wu (1998) and Gourinchas and Tornell (2004).

In this paper, we provide empirical evidence that the Meese and Rogoff puzzle stems not from the irrationality of currency traders, but from REH's inherent inability to represent rational forecasting in real-world markets. Frydman and Goldberg (2013a) show that REH models are compatible with rational forecasting only in "markets" in which participants can fully foresee when and how their understanding of the process driving outcomes might change: REH models are in effect abstractions of rational decision-making in markets in which knowledge does not grow. Indeed, the REH exchange-rate models that underpin the Meese and Rogoff puzzle are all time-invariant: they assume that market participants' forecasting strategies and the underlying global economy have remained unchanged since March 1973, when the modern period of floating exchange rates began.[4]

It is self-evident that in real-world markets, knowledge does grow. For example, participants find new ways to understand the effects of economic policy on the structure of the economy. Thus, in real-world markets, REH models represent decision-making by individuals who forgo obvious profit opportunities, making them appear grossly irrational.

Frydman and Goldberg (2013b) propose an analog to REH, which they call the contingent expectations hypothesis (CEH), in order to build models that are compatible with rational decision-making in real-world markets. Such a model must recognize that the knowledge that underpins the market's forecast is imperfect and contingent: it changes at times and in ways that no one can fully foresee.[5] REH models are inconsistent with such contingent structural change. Moreover, they fail to recognize that rational market participants do not rely on fundamentals and calculation alone. Their imperfect and contingent knowledge implies that they also depend on psychological

[4]Sometimes REH models allow for the process driving market outcomes to change, owing, for example, to shifts in economic policy. But, in order to obtain a probabilistic representation of the price process, these models must specify in probabilistic terms all such structural change in advance, thereby representing any change in the market's understanding as though it could be fully anticipated. Such representations, therefore, assume away growth in participants' knowledge, which follows from Popper's (1957, xii) proposition: "If there is such a thing as growing human knowledge, we cannot anticipate today what we shall only know tomorrow."

[5]CEH also implies that, in order to be compatible with rational forecasting, a model's representations of participants' forecasting cannot imply regularities in time-series data that conflict with the model's representation of these regularities. This principle of internal coherence, like internal consistency in REH models, connects a model's representation of forecasting to the specifications of its other components. It also implies restrictions on structural change in a model. For extensive discussion and an example of how this principle is applied in economic models, see Frydman and Goldberg (2013a).

considerations, such as their confidence in their current strategy or their intuition about possible structural change. As Keynes (1936, p. 162) put it,

> We are merely reminding ourselves that human decisions affecting the future, whether personal or political or economic, cannot depend on strict mathematical expectation, since the basis for making such calculations does not exist; and... that our rational selves [are] choosing between alternatives as best as we are able, calculating where we can, but often falling back for our motive on whim or sentiment or chance.

Rational market participants' imperfect and contingent knowledge, and their reliance on psychological considerations for their decision-making, imply that the process driving outcomes in currency or other markets undergoes change at times and in ways that no one can fully foresee. Consequently, the rationality of market participants implies that estimating one linear model for the entire floating-rate period, as Meese and Rogoff (1983) and subsequent researchers do, is likely to yield the usual finding that structural models fail to outperform the simple random-walk model. In order to uncover econometric evidence of a connection between exchange rates and macroeconomic fundamentals, our analysis must start by recognizing the inherent instability of the process driving outcomes.

Recent exchange-rate researchers have recognized that market participants do revise their forecasting strategies. They have relied on algorithmic or so-called adaptive learning rules, such as least squares with a small constant gain-adjustment factor.[6] By design, these rules do not accord any role to psychological considerations in forecasting. Molodstova and Papell (2009, 2011) incorporate an adaptive learning rule into a Meese and Rogoff (1983) analysis of a Taylor-rule model. They report that their model outperforms the random walk in out-of-sample forecasting.

Similarly, Evans and Honkapohja (2013, p. 68-69) have argued that adaptive learning rules provide a non-REH rational foundation for macroeconomic and finance models. However, these models specify fully in advance how learning takes place; thus they assume that the knowledge underlying the market's forecast does not grow. As Frydman and Goldberg (2013a) argue, learning models, like their REH counterparts, represent decision-making by irrational individuals.

[6] See Mark (2009) for currency markets, and Adam and Marcet (2011) for stock markets.

Frydman and Goldberg's (2007, 2013a,b) imperfect knowledge economics (IKE) model of currency swings and risk provides a very different way to represent participants' revisions of forecasting strategies, and, because the model incorporates CEH, it is compatible with rational decision-making. According to this model, there are stretches of time of unpredictable duration in which market participants maintain their forecasting strategies or revise them only moderately. The resulting piece-wise linear specification of the model implies that each linear piece is characterized by a distinct temporary equilibrium, or cointegrating, relationship between the exchange rate and macroeconomic fundamentals. To be compatible with individual rationality, the model specifies in advance neither the timing of structural change, which determines when a linear piece begins and ends, nor which fundamentals enter any temporary cointegrating relationship or the precise way that they do.

In our empirical analysis, we compare the forecasting performance of an adaptive learning model with an IKE model. The former fully prespecifies structural change, which implies that it represents irrational decision-making. The CEH-based IKE model leaves structural change partly open. In order to estimate this model, we first need procedures to detect points of structural change in the data and identify which fundamental variables might enter market participants' forecasting strategies and thus the reduced form in any time period. To address these issues, we rely on a novel dataset developed by Sullivan (2013), which was constructed by reading every daily *Wall Street Journal* (*WSJ*) currency column from January 1999 (the inception of euro) to December 2010 and scoring each for the main factors reported to have driven the exchange rate that day.[7]

The *WSJ* data provide support for IKE's piece-wise linear approach. They indicate that there are stretches of time over the sample during which the composition of fundamental variables that are reported to drive the exchange rate remains largely unchanged, but that it changes at unpredictable points. The data suggest that there are three breakpoints in the sample, giving rise to four exchange-rate regimes. Two of these breakpoints are proximate to major reversals in how the exchange rate was

[7] Other studies - for example, Ehrmann and Fratzscher (2005) - have used textual data in examining behavior in asset markets. But, unlike these analyses, Sullivan's *WSJ* data are not based on simple word counts. By reading each currency column, Sullivan is able to catalogue which variables from the many that are mentioned in a story actually drove the market, and whether a particular variable mattered positively or negatively for the exchange rate.

trending, which is consistent with Frydman and Goldberg's (2007, 2013b) IKE model.[8]

The *WSJ* data also indicate that overall economic activity, interest-rate expectations, and inflation rates tend to drive the dollar-euro exchange rate during many of these regimes, which is consistent with Molodstova and Papell (2009, 2011) and other recent studies that estimate a Taylor-rule model. But this is not the case in every regime. Moreover, there are other fundamental factors that are specific to each regime; for example, as we discuss below, US stock prices were reported as important drivers of the exchange rate during the first regime, but not during subsequent regimes. The overall conclusion from the *WSJ* data is that the instability of the process driving the exchange rate takes a striking form: different sets of fundamentals matter during different time periods. No one could have foreseen the points of structural change, let alone which fundamentals would matter for the exchange rate under each regime.

