Finding a Connection Between Exchange Rates and Fundamentals

How Should We Model Revisions to Forecasting Strategies?*

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Abstract

In this paper I compare the performance of three approaches to modeling temporal instability of the relationship between the euro-dollar exchange rate and macroeconomic fundamentals. Each of the three approaches considered — adaptive learning, Markov-switching and Imperfect Knowledge Economics (IKE) — recognize that market participants revise forecasting strategies, at least intermittently, and, as a result, the relationship between the exchange rate and fundamentals is temporally unstable. The central question in the literature addressed by this paper is which of the three approaches to modeling revisions of market participants' forecasting strategies is most empirically relevant for understanding the connection between currency fluctuations and fundamentals? One of the objectives of comparing the out-of-sample forecasting of the three approaches to change is to test to what extent growth-of-knowledge considerations, as proposed by Frydman and Goldberg (2007, 2011), are empirically relevant for our understanding of currency fluctuations. I find that only the IKE model, developed from Sullivan (2013) is able to significantly outperform the random walk benchmark, suggesting that different sets of fundamentals matter during different time periods in ways that do not conform to an overarching probability law.

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In this paper, I consider a long-standing question in International Macroeconomics: Are exchange rate movements related to macroeconomic fundamentals, such as interest rates and national output? Over the last four decades, empirical researchers have uncovered little statistical evidence that fundamentals actually matter for currency fluctuations. Meese and Rogoff (1983) is perhaps the most often cited study showing what has come to be known as the "exchange rate disconnect puzzle". They compared the out-of-sample forecasting performance of the most popular exchange rate models of the 1970's, which were based on the rational expectations hypothesis (REH), with the performance of a simple random-walk model. Strikingly, Meese and Rogoff found that none of the exchange rate models' predictions would enable an economist to do any better than if they had merely flipped a fair coin.[1] Until recently, the consensus has been that "not only have a subsequent twenty years of data and research failed to overturn the Meese-Rogoff result, they have cemented it".[2] The dismal results have led many researchers in the field to conclude that macroeconomic fundamentals play no role for currency fluctuations.

However, in the past ten years, research on exchange rates shows promise that fundamentals may matter after all. A key insight of much of this work is the recognition that market participants revise their forecasting strategies, at least intermittently, and, as a result, the relationship between the exchange rate and fundamentals is temporally unstable. The literature has considered several approaches in modeling this change, including adaptive learning, Markov-switching, and imperfect knowledge economics (IKE). Research shows positive results for each of these approaches, although the various studies rely on different metrics, including in-sample regression, out-of-sample forecasting performance, or an ability to account for particular aspects of exchange rate dynamics, such as the persistence of fluctuations.[3]

The implications of these specifications of change have been examined in the context of both older monetary models and newer Taylor-rule models. Molodstova and Papell (2009, 2011), among others,[4] suggest that progress in solving the Meese and Rogoff puzzle stems

[1]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. Of course, a real forecasting exercise would need to predict the future values of the fundamental variables.

[2]Rogoff (2001, p. 1). For overviews of this literature, see Frankel and Rose (1995), Cheung, Chinn, and Pascual (2005), and Frydman and Goldberg (2007).

[3]For findings based on adaptive learning, see Molodstova and Papell (2009, 2011) and Mark (2009), for Markov switching, see Alta Villa and De Grauwe (2010) and Frömmel, MacDonald, and Menkhoff (2005), and for IKE, see Frydman and Goldberg (2007) and Beckmann, Belke, and Kühl (2011).

[4]See also Bengino (2004) and Engle and West (2006).

largely from not allowing for structural change, but from relying on models in which the conduct of monetary policy entails setting the short-term interest rate rather than monetary growth as is assumed in by the older monetary models.

In Sullivan (2013), I address the question of which exchange rate model—and thus which set of fundamentals—is most relevant for explaining short-term exchange rate movements. Researchers typically employ regression analysis in exploring this question. However, Sullivan (2013) relies on a less restrictive and arguably more informative approach to determine the set of relevant fundamentals. The analysis makes use of a novel dataset that was constructed by reading every *Wall Street Journal* (*WSJ*) daily currency report for the main factors that it reported drove the euro-dollar exchange rate on a particular day and whether these factors influenced this rate positively or negatively.[5] In contrast to econometric studies that largely test whether the an asset price is related to a particular set of fundamental variables, *WSJ* stories are unconstrained as to which variables they might report as being important on a particular day.[6] The results of this study imply that interest rate expectations play a key role as a driver of daily exchange rate movements. They therefore provide support for Taylor-rule models, which relate currency movements to expected-inflation and output gaps.

In this paper, I make use of and extend my *WSJ* results to explore another central question in the literature: Which of the three approaches to modeling revisions of market participants' forecasting strategies — adaptive learning, Markov-switching, or IKE — is most empirically relevant for understanding the connection between currency fluctuations and fundamentals? Individual studies report varying degrees of success using different approaches and different metrics of empirical relevance. No one study has compared the relative performance of the three approaches, which would entail evaluating non-nested models. In order to deal with this difficulty, I compare relative performance on the basis of out-of-sample forecasting. My main objective is to shed new light not only on whether fundamentals matter for currency fluctuations, but also on how best to understand the nature of this connection.

[5] Other studies - for example, Dominguez and Panthaki (2006) and Andersen and Bollerslev (1998) - have used textual data in examining behavior in asset markets. These studies are largely based on simple word counts, which, unlike Sullivan's *WSJ* data, neither discriminate between factors that are reported to have mattered for exchange rates and those that are merely mentioned, nor provide an indication of the qualitative relationships driving the market.

[6] In addition to fundamental considerations, such as interest rates, income and inflation, *WSJ* journalists report that psychological considerations, such as confidence, optimism, and fear, as well as chartist considerations, such as momentum trading, also play important roles in the day-to-day trading decisions of professional players. See Sullivan (2013) for an extensive discussion of the role of non-fundamental factors in driving currency fluctuations.

On the question of whether fundamentals matter, the econometric evidence is mixed even after allowing for time-varying parameters in the analysis. This evidence shows that each of the approaches for doing so enables researchers to out-perform linear versions of these models. However, the evidence is less clear about whether any of the three approaches to allowing for structural change enables the resulting non-linear exchange rate models to beat the random walk in out-of-sample forecasting.