In section 1, we sketch an IKE model of the exchange rate that is consistent with such contingent structural change. We also sketch Molodstova and Papell's (2009, 2011) adaptive Taylor-rule model. In section 2, we discuss how Sullivan's (2013) *WSJ* dataset is constructed, and how we use it to help locate points of structural change. The *WSJ* data indicate that at least one fundamental variable was a major driver of the exchange rate on virtually every day in the sample. They also show that psychological considerations, such as confidence and optimism, are important in driving market outcomes, as we would expect from assuming rationality in a world of contingent knowledge.[9] Remarkably, *WSJ* journalists and market participants rationalize the role of psychological factors almost entirely in terms of news about fundamentals. The implication of bubble models, that psychological factors and momentum trading alone can sustain currency swings, receives little support in the WSJ data.

In section 3, we carry out a Meese and Rogoff forecasting analysis of our empirical IKE and adaptive Taylor-rule models and report its results. Our piece-wise linear IKE model supposes that the distinct sets of fundamentals that matter for the exchange rate under each of the four regimes are those that are implied by the *WSJ* data. To give our adaptive Taylor-rule model the benefit of the doubt, we suppose that learning is based on a composite specification that includes all of the fundamental variables that were included in the IKE model under all four regimes.

[8] In Frydman, Goldberg, and Sullivan (2013), we show that the results of recursive structural-change procedures support the breakpoints found on the basis of the *WSJ* data.

[9] For a discussion of these results, see Sullivan (2013).

To highlight our results, we find, like other studies, that our composite specification is unable to outperform the random-walk model in out-of-sample forecasting when structural change is ignored. Allowing for structural change by means of a constant-gain learning rule yields a no improvement over the traditional approach. By contrast, IKE's piece-wise linear approach to structural change delivers forecasting performance that is superior to the random-walk model by a considerable margin. Our results also support the conclusion from the *WSJ* data that different sets of fundamentals matter during different time periods. Overall, our results indicate that algorithmic learning rules are unable to account for the contingent change that has characterized the process underlying the dollar-euro exchange rate since 1999. Moreover, the empirical difficulties that REH exchange-rate models have encountered in the literature stem not from the presence of irrational traders, but from these models' inability to represent rational market participants' forecasting behavior.

1 Algorithmic Learning and Contingent Knowledge

Our algorithmic learning and IKE models make use of a well-known equilibrium condition for the foreign exchange market, uncovered interest rate parity (UIP), which we express as follows:

$$s_t = \hat{s}_{t|t+1} + i_t^* - i_t \tag{1}$$

where s_t denotes the logarithm of the spot exchange rate, i_t and i_t^* are the domestic and foreign nominal interest rate, and $\hat{s}_{t|t+1}$ denotes the market's time-t point forecast of s_{t+1} conditional on available information. UIP is one of the building blocks of REH monetary and Taylor-rule models. It assumes that market participants are risk neutral and bid the exchange rate to the point where the expected return on holding either a long position, $\hat{s}_{t|t+1} - s_t + i_t^* - i_t$, or a short position, $i_t - i_t^* + s_t - \hat{s}_{t|t+1}$, in foreign exchange equals zero. Frydman and Goldberg's (2007) IKE monetary model of the exchange rate assumes that market participants are loss averse and bid the exchange rate to the point where, in the aggregate, the uncertainty adjusted expected return on holding open positions in foreign exchange is zero. To simplify our analysis here, we will incorporate these risk considerations in our $\hat{s}_{t|t+1}$ representation.[10]

Our representation of the market's point forecast at each point in time is given by:

$$\hat{s}_{t|t+1} = \beta_t z_t \tag{2}$$

where z_t characterizes the union of information variables used by market participants and β_t represents aggregates of the weights that market participants attach to these variables in forming their forecasts. The representation in (2) is quite general and encompasses the specifications used in both REH and IKE monetary models and Molodstova and Papell's (2009, 2011) Taylor-rule model.

For example, if we were to assume flexible goods prices and the usual money market specification for both countries:

$$m_t = p_t - \phi y_t + \lambda i_t \tag{3}$$

where standard m_t, p_t, and y_t denote the logarithms of money supply, good prices, and overall income, respectively, the following time-invariant REH representation would result:

$$\hat{s}_{t|t+1} = m_t - m_t^* - \phi\left(y_t - y_t^*\right) + (1+\lambda)\left(i_t - i_t^*\right) \tag{4}$$

Molodstova and Papell's (2009, 2011) Taylor-rule model also assumes that market participants' forecasting strategies can be represented by a fixed set of fundamentals. Its representation can be expressed as:

$$\hat{s}_{t|t+1} = \alpha_t + s_{t-1} + i_t^* - i_t + \delta_t\left(u_t - u_t^*\right) + \eta_t\left(\pi_t - \pi_t^*\right) \tag{5}$$

where α_t depends on the central bank's inflation target and full employment output and u_t and π_t denote the domestic unemployment and inflation rates, respectively. But, the model allows for the parameters of its representation to change over time according to what is essentially a constant-gain least-squares learning rule. Consequently, Molodstova and Papell's (2009, 2011) adaptive learning rule not only presumes that market participants always use the same set of fundamental variables to

[10] Frydman and Goldberg'(2007, 2013b) IKE model makes use of endogenous prospect theory, which assumes that participants' degree of loss aversion – their greater sensitivity to potential losses than to potential gain of the same size – increases with size of their open positions.

forecast at every point in time, but they never alter how they update their strategies.

Frydman and Goldberg's (2007) IKE monetary model includes equation (4)'s fundamental variables in its representation of the market's forecast in (2). But, it recognizes that rational participants will not only rely on a broader information set, but they will revise their forecasting strategies at times and in ways that no one can specify in advance. These revisions will, in general, imply that the market makes use of different sets of fundamentals during different time periods in forecasting the exchange rate.