Molodstova and Papell (2009, 2011) report such success for a Taylor-rule model in which parameter updating occurs using a rolling-window regression.[7] But, Rogoff and Stavrakeva (2008) question the validity of the study's test statistic and the robustness of its results to alternative sample periods. Frömmel, MacDonald, and Menkhoff (2005) and Alta Villa and De Grauwe (2010) consider Markov-switching models based on a monetary specification and report clear evidence of regime switching, and thus of piece-wise linearity. But, these studies report only limited evidence of out-of-sample forecasting that is superior to the random walk. Frydman and Goldberg (2007) and Beckmann, Belke, and Kühl (2011) also consider piece-wise-linear monetary models. But, instead of imposing a Markov chain on switching, they use less restrictive procedures that are consistent with IKE's premise that change in the exchange rate process does not conform to an overarching probability rule. Both studies report piece-wise-linear cointegration between the exchange rate and monetary fundamentals. Frydman and Goldberg (2007) explore the out-of-sample forecasting performance of the IKE approach. They report that their model beats the random walk by considerable margins in terms of root-mean-square error, but provide no measure of the statistical significance of these margins.

Frydman and Goldberg (2007, 2011, 2013a) argue that the reason why the Meese-Rogoff result is found in so many studies is not simply because researchers ignore temporal instability, but because they fail to recognize the importance of unanticipated change and the growth of knowledge concerning the exchange rate process. Both adaptive-learning and Markov-switching models impose an overarching probability distribution on how participants might change the ways they think about the future. As such, these determinate accounts assume away the importance of the growth of knowledge for driving outcomes.[8] By contrast, Fryd-

[7] As I discuss in more detail in section 1.1, Orphanides and Williams (2005) show that the rolling window regression employed by Molodstova and Papell (2009) is conceptually equivalent to a least square learning rule with a small constant gain parameter. See also Evans and Honkapohja (2001) for a detailed discussion of learning algorithms.

[8] As Karl Popper put it, "[i]f there is such a thing as growing human knowledge, we cannot anticipate today [even in probabilistic terms] what we shall only know tomorrow" (Popper, 1957, p. xii). Popper (1957) provides a proof of this "self-evident" proposition.

man and Goldberg's (2007) piece-wise linear, IKE approach is open to the growth of knowledge. It does restrict change by supposing that there are extended stretches of time in which revisions and other changes in the currency process are relatively stable. But, it is also supposes that at unpredictable moments of time, the currency process undergoes significant change that could involve different sets of relevant fundamentals. Frydman and Goldberg (2013a,b) argue that allowing for such growth of knowledge is central for understanding outcomes in asset and other markets. One of the objectives of comparing the out-of-sample forecasting of the three approaches to change is to test to what extent growth-of-knowledge considerations are empirically relevant for our understanding of currency fluctuations.

Sullivan (2013) finds that the *WSJ* data are consistent with the implications of the piece-wise linear approaches, that there are extended stretches of time over the sample during which the composition of fundamental variables that are reported to drive the exchange rate remains largely unchanged. He also finds that there are more-or-less discrete points in the data at which the composition of relevant fundamentals changes and that different sets of fundamentals matter during different time periods.[9] These results suggest that the Markov-switching and IKE approaches may be superior to the adaptive learning approach. Sullivan's (2013) *WSJ* analysis is also suggestive of the importance of unanticipated change and the growth of knowledge for understanding the connection between exchange rate movements and fundamentals. In the present paper, I examine this issue on the basis of out-of-sample forecasting performance.

In section 1, I review the three different approaches to modeling revisions of market participants' forecasting strategies. Section 2 discusses the *WSJ* dataset and summarizes Sullivan's (2013) results concerning the importance of Taylor-rule fundamentals and temporal instability. These results lead me to carry out my Meese and Rogoff analysis of the three approaches to revisions in the context of a Taylor-rule exchange rate model. However, Sullivan's (2013) *WSJ* analysis shows that variables other than the expected-inflation and output gaps are at times important for euro-dollar fluctuations. To capture the influence of these other variables, I include in my empirical specifications factors such as world GDP and the US TED spread.[10] I show in section 2 how the Taylor-rule model can be modified to incorporate these additional variables.[11] Section 3 reports the results of an out-of-sample

[9]Other findings in the literature similarly find that the importance of fundamentals appears to change over time. See for example Frömmel, MacDonald, and Menkhoff (2005) and references therein.

[10]The US TED spread is the difference between the three-month USD LIBOR and the three-month US T-bill interest rate.

[11]See Mark (2009), Engel, Mark, and West (2008) and Molodstova and Papell (2009), among others, for examples of papers that employ a Taylor-rule fundamentals exchange rate model.

forecasting analysis. It employs two test statistics, one based on root-mean-square error and the other on correctly predicting the direction of change of the exchange rate.

To highlight my results, I find, like other studies, that my "Taylor-rule-plus" model 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 an adaptive-learning rule yields little improvement over this baseline result. By contrast, both the Markov-switching and IKE approaches show considerable improvement in forecasting performance relative to the linear, no-change model. However, only the IKE model is able to significantly outperform the random walk benchmark using both prediction-error and direction-of-change metrics. The results support those of Frydman and Goldberg (2007) and Sullivan (2013), which indicate that different sets of fundamentals matter during different time periods in ways that do not conform to an overarching probability law. They are also consistent with Frömmel, MacDonald, and Menkhoff (2005), who conclude that "although the [Markov-switching model] captures most of the structural instability in the coefficients, there is still some additional source of time variation left."[12]

1 Changes in Expectations

A key insight of much of the recent research that has shown progress on resolving the Meese-Rogoff finding is the recognition that market participants revise their forecasting strategies, at least intermittently, and, as a result, the relationship between the exchange rate and fundamentals is temporally unstable.

This is in sharp contrast to much of the work that underpins the exchange rate disconnect puzzle that assumes a time-invariant structure, often implying that the causal process has remained unchanged since the end of the Bretton Woods agreement. Increasingly there is evidence that the widespread use of time-invariant models has likely led to the common finding that "model/specification/currency combinations that work well in one period do not necessarily work well in another period".[13]

The persistent finding of unstable empirical results has motivated the development of many approaches to modeling temporal instability in the relationship between the exchange

[12]Frömmel, MacDonald, and Menkhoff (2005, p. 500).

[13]Cheung, Chinn, and Pascual (2005, p. 1150). See also Meese (1986, p. 365), who comments that "the most menacing empirical regularity that confronts exchange rate modelers is the failure of the current generation of empirical exchange rate models to provide stable results across subperiods of the modern floating rate period."

rate and its fundamentals. These approaches include smooth time-varying parameter models, such as random coefficients and adaptive learning models, and regime changing models, such as STAR, Markov-switching and IKE models. While individual studies report varying degrees of success using one of the approaches, no study has compared the empirical performance of all three approaches. This papers aims to begin to fill this void.