In both our adaptive Taylor-rule and IKE models, movements in the exchange rate stem from movements in the fundamentals and revisions of market participants' forecasting strategies:

$$\Delta \hat{s}_{t|t+1} = \Delta \beta_t z_t + \beta_{t-1} \Delta z_t \tag{6}$$

where Δ denotes the first difference operator. We now sketch how these models represent revisions to forecasting strategies, that is $\Delta \beta_t$.

1.1 Constant-Gain Least Squares

The algorithmic, or adaptive, learning approach that is used in the asset market literature typically relies on a constant-gain least squares updating rule. This rule represents market participants' forecasting strategies with the same structure as the economist's model. In terms of our example, with equation (5) and its fixed set of fundamental variables. Market participants' learning is represented by a recursive least squares algorithm that relies on a small constant gain.[11]

Following Evans and Honkapohja (2001), this adaptive learning rule can be seen as estimating the equation

$$s_t = c_t z_t + \varepsilon_t \tag{7}$$

using data from $i = 1, \ldots, T$ and a coefficient vector c_t that minimizes the sum of squared errors. This coefficient vector is computed recursively on the basis of the following least squares formulas:

[11] Our sketch abstracts from several aspects of what is called the "adaptive learning approach", including the distinction between the actual and perceived laws of motion and the potential for learning to create nonlinear dynamics. See Evans and Honkapohja (2001) for a detailed discussion of these aspects.

$$c_t = c_{t-1} + \gamma_t R_t^{-1} z_t \left(s_t - z_t' c_{t-1}\right) \tag{8}$$

$$R_t = R_{t-1} + \gamma_t \left(z_t z_t' - R_{t-1}\right) \tag{9}$$

where R_t denotes the moment matrix of z_t using data from $i = 1, \ldots, t$. The gain parameter, γ_t, determines the extent to which c_t changes given new information available at time t. If we were to set $\gamma_t = t^{-1}$, the foregoing recursive rule would generate the standard least squares estimate at each time t, provided that the initial values of coefficient vector and moment matrix are determined by least squares. Proponents of this adaptive learning approach typically set the gain in the recursive estimation to be a small constant, $\gamma = 0.02$ is widely used. This formulation places greater emphasis on more recent observations than that implied by Meese and Rogoff's (1983) standard recursive least squares estimates. The constant gain formulation is conceptually equivalent to Molodstova and Papell's (2009, 2011) rolling-window or a weighted least squares regression with geometrically declining weights. In terms of the average "age" of the data used, a rolling window of length L is equivalent to a constant gain $\gamma = 2/L$.[12]

Macroeconomists represent the understanding that underpins the market's forecast with the structure of their model. In the case of Molodstova and Papell's (2009, 2011) adaptive Taylor-rule model, this structure is assumed to entail an unchanging set of causal variables whose movements are assumed to be governed by unchanging stochastic processes. By also fully specifying in advance how the parameters of this structure change over time, one can anticipate fully, in probabilistic terms, the structures that the model will use in representing the market's understanding in future periods. But, as Popper (1957, 1992) showed, although the model allows participants' understanding of the price process to change, ruling out unanticipated change is tantamount to representing decision-making in markets in which knowledge does not grow. Popper's proposition (see footnote 4), slightly paraphrased, can be restated as follows:

> If there is such a thing as growing human knowledge, then no individual, such as an economist or a market participant, or group of individuals, such as market participants in the aggregate, can anticipate today what they shall only know tomorrow. (Popper, 1957, xii)

[12] See Orphanides and Williams (2005, pg. 9).

Although adaptive learning models are abstractions of forecasting in markets in which knowledge does not grow, they may nonetheless be relevant for modeling outcomes in real-world markets in which participants' knowledge changes in ways that no one can fully anticipate. After all, no one would claim that these models are literal descriptions; rather they are bold abstractions that might provide a "rational foundation for macroeconomic and finance [models]" (Evans and Honkapohja, 2013, pg. 69) in real-world markets. However, Frydman and Goldberg (2013a) show that determinate models – those in which any change in structure is fully anticipated – do not adequately approximate decision-making by rational individuals: in markets in which knowledge grows, these models represent forecasting by individuals who forgo *obvious* profit opportunities.

1.2 IKE Piece-Wise Linear

To be relevant for representing rational decision making in real-world markets, economic models must recognize that no one can fully anticipate when or how market participants' understanding of the price process and thus their forecasting strategies will change. Our IKE model's constraints on structural change are compatible with such contingent change. In modeling this change, Frydman and Goldberg (2007) appeal to Keynes's 1936 account of asset markets. In using their "knowledge of the facts" to form forecasts, participants

> fall back on what is, in truth, a convention... [which] lies in assuming that the existing state of affairs will continue indefinitely, except in so far as we have specific reasons to expect a change.(Keynes, 1936, pg. 152)[13]

This insight suggests that market participants tend to stick with a forecasting strategy for stretches of time. Indeed, it is often unclear whether one should alter her strategy. A quarter or two of poor forecasting performance may be the result of random events rather than an indication of a failing strategy. So, unless an individual has "specific reasons to expect a change" in the market, she may leave her current strategy unaltered – even if its performance begins to flag over several periods. Moreover, even armed with "specific reasons to expect a change," it is entirely unclear what new forecasting strategy, if any, she should adopt.

[13] By "existing state of affairs," Keynes means "knowledge of the facts."

IKE formalizes this insight with qualitative and contingent constraints, applied to the expression for structural change given by (6), that Frydman and Goldberg (2007, 2013b) call "guardedly moderate revisions" – there are stretches of time during which participants either maintain their strategies or revise them gradually. It is clear from equation (6) that any stretch of time in which market participants, in the aggregate, kept their forecasting strategies unchanged would involve a temporary but stable equilibrium relationship between the exchange rate and the set of causal variables in z_t. Moreover, if during a stretch of time revisions of strategies were instead sufficiently moderate, the model would continue to imply that the sign of each of the weights that were attached to the causal variables would remain unchanged. Frydman and Goldberg (2013a) show that CEH imposes such guardedly-moderate restrictions on the model's representation of forecasting.[14]

Hence, if we were to run a regression of the exchange rate on these variables during a stretch of time in which revisions were guardedly moderate, we would expect to find an approximate cointegrating relationship, given that exchange rate models' causal variables are often characterized as having stochastic trends.