Recent positive findings in the literature employing the adaptive learning and Markov-switching approaches led me to select these two approaches as representative examples of the smooth time-varying and regime switching classes of models. Specifically I consider Molodstova and Papell (2009) and Frömmel, MacDonald, and Menkhoff (2005) as characterizing these two classes of models.[14] The IKE approach, as discussed in more detail below, is differentiated from the Markov-switching because it represents what Frydman and Goldberg (2013c) call a partly-open model. They consider the partly-open class of models to be mutually exclusive from what they refer to as determinate models, which they argue includes both adaptive learning and Markov-switching. It is therefore relevant to consider two types of regime changing models for comparison.

The degree of "restrictiveness" of the models, both in terms of whether the models are open to unanticipated change and limitations on the type of change that may take place, can be seen be examining the restrictions each approach places on how market participants might revise their forecasting strategies over time. Adaptive learning models assume that market participants know the "correct" structural model, i.e. functional form and information set, yet must learn about the parameters of the model over time using least squares learning. This approach restricts the composition of factors to be constant, but allows for continuous movement in the parameter values following a fixed learning rule. In contrast the Markov-switching and IKE approaches highlight the potential for discrete breaks in the driving process, but assume stable parameters within regimes (or states) — implying a piece-wise linear relationship. The Markov-switching approach allows for multiple state dependent regimes, allowing the composition of factors to differ across states. The parameters are assumed to be constant within states, implying that the parameter values and composition of factors are the same for all regimes of a given state. The IKE approach highlights the potential role of non-routine change due to the growth of knowledge and the importance of psychological and technical considerations in the driving process. It assumes that each regime may be distinct and does not specify precisely either when or how change may take

[14]As I discuss in more detail in section 1.1, while Molodstova and Papell (2009) employ a rolling window regression rather than a least squares learning algorithm, Orphanides and Williams (2005) show that these are very closely related estimation procedures.

place, instead imposing qualitative and contingent restrictions on change.

All three of these approaches can be nested within the following general framework, making use of a well-known equilibrium condition for the foreign exchange market, uncovered interest rate parity (UIP), which I 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 many exchange rate 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 or a short position in foreign exchange equals zero.

A general 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 many types of fundamentals based models, including monetary and Taylor-rule fundamentals.

As is clear from (1) and (2), movements in the exchange rate stem from movements in the fundamentals and revisions of market participants' forecasting strategies, given by:

$$\Delta\hat{s}_{t|t+1} = \Delta\beta_t Z_t + \beta_{t-1}\Delta Z_t \tag{3}$$

where Δ denotes the first difference operator. I 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. Market participants' learning is represented by a recursive least squares algorithm that relies on a small constant gain.[15]

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

$$s_t = c_t Z_t + \varepsilon_t \tag{4}$$

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:

$$c_t = c_{t-1} + \gamma_t R_t^{-1} Z_t \left(s_t - Z_t' c_{t-1}\right) \tag{5}$$

$$R_t = R_{t-1} + \gamma_t \left(Z_t Z_t' - R_{t-1}\right) \tag{6}$$

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 $\gamma = 2/L$.[16]

Recent examples of adaptive learning models include Mark (2009) and Molodstova and Papell (2009), who using Taylor-rule fundamentals models report positive results in modeling exchange rate persistence and short-term out-of-sample forecasting, respectively. These results, along with other studies such as Orphanides and Williams (2005), suggest that the dynamics caused by the learning process may have interesting applications to the study of exchange rates.

Yet, there is also conflicting evidence regarding their applicability. Kim (2009), along with many others, finds evidence of several important regime changes in US monetary policy that may imply that market participants face unanticipated occasional regime shifts in

[15] This 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.

[16] See Orphanides and Williams (2005, p. 9).

the economic environment.[17] When these are incorporated into his simulation study of an adaptive learning model he finds that the adaptive learning model combined with a small number of structural breaks, which results in piece-wise specification, performs better than a model without breaks in terms of volatility and persistence.[18]

Similarly, surveys of foreign exchange market participants, reported in Menkhoff (1998), Cheung and Chinn (2001) and Cheung, Chinn, and Marsh (2004), present strong evidence that market participants regard the importance of fundamentals as time-varying. The studies of Cheung and Chinn (2001) and Cheung, Chinn, and Marsh (2004) report the results of surveys conducted of US and UK foreign exchange dealers, respectively. In particular the dealers were asked which announcements of fundamentals they regarded as most important for their market. Their responses, summarized in Frömmel, MacDonald, and Menkhoff (2005), indicate that while the importance of fundamentals differs somewhat across countries, the difference in importance over time of individual factors is “enormous”. For example the change in the response to the importance of unemployment in the US between 1991 and 1996 was an increase of 16.7%. Over a similar time period the importance of UK unemployment similarly increased by 17.8%, from 9.2% of responses in 1993 to 27% in 1998.

Together the survey results, along with empirical results, such as Sarno and Valente (2009), Bacchetta and Van Wincoop (2004) and Beckmann, Belke, and Kühl (2009), among others, suggest that there is strong empirical evidence that the importance and/or composition of factors that appear to drive exchange rate movements changes significantly over time. Importantly for the adaptive learning approach, there appears to evidence that this change may be more abrupt than the constant gain algorithms may be able to accommodate. But the impact this may have on the out-of-sample performance of the models is unclear from the existing literature.

1.2 Markov Switching

Motivated in large part by the survey findings discussed above, Frömmel, MacDonald, and Menkhoff (2005) employ a Markov-switching real interest differentials (RID) model. Their study, along with other examples such as Clarida et al. (2003) and De Grauwe and Vansteenkiste (2001), present evidence of regime switching in several currency pairs, find-

[17] The presence of structural instability in macroeconomic time series data has been well documented in the literature, see for example Stock and Watson (1996) and Bai and Perron (1998).

[18] Kim (2009, p. 844).

ing that their regime switching models significantly outperform linear versions of their models.

The Markov-switching model, popularized by Hamilton (1989) and Engle and Hamilton (1990), allows the coefficients of the model to be state dependent, such that for a two state model:

$$\hat{s}_{t|t+1} = \begin{cases} \beta_1 Z_t + \epsilon_t, \text{if } S_t = 1 \\ \beta_2 Z_t + \epsilon_t, \text{if } S_t = 2 \end{cases} \tag{7}$$

where S_t is the unobserved state of the model. This of course can be generalized to be an n-state model, but in practice is most often estimated using two and less frequently three states. For simplicity in this sketch I will limit the discussion to two states, although the main points can be generalized to higher state processes.

The state variable S_t is assumed to follow a first-order Markov process and is characterized by the matrix Π consisting of the transition probabilities p_{ij} from state i to state j:

$$\Pi = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix}, p_{ij} = Pr(S_t = j | S_{t-1} = i) \tag{8}$$

where p_{ij} is the probability of being in state j conditional on being in state i in the preceding period. Using these switching probabilities, the sample period can be delineated into two or more state dependent regimes. An individual regime is defined as the subsample occurring between switches in the state variable, as defined by p_{ii} going from greater than 0.5 to less than 0.5 or vis-versa.