However, although market participants have a tendency to maintain their strategies or revise them gradually, this qualitative regularity is contingent: it manifests itself at times and in ways that no one can fully foresee. There are occasions when exchange rate movements or news about economic and political developments lead participants to revise their forecasting strategies in non-moderate ways. Such revisions can have a dramatic impact on the price process and spell the end of any stretch of time that was characterized by a temporary cointegrating relationship between the exchange rate and fundamentals. As such, the IKE model implies that the process underlying the exchange rate is contingent and approximately piece-wise linear: there are stretches of time in the data of unforeseeable duration that are characterized by distinct cointegrating relationships.

Frydman and Goldberg (2007, 2013b,c) and Frydman et al (2013) show that this IKE model can account for the puzzle in International Macroeconomics that exchange rate fluctuations are too persistent to be rationalized with standard REH models. Two

[14]The conditions that are needed for the model to imply these qualitative relationships is $\left|\beta_{t-1}^{h}\Delta z_t^h\right| > \left|\Delta\beta_t^h z_t^h\right|$, where $|\cdot|$ denotes an absolute value, the index $h = 1...n$, and n is the number of variables in z_t. The Meese and Rogoff (1983) forecasting exercise ignores the sign restrictions implied by structural models and so we refer the reader to Frydman and Goldberg (2013a) for a detailed analysis of how guardedly moderate constraints are implied by CEH and the assumption of individual rationality.

assumptions are needed: market participants' tendency to stick with their current strategies or revise them gradually is pronounced and the fundamental factors on which they form their forecasts entail persistent trends.

In this paper, we focus on out-of-sample forecasting performance. Testing the adaptive learning model along this metric is straightforward: we use the first 12 months of our sample (which runs from January 1999 through January 2009) to obtain initial least-squares estimates of the coefficients and then recursively update the model one observation at a time according to equations (8) and (9), computing forecast errors at every step. We measure forecasting performance at each horizon by averaging the forecast errors that are produced over the entire sample.

To test the performance of the IKE model we need a procedure for locating points of structural change and determining which fundamental variables are relevant for the market in each linear piece of the data. In fact, there are no strictly objective criteria, statistical or otherwise, to determine the precise nature of the fundamental relationship and points of change, i.e. breaks in the data when a new relationship arises, in the historical record. Different models and different testing procedures will lead to different break points and different estimated relationships. In this paper we rely on Sullivan's (2013) *WSJ* data to address these aspects of the analysis.

2 Rationality in Wall Street Journal Data

The Wall Street Journal data set was constructed for the euro-dollar exchange rate from reading the daily Wall Street Journal (*WSJ*) currency column for the period from January 1999 (the inception of euro) through December 2010. Each column is read for the main factors that it reports drove the exchange rate each day. Unlike data typically used by researchers, *WSJ* stories are not constrained to track the importance of only quantifiable fundamental considerations.[15] They also report on the importance of changes in the expectations of a range of fundamental factors, the "political and social atmosphere" as Keynes (1936, p. 162) put it, psychological considerations, such as confidence, optimism, and fear, and technical considerations, such as momentum trading and profit taking. Sullivan's (2013) data consists in part of the quarterly and sample frequencies with which causal factors were mentioned in

[15] For the purposes of this study, fundamental factors include macroeconomic data, financial, and political and social factors. Psychology, such as fear or confidence, and technical trading factors are considered to be non-fundamental.

the daily reports as main drivers of the exchange rate. The data also indicate whether a factor had a positive or negative impact on the exchange rate.

These data enable us to examine which factors - fundamental, psychological, or technical - were the most important in driving the exchange rate over our sample without having to estimate or take a stand on any model as in other empirical studies. Moreover, the data do not constrain when or how any of these factors may have mattered for the exchange rate. Consequently, they enable us to explore how the composition of relevant causal factors and their qualitative relationships with the exchange rate changed over time without having to specify in advance when or how such structural change occurred. Sullivan's (2013) data clearly support CEHs principles for representing rational participants' decision making in real-world markets: they rely on fundamental and psychological considerations in forecasting and recognize that how these factors matter for currency movements changes in contingent ways. The study reports that fundamental factors, including social and political developments, are the primary drivers of exchange rate movements. Of the more than 6,000 events recorded between 1999 and 2010, these factors were mentioned 71% of the time over the sample as major drivers of the exchange rate. The following excerpt from October 31, 2003 illustrates how these factors were reported:

> The dollar sailed higher on exceptionally strong U.S. economic growth data and was underpinned by the conciliatory tone of U.S. Treasury Secretary John Snow's congressional testimony on currency market manipulation. The currency's surge came in two phases. The first was early in the morning when the Commerce Department released data showing U.S. gross domestic product grew at a rate of 7.2% in the third quarter, the fastest rate of expansion in nearly 20 years. The dollar spiked again once it became apparent Mr. Snow wasn't going to directly accuse China or Japan of manipulating their currencies to generate a competitive price advantage for their exports during testimony on Capitol Hill.

Although fundamental factors were found to be the main drivers in currency markets, psychological considerations were reported to be important for the market 15% of the time. The following two excerpts from September 7, 2001 and March 26, 2003, respectively, illustrate how these factors were reported:

> "After struggling to hold its overnight strength…the U.S. currency for-

> feited a chunk of those gains as dollar sentiment generally soured in the wake of the National Association of Purchasing Management's nonmanufacturing business index. The news came as a setback for dollar bulls who had interpreted Tuesday's strong manufacturing report as a sign the U.S. economy was on track for a turnaround. The two reports appeared to contradict each other, once again casting a pall of uncertainty over the economic outlook."

> "The dollar slipped on fears of a longer, more convoluted-than-expected war with Iraq, but pared most of its losses in late trading on hopes sparked by reports of an uprising against Iraqi President Saddam Hussein in the city of Basra."

2.1 The Importance of Interest Rate Expectations

The exchange rate models sketched in section 2 all imply that short-term interest rates are key drivers of the exchange rate. Although the daily *WSJ* columns provide some evidence for this implication, they reveal that what mostly matters is the expectation of future interest rates. In fact, 90 percent of all of the columns citing interest rates as one of the main drivers of exchange rate movements, do so with respect to changes in interest rate expectations rather than actual changes in interest rates. The following excerpt illustrates this point:

> "What we're seeing in terms of currency movements – and it will probably continue at least over the near term – is a shift in global monetary-policy expectations," said Marc Levesque, chief strategist for North American foreign exchange and fixed income at TD Securities in Toronto. "There's a gearing-down of expectations for Fed tightening, coupled with increased tightening expectations elsewhere."(*WSJ*, Nov. 28, 2005)

The column goes on to report that the minutes from FMOC's November 1st meeting revealed that some members of the committee expressed "reservations about a commitment to regular rate increases, along with some concern about the possibility of going too far in the tightening cycle."

There is also considerable textual evidence that market participants often relate interest rate expectations to movements in macroeconomic fundamentals, particularly unemployment and inflation rates, which is consistent with a Taylor-rule formulation.[16]

A report from January 12, 2004 provides an example of this connection:

> Hopes the U.S. currency would show a near-term recovery were nearly dashed by the generally weak December employment report published Friday. News that only a net 1,000 jobs were created last month strengthened the view that U.S. interest rates will remain low for some time, further diminishing the dollar's allure. "This [number] is unambiguously bad for the dollar, not just because of the number itself, but because of the implications it has for U.S. interest rates," said Rebecca Patterson, senior currency strategist at J.P. Morgan Chase in New York.

2.2 Contingent Structural Change

Sullivan's (2013) *WSJ* study finds that although fundamentals factors are the main drivers of currency markets, how they do so does not remain fixed. The data indicate that there are stretches of time over the sample in which the composition of fundamental variables that are reported to drive the exchange rate, and the qualitative relationships with which they do, remain largely unchanged. But, at unpredictable points in the sample, this composition changes.

Analysis of the *WSJ* data suggest that there are three break points in the sample, giving rise to four exchange rate regimes, each with a distinct set of fundamental factors. Table 1 presents the dates of each regime and the fundamentals that were reported to be the most important in each sub-period.

The first regime, which spans 1999 and 2000 and saw an upward trend in the value of the dollar, was largely a continuation of a US growth story that began in the mid-'90's. Throughout this period, a strong flow of foreign direct investment into the U.S. was a key factor in the economy easily sustaining its current account deficit and in the strength of the dollar. The US economy's performance during this time led many European companies to seek a foothold in the US, leading to strong merger and acquisitions flows. The *WSJ* reporting also indicates that rising US stock prices during the period were viewed by market participants as an indication of future strength in the US economy. Our empirical model for this regime proxies

[16] Frydman, Goldberg, and Sullivan (2013) develop an IKE Taylor-rule model.

these influences with the unemployment differential between the the US and EU and the S&P 500 price index.

Several economic and geopolitical events coincided to cause a reversal in the trend of dollar appreciation. A sharp drop in US interest rates in response to the US recession that began in late 2000 along with heightened global turmoil due to the terrorist attacks of 9/11 combined to focus the market's attention on concerns about the US's continued ability to fund its current account deficit, requiring daily inflows of over $1 billion. This transition signaled the end of the first regime and the beginning of the second, which continued until the end of 2004 and was characterized by a downward trend in the dollar. According to the *WSJ*, signs of global growth led investors to seek higher returns elsewhere. At the same time, increases in global turmoil led investors to seek shelter not in the dollar, but in other currencies such as the Swiss franc, due to continued concerns about the US current account.

This regime was also characterized by market participants' increased focus on interest rate expectations. Between January 2001 and January 2002 the Federal Reserve cut interest rates by 4.75% leading to increased use of the dollar as a global funding currency. Throughout 2002-2004 market participants paid close attention to any signals from the economy as to the future course of US monetary policy, as shown in the previous excerpt from January 12, 2004.

Our empirical model for the second regime approximates these drivers in two ways. First, the *WSJ* provides support to a Taylor-rule models connection between interest rates and unemployment and inflation rates. We thus include unemployment and inflation rate differentials for the US and EU to capture the effect of interest rate expectations on the exchange rate. Second, to more fully account for market participants' concern regarding the US current account, we include the interest rate differential and world GDP.

By late 2004 the situation was again in transition. Responding to the rapid growth in the US economy, the Federal Reserve executed 12 consecutive interest rate increases from mid-2004 through mid-2006. This rapid increase in rates caused a stark reversal in the process driving exchange rates – the US dollar stopped serving as funding currency, as it was when rates were 1%, and became a high-yield currency, with interest rates toping out at 5.25% with a 2% advantage over the ECB rate. Yet the dollar did not appreciate against the euro during the entire time that US rates were on the rise. Instead, in late 2005 when market participants began to expect a slow down or potential end to the Fed's rate-tightening cycle, due to the signals coming from the economy, the dollar reversed course, giving back all of its gain made in 2005.

This regime is primarily a story of interest rate expectations, especially regarding US rates. Consequently, our empirical model for the third regime includes unemployment and inflation rate differentials to approximate the importance of this consideration. Given the added emphasis on US rates, we also include an alternative measure of interest rate expectations, given by the spread between the US 10-year bond rate and the 1-year Treasury-bill rate. Together we can think of the unemployment and inflation rate differentials and the term-spread as providing near-term and medium-term measures of interest rate expectations, respectively.

This regime continued until the start of the US housing and sub-prime mortgage crisis in early 2007. As the scope of the crisis grew and its ability to impact global financial markets became more apparent, there was again a reversal in the direction of safe haven flows – this time into the US rather than away from it. According to the *WSJ*, market participants during this period watched for any news on whether the crisis was deepening or dissipating, moving into and back out of the dollar as the news oscillated between the two.

Our empirical model in the fourth regime captures this effect by including both world GDP and the US LIBOR-OIS spread, along with unemployment and inflation rate differentials to account for interest rate expectations. The LIBOR-OIS spread is the difference between the USD LIBOR interest rate and the overnight indexed swap rate. This spread was a closely watched barometer of financial stress in the interbank loan market during the financial crisis. Prior to August 2007 the spread was around 10 basis points, but following the onset of the crisis the spread rose to between 50 and 90 basis points, reaching a peak of 350 basis points following the announcement that Lehman Brothers had filed for bankruptcy.[17]

Sullivan (2013) discusses in detail how the selection of factors and regime dates is carried out and the results of recursive structural change procedures that support the breakpoints found on the basis of the *WSJ* data. It is clear from this analysis that no one could have fully anticipated when the shifts in the currency process would occur, let alone which fundamentals would be relevant or how they would matter for the exchange rate in each of the resulting regimes. For example, no one could have

[17] See Sengupta and Tam (2008) for more details regarding the LIBOR-OIS spread.

predicted the 2001 reversal of the US's traditional roll as a safe haven for investors, and few predicted the financial crisis, which saw a return of the US as a safe haven.

As we show now, allowing for such contingent change is crucial for uncovering a connection between macroeconomic fundamentals and exchange rate movements.

3 Resolving the Disconnect Puzzle: Learning vs. Contingent Knowledge

We carry out a Meese and Rogoff forecasting analysis of our empirical IKE and adaptive Taylor-rule models. This analysis compares the predictive accuracy of the economic models to that of a simple random walk, using mean-square error and direction of change metrics.[18] The details of the testing procedure are provided in the appendix.