For example, if the full sample runs from $t = t_o, \ldots, T$ and p_{11} switches from greater than 0.5 to less than 0.5 only once at time t_1, this would define two regimes in the data. This first existing between t_0 and t_1 and the second from t_{1+1} to T. In the case of a single switch, each state corresponds to a single regime.

The Markov process has important implications for how market participants' forecasting strategies are assumed to unfold over time. As motivated by the evidence of changing importance of fundamentals over time given the survey studies, the structure of (7) allows for the both the composition of factors and their interpretation, i.e. the parameter values, to change between states. Importantly this approach requires no *a priori* assumptions regarding the exact timing of regime change or the composition and sign of factors in a particular state or differences between states, but does assume a fixed probability distribution.

This approach incorporates a greater degree of freedom for how market participants might change their forecasting strategies over time as compared to the adaptive learning approach, in that the composition of factors is allowed to change over time. Although, unlike the adaptive learning model the Markov model assumes constant parameter values within states.

Yet, the freedom to change composition and parameter values is restricted by the number of states. For example, if a given state corresponds to multiple regimes, the forecasting strategy is assumed to be state dependent and therefore is the same across the multiple regimes of a given state. This implies not only that the same coefficients, but also the same set of causal factors is assumed to be used by market participants (at least in the aggregate) every time a given state arises. The broader implication of this, is that for a fixed number of states changes in forecasting strategies are assumed to unfold the same way over time, where changes between states are governed by the switching properties of the Markov chain.

1.3 Imperfect Knowledge Economics

One of the motivations for considering which approach is best supported by the data are questions posed by the recent work of Frydman and Goldberg, who draw a sharp distinction models that are open to unanticipated change and those that are not. In their recent work they propose that models that are closed to unanticipated change, which they call determinate models, of which they consider all REH models to be apart of, to be "abstractions of rational decision-making in 'markets' in which knowledge does not grow."[19]

Frydman and Goldberg (2013d) define determinate models as being models that, conditional on their structure at any point in time, specify in advance all potential structures that might represent the process driving outcomes at any other point in time. They argue that most time-varying parameter approaches, including adaptive learning and fixed state Markov-switching models, fall into this class of models because the economist must fully specify in advance when and how changes between structures might occur, at least probabilistically.

Yet, they recognize that if as they propose, determinate 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. This uncertainty gives rise to the question of which approach is best supported by the data.

[19]Frydman and Goldberg (2013c, p. 3).

Motivated by Karl Poppers' insight that "If there is such a thing as growing human knowledge, we cannot anticipate today what we shall only know tomorrow"[20], Frydman and Goldberg (2013a) propose an analog to REH that they call the contingent expectations hypothesis (CEH). This hypothesis proposes that in order to build models that are compatible with rational decision making in the 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.[21]

Recognizing the importance of non-routine change, they propose what they refer to as partly-open models. That is, models that are left partly-open to unanticipated change. Yet, change must still be constrained in order to produce testable implications. They propose that "conditional on a causal structure at any point in time, a partly-open model does not specify in advance the exact structures that may be need to represent the market process at any other point in time."[22]

This proposition assumes that their are certain qualitative aspects of an economist's knowledge that do no change over time. If the model is fully-open to change, there would be no persistent regularities present to represent economist' or market participants' understanding of the causal process.

Motivated by Keynes' (1936) insight that market participants do not rely on fundamentals and calculation alone, but also "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"[23], Frydman and Goldberg propose qualitative and contingent constraints to structural change. These constraints recognize that even armed with "specific reasons to expect a change," it is entirely unclear what new forecasting strategy, if any, she should adopt.

Frydman and Goldberg formalizes the concept of qualitative and contingent constraints, applied to the expression for structural change given by (6), with what they 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 (3) that any stretch of time

[20]Popper (1957, p. xii).

[21]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).

[22]Frydman and Goldberg (2013c, p. 6).

[23]Keynes (1936, p. 152).

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.[24]

They propose however, that 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.

Continuing from equation (2) and following Beckmann, Belke, and Kühl (2011) and Hansen (2003), an IKE model can be expressed as follows. Let structural changes be introduced by allowing the parameters of the model to change their values at each of the break points: $T_1, \ldots, T_{m-1}$, where $0 < T_1 < \ldots < T_{m-1} < T$. Let m denote the number of independent regimes (or subsamples), such that

$$1_{jt} = \begin{cases} 1 & \text{if } T_{j-1} + 1 < t < T_j, \quad j = 1, \ldots, m \\ 0 & \text{else} \end{cases} \tag{9}$$

with the convention that $T_0 = 0$ and $T_m = T$. Applying this indicator function to equation (2), it can now be expressed as

$$\hat{s}_{t|t+1} = \beta(t) Z_t \tag{10}$$

[24] 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 $h = 1 \ldots n$, 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 I 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.

where the piece-wise constant time-varying coefficients are give by:

$$\beta_j(t) = \beta_1 1_{1t} + \ldots + \beta_m 1_{mt} \tag{11}$$

where β_j denotes the vector of coefficients in each of the m regimes. This is equivalent to estimating each of the regimes independently.

Examples of this approach include Goldberg and Frydman (2007) and Beckmann, Belke, and Kühl (2011). These studies estimate piece-wise linear monetary models, with independent regimes, estimated for the Deutschmark/euro-dollar exchange rate. The determination of break points between regimes is econometrically estimated using the CUSUM squared and Bai and Perron's (1998) testing procedure for structural breaks, respectively. Both papers report evidence of piece-wise cointegration between the exchange rate and fundamentals. In addition Goldberg and Frydman report that their model generates numerically lower prediction errors than the random-walk, although no tests of statistical significance were available.

The use of econometric structural break tests that are designed to minimize the residuals of the model, together with the significant increase in the number of free parameters in the composite model covering the full sample, i.e. the number of parameters in β_j in equation (11), raises possibility that the positive results from these IKE models are merely byproducts of over fitting the data.[25]

To alleviate the potential issue of over fitting the data, in this paper I make use of external information to both determine the break-dates and composition of each regime. Instead I make use of Sullivan's (2013) WSJ data, summarized in the following section, to address these aspects of the analysis. In this way the break dates and specific composition of factors in each regime of the IKE are chosen independently of the empirical model.

2 Wall Street Journal Data

Sullivan (2013) develops a novel data set from the *Wall Street Journal*'s daily currency column. The purpose of this data set is gain as close to direct insight as possible into the workings of the euro-dollar exchange rate market, so as to reveal to the greatest extent possible the process driving exchange rate movements. This insight sheds new light on several key debates in the exchange rate literature and provides new means of assessing the support

[25] In Beckmann, Belke, and Kühl (2011), there are at least thirteen free parameters in each of the nine regimes, spanning 1975 through 2007.

for different approaches to describing exchange rate movements, particular with regards to the characterization of structural change in the process driving exchange rates and choice of economic model. In addition this data allows for a non-statistical approach to specifying both the timing of regimes and the composition of factors within each regime of the IKE model.