Our piece-wise linear IKE model supposes that the distinct sets of fundamentals that matter for the exchange rate in each of the identified four regimes are those that are implied by the *WSJ* data. To give our adaptive Taylor-rule model the benefit of the doubt, we suppose that learning is based on a composite specification that includes all of the fundamental variables that were included in the IKE model in all four regimes.

3.1 Models that Fully Anticipate Structural Change

Examining the forecasting performance of the composite model and assuming that the process generating the exchange rate is stable, as Meese and Rogoff (1983) and subsequent researchers do, yields results that reconfirm the results presented in the literature – the structural exchange rate model generates out-of-sample predictions that are inferior those of the random walk. These results are presented in table 2.

Figure 1 depicts the time-series of the logarithmic exchange rate and the one-period ahead predictions of the three specifications of the economic model – representing the stable (REH), adaptive learning and IKE approaches. Focusing first on the stable composite model, which is given by the medium gray solid line, we see that the predictions appear to track the exchange rate reasonably well in the early part of

[18] Statistical significance of the difference between the MSE of the structural economic model and that of the random walk is estimated using the Diebold-Mariano (1995) test statistic.

the sample, but steadily deteriorate over the course of the sample becoming markedly inconsistent in late 2007. The deterioration of the accuracy of the predictions is what we would expect given the *WSJ* evidence that the causal process undergoes structural change over the course of the sample.

The dotted line in figure 1 depicts the 1-period ahead predictions of the constant gain adaptive learning model model, using a gain of $\gamma = 0.02$. This is conceptually equivalent to using a rolling window of 100 periods, or $8^1/_3$ years with monthly data. This is the same gain as used by Mark (2009) and is in the neighborhood of the rolling window used by Molodstova and Papell (2009, 2011), who use a window of 120 months. As we see in the MSE results shown in table 2, the adaptive learning model actually reduced the accuracy of the predictions compared to the stable composite model, which shows that this approach provides no help in modeling the contingent change underlying the data.

An alternative way to evaluate the forecasting performance of a model is to examine its ability to predict the direction of change (DC) of the exchange rate over the forecasting horizon. The DC statistic is the sample average, expressed in percentage terms, where 100% denotes that the model is correct 100% of the time for a given forecast horizon and time period. This approach emphasizes the qualitative accuracy of the model's predictions rather the point-forecast accuracy as given by MSE.

The results presented in table 3 indicate that the stable composite model and constant-gain adaptive-learning model are only able to predict the direction of change of the exchange rate roughly as well as the flip of coin. Again we see that the adaptive learning approach misses the unanticipated change in the currency process that occurs in the sample. Assuming that market participants continue to stick with this strategy would presume that they forgo profit opportunities. This conclusion results even if we use the ex-post optimal constant gain, as determined by the minimum MSE.[19]

[19] For these results, see Frydman, Goldberg, and Sullivan (2013). Interestingly the ex-post optimal gain is between 0.07 and 0.09 for $k = 1$, 3, 6 and 12. This corresponds to a rolling window of between 22 and 28 periods. A shorter window is consistent with higher levels of structural change as the model more quickly "moves past" the breaks, but as Kim (2009) notes the shorter the window the higher the variance of the estimates. It should be noted that using the ex-post optimal gains in the adaptive learning model results in significant improvements over the stable composite model, but as noted above this improvement is not sufficient to out-perform the random walk.

3.2 The IKE Piece-Wise Linear Model

The IKE piece-wise linear model is estimated separately for each of the four regimes, spanning January 1999 through January 2009. At the start of each regime, the coefficients are initialized using the first twelve observations of the sub-sample, after which predictions are generated until the end of the regime.

Returning to figure 1 and focusing on the solid and dashed light gray lines that denote the 1-period ahead predictions and initialization periods of the piece-wise linear model, we see that the light gray lines appear to track the exchange rate reasonably well over the entire sample and do not show the marked deterioration exhibited by either the stable composite or adaptive learning models.

The visual evidence is supported by the MSE results presented in table 2. We see that the piece-wise linear model generates significantly lower MSEs than the random walk at the 3 and 6 month horizons, and numerically lower MSEs at the 12-month horizon. The direction of changes statistics reported in table 3 tell a similar story. Based on this statistic, the piece-wise model outperforms the random walk model by significant margins, especially at the longer forecast horizons. At the 6- and 12-month horizons, the models is able to predict the right side of the market 82% and 100% of the time.[20]

Evidence that different sets of fundamentals matter in different sub-periods can be seen by estimating a model with one regime's fundamental factors for all other regimes. The results in tables 4 and 5 are based on using each set of regime specific factors to estimate the other regimes. They show a marked decrease in prediction accuracy. Strikingly, in only 12 of the 48 combinations of forecast horizons and regimes did the cross-regime factors generate numerically lower MSEs than the random walk. In contrast, the piece-wise linear model generates numerically lower MSEs in 75% of the 16 combinations of forecast horizons and regimes.

Returning to the direction of change metric we find that the cross-regime estimation results in average direction of change statistics of 55%, 70%, 62% and 66%, for each of the four sets of regime specific factors, respectively, averaged across all forecast horizons. Again this represents a marked decrease in accuracy when compared to the piece-wise linear model, which generates an average direction of change statistic of 77% correct.

[20]Statistical significance of the direction of change statistics is based on a binomial test using the null that the probability of success and failure are both $^1/_2$.

Together these findings show that the Meese and Rogoff exchange rate disconnect puzzle stems from a failure to recognize that the process underpinning the exchange rate undergoes contingent change and that rational market participants understand this feature of real-world markets. The adaptive learning model is unable to account for this contingent change. But, when we do, we find strong evidence of what the *WSJ* data revealed: exchange rate movements are driven by macroeconomic fundamentals.

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Appendix: Testing Procedure

Testing Procedure

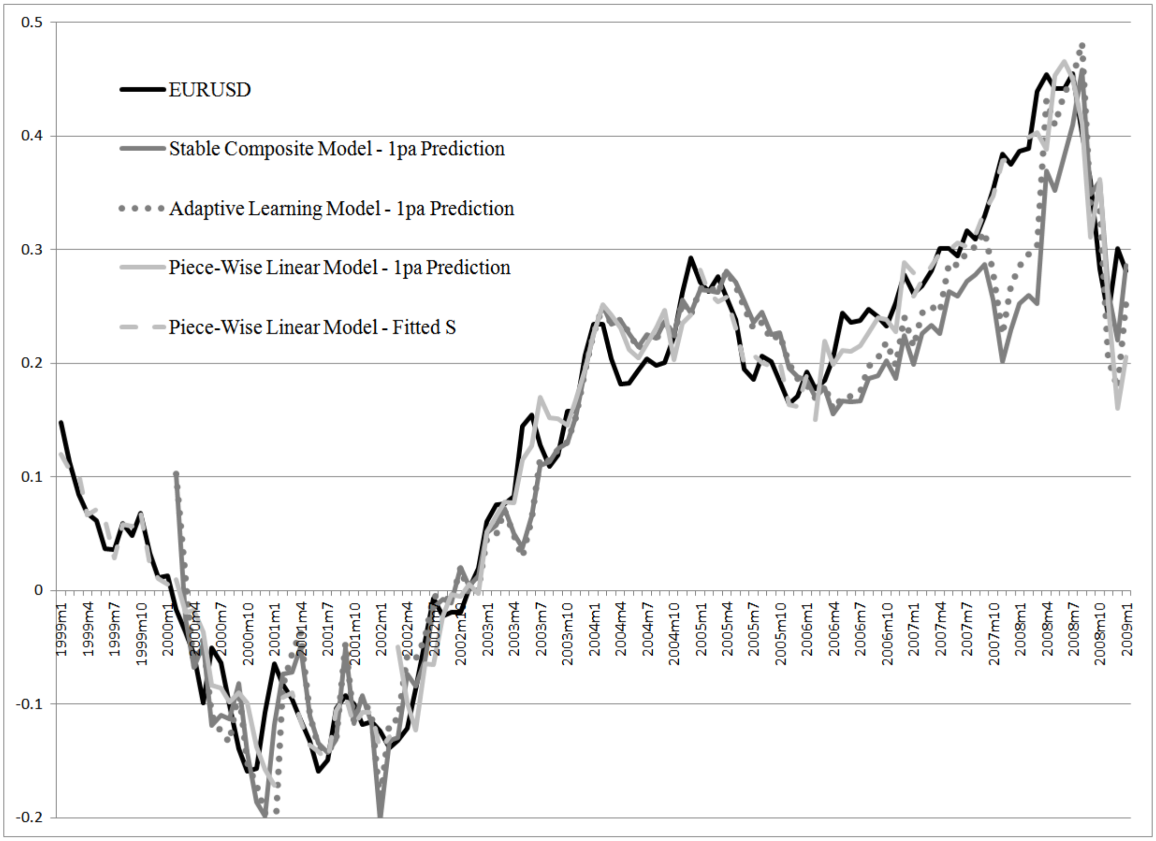
This study evaluates the out-of-sample fit of the model following the tradition of Meese and Rogoff (1983). This method compares the predictive accuracy of the structural economic model to that of a simple random walk, using mean-square error and direction of change metrics. In the tradition of Meese and Rogoff this is a prediction exercise rather than forecasting because the actual values of the future X's are used to generate the out-of-sample predictions as opposed to requiring these to be forecasted as well.

Predictions are made by estimating the model up to time t, which generates initial coefficient estimates for the model. These estimates are combined with the actual values of the X's at time t+k, where k is the forecast horizon. Predictions are generated for 1, 3, 6 and 12 month horizons. Then t is moved forward by one period and the model is re-estimated and new predictions are generated.

The random walk predictions are generated very simply. It assumes that the best prediction of the exchange rate for any point in the future is given by today's exchange rate. In terms of this out-of-sample exercise, this implies that the random walk prediction made at time t for $t+k$ is given by s_t, for k = 1, 3, 6 and 12.

From these predictions forecast error statistics are calculated for both the economic model and the random walk model. In this paper I evaluate the predicative ability of the model using mean square error statistic (MSE) and direction of change metrics. Statistical significance of the difference between the MSE of the economic model and that of the random walk is estimated using the Diebold-Mariano (1995) test statistic. The direction of change statistic reports how frequently the economic model correctly predicts the direction of change of actual exchange rate between t and $t+k$. The reported statistic is the sample average, expressed in percentage terms where 100% denotes that the model is correct 100% of the time for a given forecast horizon and time period. Statistical significance is based on a binomial test using the null that the probability of success and failure are both $^1/_2$

Figure 1: Fitted and Predicted Exchange Rate



This figure depicts the 1-period ahead predicted value from three models against the log euro-dollar exchange rate:

1. Stable composite model - estimated using the sample period: 1999m1-2009m1, predictions are made for 2000m2-2009m1.

2. Adaptive learning model - estimated recursively using a gain = 0.02 and using the sample period: 1999m1-2009m1, predictions are made for 2000m2-2009m1.

3. Piece-wise linear model - estimated separately for each of the four regimes: 1999m1-2001m1, 2001m1-2004m12, 2005m1-2007m1, 2007m1-2009m1. Predictions are made for: 2000m2-2001m1, 2002m3-2004m12, 2006m2-2007m1, 2008m1-2009m1.

"Fitted S" denotes the fitted value of the exchange rate during the initialization periods of the piece-wise linear model.

Table 1: Piece-Wise Regimes

Regime	Start	End	Factors
1	1999m1	2001m1	US & EU Unemployment, US Stocks
2	2001m2	2004m12	US & EU Unemployment, US & EU Inflation, US & EU 3m Interest Rates, World GDP
3	2005m1	2007m1	US & EU Unemployment, US & EU Inflation, US Term Spread
4	2007m1	2009m1	US & EU Unemployment, US & EU Inflation, World GDP, US LIBOR-OIS Spread

Data Description

- Unemployment - Unemployment Rates, in percentage terms. Source FRED and ECB
- Inflation - Year-over-year CPI(HCPI) inflation rates, in percentage terms. Source FRED and ECB
- 3m Interest Rates - 3-month LIBOR(EURIBOR) interest rate, month-end, in percentage terms. Source: FRED
- US Stocks - S&P 500 index, in log terms. Source: Moody's
- US Term Spread - Spread between 10-year US bond and 1-year T-bill rates, in percentage terms. Source: FRED
- US LIBOR-OIS Spread - Spread between the USD LIBOR interest rate and the Overnight Index Swap (OIS) rate, in percentage terms. Source: Bloomberg
- World GDP - Sum of the 40 countries who report quarterly GDP, interpolated from quarterly to monthly using the Chow-Lin procedure in RATS, billions of US dollars converted at current PPPs, in log terms. Source: OECD