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.[26] They also report on the importance of changes in the expectations of a range of fundamental factors, the "political and social atmosphere" as Keynes put it[27], 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 monthly and sample frequencies with which causal factors were mentioned in 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 Sullivan to examine which factors — fundamental, psychological, or technical — were the most important in driving the exchange rate over the 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 him 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 CEH's 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 — at least one fundamental factor is reported to be a driver of exchange rate movements on 70% of trading days and account for 71% of the more than 6,000 events recorded between 1999

[26]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.

[27]Keynes (1936, p. 162)

and 2010. 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 forfeited 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 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.

This finding that the composition of factors changes over time, likely corresponding to discrete breaks in the process, would seem to deal a serious blow to the support for the narrative of the adaptive learning approach that assumes a fixed and known information set. Kim (2009) finds in his simulation study that in the presence of structural breaks in the data generating process an adaptive learning model combined with a small number of structural breaks, which results in piece-wise specification, performs better than a an adaptive learning model without breaks in terms of volatility and persistence.[28] Yet, this evidence alone is insufficient to remove the adaptive learning approach from consideration.

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. This finding is used to specify both the timing of regime breaks and the composition of factors within each regime of the IKE model. 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. The empirical model for this regime proxies 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

[28] Kim (2009), pg 844.

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.

The 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, the 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.

The empirical model in the fourth regime captures this effect by including both world GDP and the US TED spread, along with unemployment and inflation rate differentials to account for interest rate expectations. The TED spread is the difference between the 3-month US T-bill interest rate and 3-month USD LIBOR 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.

Sullivan (2013) discusses in detail how the selection of factors and regime dates is carried out. It would seem 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 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.

The apparent unanticipated nature of the changes and the lack of repeating regimes would seem to provide evidence against the Markov-switching approach to modeling temporal instability. Yet, the magnitude of the impact of the differences in modeling change between the IKE an Markov-switching approaches, namely determinate versus partly-open change, remains uncertain and requires empirical analysis.

2.2 The Importance of Interest Rate Expectations

The exchange rate models sketched in this section 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.

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.

2.3 Exchange Rate Model

The *WSJ* reports provide a narrative of the causal process, emphasizing the role of interest rate expectations, which themselves are driven by movements in unemployment and inflation, along with additional, potentially regime specific, economic factors. In this paper I formalize this narrative into a Taylor-rule "plus" exchange rate model.

Taylor (1993) proposed that central banks sets monetary policy according to a reaction function, which has come to be known as a Taylor Rule. He proposed that central banks set their target policy interest rates, e.g. the Federal Funds rate in the US, according to a loss-function between deviations of inflation and output from their target and potential levels respectively. Following Taylor (1993) the monetary policy rule can be given by:

$$i_t^T = \pi_t + \delta y_t + \sigma(\pi - \bar{\pi}) + \bar{r} \tag{12}$$

where i_t^T is the policy rate, π_t is annual inflation, $\bar{\pi}$ is the target inflation rate, y_t is the output gap and $\bar{r}$ is the equilibrium real interest rate. Taylor proposed that $\gamma = \sigma = 0.5$ and that the target inflation and equilibrium real interest rates both equal 2%. This implies that inflation above 2% or output above its potential level causes the central to raise its target interest rate, and similarly decrease it if either of these are below their target or potential levels. Letting $\alpha = \bar{\pi} + \bar{r}$, the rule can be re-written as:

$$i_t^T = \alpha + \beta\pi_t - \delta y_t \tag{13}$$

Clarida, Galí and Gertler (1998) estimate monetary policy reaction functions for Germany, Japan and the US, for the period from 1979 to 1994. Similarly, Mark (2009) estimates reaction functions for the US and Germany/EU for the period from 1976-2007. Both papers conclude that the US and European monetary policy, in terms of their overnight policy rates, are well approximated by Taylor Rule style reaction functions. Due to complexities in deriving potential output and therefore the output gap, the closely related gap between the current unemployment rate and its natural rate is often used in its place.[29]

Exchange rate news-impact studies, such as Andersen et al. (2003), Clarida and Waldman (2007) and Faust et al. (2007), which look at the effects of news announcements on exchange rates using high frequency data, commonly find that the response of exchange rates to "news", i.e. the unexpected component of data releases, is "precisely in line with the predictions of Taylor-rule models."[30] That is, that higher than expected inflation or economic activity leads to an appreciation of that country's currency.

Motivated by the *WSJ* data and bolstered by the findings above, I incorporate the reaction functions into an exchange rate model. Like many exchange rate models, my starting point is the well-known equilibrium condition for the foreign exchange market, uncovered interest rate parity (UIP), which I express as follows:

$$s_t = \hat{s}_{t|t+1} + \omega_t(i_t^* - i_t) \tag{14}$$

where s_t denotes the logarithm of the spot exchange rate, i_t and i_t^* are the domestic and

[29] See for example Molodstova and Papell (2009, 2011), Mark (2009) and Clarida, Galí and Gertler (1998).

[30] Engel, Mark, and West (2008, p. 384).

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.

Again motivated by the *WSJ* data, I specify the market's exchange rate forecast to be a function of the expected policy rate and additional economic factors, as discussed above, where the policy rate is given by a reaction function, such that:

$$\hat{s}_{t|t+1} = \gamma_{1,t}\hat{i}_t^T + \gamma_{2,t}\hat{i}_t^{T*} + \Gamma_t Y_t \tag{15}$$

where $\hat{i}_t^T$ denotes the expected policy rate for each country, given by (13), and Γ_t is vector of coefficients associated with Y_t, a vector of additional economic factors. Substituting equations (13) and (15) into (14) yields the following expression for the exchange rate:

$$s_t = a_t + b_{1,t}\pi_t - b_{2,t}\pi_t^* - d_{1.t}u_t + d_{2,t}u_t^* + \omega_t(i_t^* - i_t) + \Gamma_t Y_t + \varepsilon_t \tag{16}$$

where the constant, a_t, captures the inflation rate targets and natural rates of unemployment for both countries.[31] In estimation the year-over-year changes in CPI and HCPI inflation rates are used along with monthly unemployment rates, and Y_t denotes additional factors, as suggested by the *WSJ* data. Specifically these data suggest that there are four sets of regime specific factors, which include the spread between US short and long interest rates, S&P 500 index, World GDP and the spread between US 3-month treasury bills and 3-month LIBOR, details of which are shown in table 1.

In estimation Y_t is assumed to include all four additional factors, except the IKE model, which is estimated using regime specific factors as given by table 1.

3 Out-of-Sample Forecasting

In this section I carry out a Meese and Rogoff forecasting analysis of each the three approaches. 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.[32] The details of the testing procedure are provided in the appendix.

Testing the adaptive learning model along this metric is straightforward: I use the first 12 months of our sample (which runs from January 1999 through January 2009) to obtain

[31]For the US and EU these terms are nearly constant over the sample period considered. Any changes should be captured by the time-varying estimate of a_t.

[32]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.

initial least-squares estimates of the coefficients and then recursively update the model one observation at a time according to equations (5) and (6), computing forecast errors at every step. I measure forecasting performance at each horizon by averaging the forecast errors that are produced over the entire sample.

Estimation of the Markov-switching model is computationally more complex because there are now two sets of coefficient estimates. I first estimate the model using the full sample to derive estimates of the switching probabilities that determine which state the model is expected to be in a a point in time. Regime classifications are reported in table 2. Taking these as given, I then recursively estimate the coefficients for each state via OLS, using the first 12 observations of each state to initialize the coefficients. Predictions are generated using the recursively estimated coefficients of each state, such that:

$$\tilde{s}_{t|t+k} = \hat{\beta}_t(S_i)X_{t+k} * \prod_{l=t}^{t+k} p_{ii_l} + \hat{\beta}_t(S_j)X_{t+k} * \prod_{l=t}^{t+k} p_{ji_l} \tag{17}$$

where $\tilde{s}_{t|t+k}$ denotes the k-period ahead prediction, given that you are in state i at time t. $\hat{\beta}_t(S_i)$ denotes the coefficient estimates conditional on being in state i and pii_t denotes the probability of remaining in state i given that you were in state i in the previous period. Similarly for $\hat{\beta}_t(S_j)$ and p_{ji_t}.[33]

The 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. This gives rise to four independent regimes, which are each estimated separately. To give the adaptive learning and Markov-switching model the benefit of the doubt, I suppose that these models are 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 Time-invariant and Adaptive Learning Models

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 the table 3 under the row “Stable Composite”.

[33] It should be noted that in the first regime, which corresponds to state 1, a state 2 regime has yet to be observed so there exist no time t estimates of $\hat{\beta}_t(S_2)$. Therefore I use the full sample estimates of $\hat{\beta}_T(S_2)$ to calculate the k-period ahead prediction during the first regime observed in the data.

Figures 1 and 2 depict the time-series of the logarithmic exchange rate and the one-period ahead predictions of the four specifications of the economic model — representing the stable (REH), adaptive learning, Markov-switching and IKE approaches. Focusing first on the stable composite model, shown in figure 1, which is given by the solid gray line, we see that the predictions appear to track the exchange rate reasonably well in the early part of the sample, apart from a large deviation aroud the start of 2001, but steadily deteriorate over the course of the sample becoming markedly inconsistent in mid 2006. The deterioration of the accuracy of the predictions is what we would expect given evidence that the causal process undergoes structural change over the course of the sample.

The dashed 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 $8\frac{1}{3}$ 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 3, the adaptive learning model only marginally increases accuracy of the predictions compared to the stable composite model. This result is consistent with the evidence presented in this paper and elsewhere that the process driving exchange rates likely undergoes periodic discrete breaks, which may include changes in the composition of factors over time.

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.[34]

[34] 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

This results is not consistent with the out-of-sample results reported in Molodstova and Papell (2009), whose results are based on an both an alternative specification of a Taylor-rule fundamentals model[35] and an alternative testing procedure, proposed by Clark and West (CW) (2006). This test is based on the assumption that the Diebold-Mariano (DM) (1995) is biased in favor of the random walk under the null of equal predictive accuracy. Rogoff and Stavrakeva (2008) question the validity of the CW test, proposing that in the presence of forecast bias, the CW test for nested models cannot be always interpreted as minimum mean square forecast error tests.[36]

In addition, the asymptotic distribution of the test is only well defined in the case of a rolling window regression.[37] It is unclear what the implications are of using a rolling window estimation of a constant gain learning model. I therefore do not consider the CW test statistic in this study.

3.2 The Markov-Switching Model

The results of the Markov-switching models, which highlight the potential for discrete breaks in the driving process, show a marked increase in performance relative to the stable composite and adaptive learning models. One-period ahead predictions, depicted in figure 2 by the solid gray line, show little visual evidence of the progressive deterioration of the model over time, as exhibited by the adaptive learning and stable composite models. This is reflected in the MSE and direction of change statistics reported in table 3 that indicate that, unlike the two previous models, the MSE of the predictions of the Markov model are statistically indistinguishable from those of the random walk model, over a matching sample of predictions, although the MSE of the Markov model is numerically higher over all prediction horizons.

A much more positive results is found by looking at the direction of change statistics. The statistics indicate that the Markov-switching model generates predictions that in terms of predicted direction of change are significantly better than 50-50, at all prediction horizons considered, yielding correct predictions of 63%, 65%, 83% and 83% at prediction horizons

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.

[35] Their specification involves an *ad hoc* exchange rate equation in first differences, where the actual interest rates has been substituted in for by the reaction functions similar to equation (13).

[36] Rogoff and Stravrakea (2008, p. 2.).

[37] Molodtsova and Papell (2009, p. 3). A rolling window regression, in contrast to a recursive regression, fixes the sample size, repeatedly adding a new observation and dropping the oldest.

of 1, 3, 6 and 12 months respectively.

These results suggest that this model presents a significant improvement over both the stable (linear) composite model and to a lesser extent the random walk forecast. This improvement is consistent with the results of the *WSJ* study and other empirical results in the literature.

Specifically, Frömmel, MacDonald, and Menkhoff (2005) find that their two state Markov-switching model "significantly improves the quality of the estimation" over the linear alternative.[38] Yet they conclude that "although the [Markov-switching model] captures most of the structural instability in the coefficients, there is still some additional source of time variation left.[39] This conclusion is consistent with the IKE view that the omission of non-routine change, which is out-side of the scope of fixed state Markov models, plays a significant role in the fields inability to uncover empirical evidence linking exchange rate movements to macroeconomic fundamentals.

An important note is that the stability of the states, i.e. how often they switch regimes, seems to very sensitive to the composition of the economic factors and the number of states. This highlights the difficulties faced in determining the timing of structural change, and would seem to further support the conclusion from Frömmel *et al* that there is still some source of time variation that is unaccounted for.