Table 2: Out-of-Sample Prediction - Mean Square Error Statistics

		Panel A	Panel B
		Full Sample Composite Model	Piece-Wise Linear Model
	Model	MSE	MSE
k = 1	Stable Composite	.00307	
	Adaptive Learning	.00258	
	Piece-wise Linear		.00154
	Random Walk	.00066**	.00083***
k = 3	Stable Composite	.00616	
	Adaptive Learning	.00619	
	Piece-wise linear		.00282****
	Random Walk	.00278*	.00372
k = 6	Stable Composite	.01005	
	Adaptive Learning	.01090	
	Piece-wise linear		.00374**
	Random Walk	.00541*	.00754
k = 12	Stable Composite	.03541	
	Adaptive Learning	.03789	
	Piece-wise linear		.01356
	Random Walk	.01089*	.01997

Where k denotes the k-period ahead prediction. Statistical significance of the test statistics are denoted by: 1%:****, 5%:***, 10%** and 20%*, based on Diebold-Mariano (1995). This is a test for equal predictive accuracy by two models, the random walk model and the economic model in this case. The null hypothesis of the test is that two models are equally accurate on average, and the alternative is that the economic model has a lower MSE.

Panel A contains the estimation results using the full sample, 1999m1-2009m1, for the stable composite and adaptive learning models, along with the random walk predictions for the same period.

Panel B contains the results of the piece-wise linear specification, estimated separately for four regimes – 1999m1-2001m1, 2001m2-2002m2, 2005m1-2007m1 and 2007m1-2009m1 – with regime specific factors (see the table 1 for a list of factors used in each regime), along with the random walk predictions from the same four regimes.

Table 3: Out-of-Sample Prediction - Direction of Change Statistics

		Panel A	Panel B
		Full Sample Composite Model	Piece-Wise Linear Model
	Model	DC	DC
k = 1	Stable Composite	53.7%	
	Adaptive Learning	53.7%	
	Piece-wise Linear		65.7%***
k = 3	Stable Composite	51.9%	
	Adaptive Learning	50.0%	
	Piece-wise Linear		75.8%***
k = 6	Stable Composite	49.5%	
	Adaptive Learning	54.4%	
	Piece-wise Linear		82.0%***
k = 12	Stable Composite	54.6%	
	Adaptive Learning	53.6%	
	Piece-wise Linear		100.0%***

Where k denotes the k-period ahead prediction. The values reported in this table are direction of change statistics. Statistical significance of the test statistics are denoted by: 1%:***, 5%:*** and 10%**, based on a binomial test using the null that the probability of success and failure are both $^1/_2$. These statistics report the percentage of the time that the economics models correctly predicted the direction of change of the exchange rate between time t and t + k. A value greater than 50% signifies that the predictive capacity of the economic model is greater than the flip of a coin, but does not signify any statistical significance.

Panel A contains the estimation results using the full sample, 1999m1-2009m1, for the stable composite and adaptive learning models.

Panel B contains the results of the piece-wise linear specification, estimated separately for four regimes – 1999m1-2001m1, 2001m2-2002m2, 2005m1-2007m1 and 2007m1-2009m1 – with regime specific factors (see the table 1 for a list of factors used in each regime).

Table 4: Cross-Regime Factor Estimation

Forecast Horizon		Regime 1 Factors		Regime 2 Factors		Regime 3 Factors		Regime 4 Factors		# of Obs
k = 1		MSE	DC	MSE	DC	MSE	DC	MSE	DC	
in Regime 1	Piece-wise	-	-	.00648	50.0%	.00564	33.3%	.00340	41.6%	12
	Random Walk	-		.00112		.00112		.00112		
in Regime 2	Piece-wise	.00136	58.8%	-	-	.00109	55.9%	.00120	64.7%	34
	Random Walk	.00065		-		.00064		.00064		
in Regime 3	Piece-wise	.00295	41.7%	.00089	58.3%	-	-	.00121	33.3%	12
	Random Walk	.00032		.00032		-		.00032		
in Regime 4	Piece-wise	.00466	50.0%	.00379	83.3%	.00372	58.3%	-	-	12
	Random Walk	.00159		.00159		.00159		-		
k = 3		MSE	DC	MSE	DC	MSE	DC	MSE	DC	
in Regime 1	Piece-wise	-	-	.01774	70.0%	.00971	30.0%	.00667	20.0%	10
	Random Walk	-		.00422		.00422		.00423		
in Regime 2	Piece-wise	.00250	78.1%	-	-	.00214	78.1%	.00267	71.9%	32
	Random Walk	.00323		-		.00322		.00322		
in Regime 3	Piece-wise	.00872	20.0%	.00294	50.0%	-	-	.00302	70.0%	10
	Random Walk	.00107		.00106		-		.00106		
in Regime 4	Piece-wise	.01610	1.0%	.00845	80.0%	.00728	70.0%	-	-	10
	Random Walk	.00743		.00743		.00743		-		

Table 5: Cross-Regime Factor Estimation

Forecast Horizon		Regime 1 Factors		Regime 2 Factors		Regime 3 Factors		Regime 4 Factors		# of Obs
k = 1		MSE	DC	MSE	DC	MSE	DC	MSE	DC	
in Regime 1	Piece-wise	-	-	.04175	100.0%	.01297	57.1%	.01016	42.9%	7
	Random Walk	-		.00580		.00580		.00580		
in Regime 2	Piece-wise	.00455	62.1%	-	-	.00355	82.8%	.00412	72.4%	29
	Random Walk	.00664	-	-		.00663		.00663		
in Regime 3	Piece-wise	.02107	0.00%	.00406	57.1%	-	-	.00157	100.0%	7
	Random Walk	.00190		.00190		-		.00190		
in Regime 4	Piece-wise	.03564	42.9%	.00406	100.0%	.00117	85.8%	-	-	7
	Random Walk	.01863		.01863		.01863		-		
k = 12		MSE	DC	MSE	DC	MSE	DC	MSE	DC	
in Regime 1	Piece-wise	-	-	.09974	100.0%	.01019	100.0%	.01100	0.0%	1
	Random Walk	-		.00599		.00599		.00599		
in Regime 2	Piece-wise	.01153	74.0%	-	-	.01025	91.3%	.00647	100.0%	23
	Random Walk	.02161		-		.02161		.02161		
in Regime 3	Piece-wise	.07762	0.00%	.00919	0.00%	-	-	.01046	0.0%	1
	Random Walk	.00477		.00476		-		.00476		
in Regime 4	Piece-wise	.00787	100.0%	.01372	100.0%	.01581	100.0%	-	-	1
	Random Walk	.01128		.01127		.01127		-		