3.3 The IKE Model

The IKE 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 2 and focusing on the dashed line, we see that this line appear to track the exchange rate reasonably well over the entire sample and does 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 3. We see that the IKE 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 IKE outperforms the random walk model by significant margins, especially at the longer forecast horizons,

[38] Frömmel, MacDonald, and Menkhoff (2005, p. 500)
[39] *ibid.*

yielding correct predictions of 63%, 76%, 80% and 100% for prediction horizons of 1, 3, 6 and 12 periods ahead.[40]

Evidence that different sets of fundamentals matter in different sub-periods can be seen by estimating a model with one regime's set of fundamental factors in 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 IKE 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 IKE model, which generates an average direction of change statistic of 77% correct.

Comparison of the direction of change statistics between the Markov-switching and IKE models, which both report statistically significant results at all time horizons, indicates that the IKE model's predictions are significantly better at the 3 and 12 month horizons, and numerically higher but insignificantly so at 1 month. Only at 6 months ahead does the Markov model generate a insignificantly higher numerical value, 83% for the Markov model versus the IKE model's 80%.

The overall positive findings of the IKE model in terms of both MSE and direction of change is consistent with the results of other studies in the literature. Specifically, Beckmann, Belke, and Kühl (2011) and Frydman and Goldberg (2007) both report strong evidence of piece-wise cointergration in their studies. In addition my results confirm the findings of Frydman and Goldberg, who report that their IKE model generates numerically lower MSE's than the random walk, but without tests of statistical significance. These findings along with the results presented in this paper are in line with what we would expect from a world of unanticipated change as proposed by CEH.

Together these results suggests that the that the Meese-Rogoff finding, which lies at the heart of the exchange rate disconnect puzzle stems from a failure to recognize that the process underpinning the exchange rate undergoes contingent change and that rational mar-

[40] 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 $\frac{1}{2}$.

ket participants understand this feature of real-world markets. The adaptive learning and Markov-switching models are 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: Out-of-Sample Testing Procedure

Testing Procedure

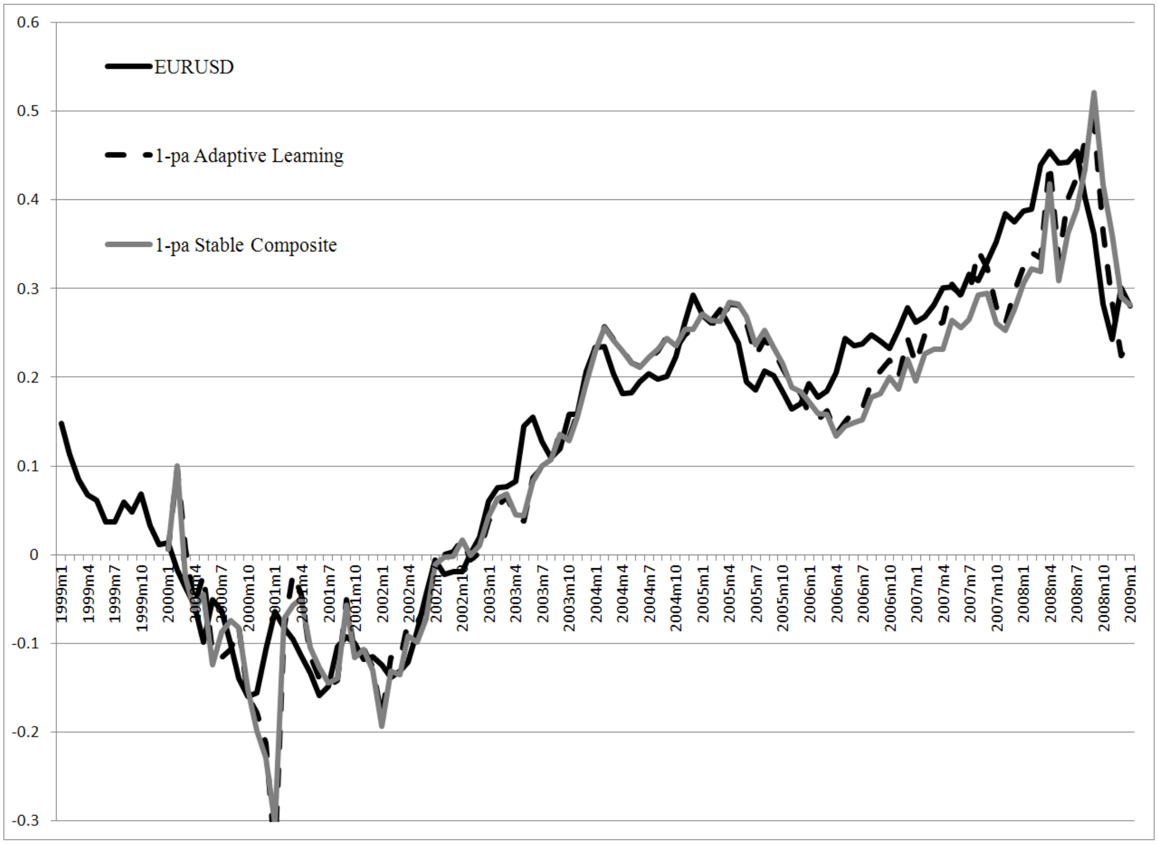
This study evaluates the out-of-sample fit of the model following the tradition of Meese and Rogoff (1983). This method compares the predictive accuracy of the structural economic model to that of a simple random walk, using mean-square error and direction of change metrics. In the tradition of Meese 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.

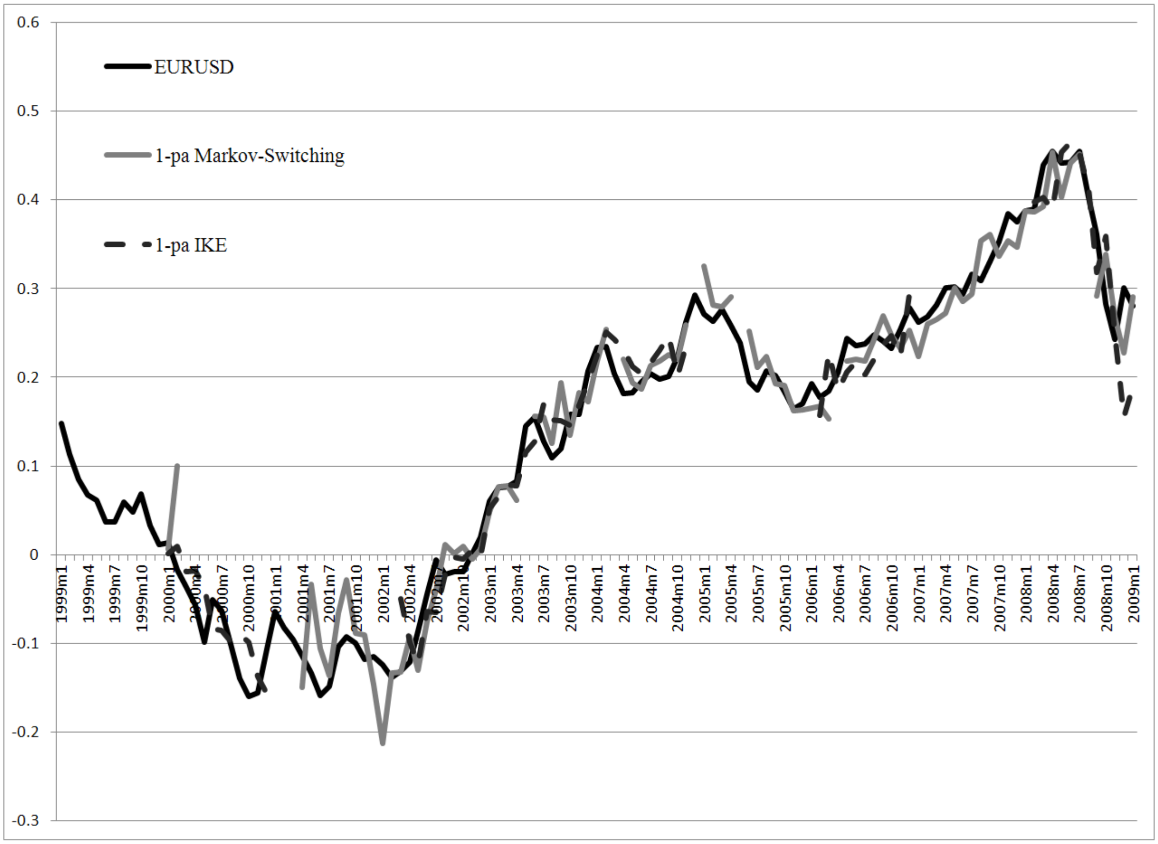
From these predictions forecast error statistics are calculated for both the economic model and the random walk model. In this paper I evaluate the predicative ability of the model using mean square error statistic (MSE) and direction of change metrics. Statistical significance of the difference between 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 $\frac{1}{2}$.

Figure 1: 1-Period Ahead Predictions: Part I



This figure depicts the 1-period ahead predicted value from stable composite and adaptive learning models against the log euro-dollar exchange rate.

Figure 2: 1-Period Ahead Predictions: Part II



This figure depicts the 1-period ahead predicted value from the Markov-switching and IKE models against the log euro-dollar exchange rate.

Table 1: IKE 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 TED 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 TED Spread - Spread between the 3-month US T-Bill interest rate and the 3-month USD LIBOR interest 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: Markov-Switching Regime Classification

	Dates	Months	Avg. Prob.
State = 1	1999:01-2000:02	14	1.000
	2002:07-2003:12	18	0.994
	2006:05-2008:07	27	1.000
	2008:12-2009:01	2	0.997
State = 2	2000:03-2002:06	28	0.991
	2004:01-2006:04	28	0.977
	2008:08-2008:11	4	0.988

State 1 occurs for a total of 60 months (49.59%) with average duration of 20.00 months.
State 2 occurs for a total of 61 months (50.41%) with average duration of 15.25 months.

Table 3: Out-of-Sample Prediction Statistics

		Economic Model	Matching Sample RW	P-Value vs RW	Direction of Change	No. of Obs
	Model	MSE	MSE			
k = 1	Stable Composite	.00323	.00066***	.0035	50.5%	109
	Adaptive Learning	.00298	.00066***	.0030	47.7%	109
	Markov Switching	.00115	.00055***	.0011	62.2%***	90
	IKE	.00161	.00082***	.0016	63.4%***	71
k = 3	Stable Composite	.01028	.00277**	.0479	44.7%	107
	Adaptive Learning	.00888	.00277**	.0783	48.6%	107
	Markov Switching	.00217	.00210	.9230	64.9%****	74
	IKE	.00292*	.00370	.1688	76.2%****	63
k = 6	Stable Composite	.02230	.00539*	.1289	47.1%	104
	Adaptive Learning	.01865	.00539*	.1601	50.1%	104
	Markov Switching	.00469	.00428	.9032	83.3%****	54
	IKE	.00381***	.007464	.0327	80.4%****	51
k = 12	Stable Composite	.07556	.01092*	.1341	51.0%	98
	Adaptive Learning	.05864	.01092*	.1355	52.0%	98
	Markov Switching	.03216	.01557	.4863	83.3%****	30
	IKE	.01335	.01975	.3090	100%****	27

Where "k" denotes the k-period ahead prediction.

Statistical significance of the MSE 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. Statistical significance of the direction of change 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 $\frac{1}{2}$. 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.

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	IKE	-	-	.00648	50.0%	.00564	33.3%	.00340	41.6%	12
	Random Walk	-		.00112		.00112		.00112		
in Regime 2	IKE	.00136	58.8%	-	-	.00109	55.9%	.00120	64.7%	34
	Random Walk	.00065		-		.00064		.00064		
in Regime 3	IKE	.00295	41.7%	.00089	58.3%	-	-	.00121	33.3%	12
	Random Walk	.00032		.00032		-		.00032		
in Regime 4	IKE	.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	IKE	-	-	.01774	70.0%	.00971	30.0%	.00667	20.0%	10
	Random Walk	-		.00422		.00422		.00423		
in Regime 2	IKE	.00250	78.1%	-	-	.00214	78.1%	.00267	71.9%	32
	Random Walk	.00323		-		.00322		.00322		
in Regime 3	IKE	.00872	20.0%	.00294	50.0%	-	-	.00302	70.0%	10
	Random Walk	.00107		.00106		-		.00106		
in Regime 4	IKE	.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	IKE	-	-	.04175	100.0%	.01297	57.1%	.01016	42.9%	7
	Random Walk	-		.00580		.00580		.00580		
in Regime 2	IKE	.00455	62.1%	-	-	.00355	82.8%	.00412	72.4%	29
	Random Walk	.00664	-	-		.00663		.00663		
in Regime 3	IKE	.02107	0.00%	.00406	57.1%	-	-	.00157	100.0%	7
	Random Walk	.00190		.00190		-		.00190		
in Regime 4	IKE	.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	IKE	-	-	.09974	100.0%	.01019	100.0%	.01100	0.0%	1
	Random Walk	-		.00599		.00599		.00599		
in Regime 2	IKE	.01153	74.0%	-	-	.01025	91.3%	.00647	100.0%	23
	Random Walk	.02161		-		.02161		.02161		
in Regime 3	IKE	.07762	0.00%	.00919	0.00%	-	-	.01046	0.0%	1
	Random Walk	.00477		.00476		-		.00476		
in Regime 4	IKE	.00787	100.0%	.01372	100.0%	.01581	100.0%	-	-	1
	Random Walk	.01128		.01127		.01127		-		