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ABSTRACT

The Scapegoat Theory of Exchange Rates: The First Tests*

This paper provides an empirical test of the scapegoat theory of exchange rates (Bacchetta and van Wincoop 2004, 2011), as an attempt to evaluate its potential for explaining the poor empirical performance of traditional exchange rate models. This theory suggests that market participants may at times attach significantly more weight to individual economic fundamentals to rationalize the pricing of currencies, which are partly driven by unobservable shocks. Using novel survey data which directly measure foreign exchange scapegoats for 12 currencies and a decade of proprietary data on order flow, we find empirical evidence that strongly supports the empirical implications of the scapegoat theory of exchange rates, with the resulting models explaining a large fraction of the variation and directional changes in exchange rates. The findings have implications for exchange rate modelling, suggesting that a more accurate understanding of exchange rates requires taking into account the role of scapegoat factors and their time-varying nature.

JEL Classification: F31 and G10
Keywords: economic fundamentals, exchange rates, order flow, scapegoat and survey data

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"The FX market sometimes seems like a serial monogamist. It concentrates on one issue at a time, but the issue is replaced frequently. Dollar weakness and US policy have captured its heart. But uncertainties are being resolved ... The market may move back to an earlier love ..." (Financial Times, November 8, 2010)

1 Introduction

A central conjecture of the work by Meese and Rogoff (1983a,b; 1988) is that the presence of time-varying parameters may be a key explanation for the failure of exchange rate models to predict future currency movements. However, time-varying parameters may not only help explain the weak out-of-sample predictive power of exchange rate models, but also the ex-post instability in the relationship between exchange rates and macroeconomic fundamentals, as pointed out by a growing literature. For example, Rossi (2006) finds a high degree of parameter instability for a broad set of models and specifications. Sarno and Valente (2009) show that the relevance of information contained in fundamentals changes frequently over time, while Cheung and Chinn (2001) illustrate through US survey data the sharp shifts in the importance foreign exchange (FX) traders attach to different fundamentals over time.

In a series of papers, Bacchetta and van Wincoop (2004, 2011) propose a scapegoat theory to explain the instability in the relationship between exchange rates and fundamentals. The scapegoat theory suggests that this instability is not explained by frequent and large changes in structural parameters, even when allowing for rationality of agents and Bayesian learning, but rather by *expectations* about these structural parameters.[1] The scapegoat theory starts from the premise that, even though agents may have a fairly accurate idea about the relationship between fundamentals and exchange rates in the long-run, there is significant uncertainty about the structural parameters over the short to medium term. This implies that when currency movements over the short to medium term are inconsistent with their priors about the underlying structural relationships, agents search for scapegoats to account for these inconsistencies. Such currency movements may be driven by unobservable fundamentals, yet for agents it may be rational to assign additional weight to some fundamental, thus making it a scapegoat for observed exchange rate changes.

In fact, there is ample anecdotal evidence – as illustrated in the quote above – that financial market participants blame individual fundamentals for exchange rate movements, with such blame often shifting rapidly across different fundamentals over time. The scapegoat theory by Bacchetta and van Wincoop (2004, 2011) entails that a particular fundamental is more likely to become a scapegoat the larger the (unexplained) exchange rate movement *and* the more this particular fundamental seems

[1] In fact, in related work Bacchetta, van Wincoop and Beutler (2010) show that allowing for time-varying structural parameters has only a marginal effect on the predictive power of fundamentals for exchange rates.

out of line with its long-run equilibrium, but consistent with the observed direction of the exchange rate movement. Over the short-run, both the scapegoat fundamental as well as the unobservable fundamental may thus help explain exchange rate movements. As a final step, Bacchetta and van Wincoop (2009, 2011) calibrate their model for five currencies of industrialized countries, using monetary fundamentals, to investigate its ability to match the moments of the fundamentals and exchange rates.[2]

The present paper constitutes - to our knowledge - the first empirical test of the scapegoat theory of exchange rates. An important difficulty in designing an empirical test in this context involves finding a suitable proxy for the weight assigned to individual economic fundamentals by market participants (needed to identify scapegoats), and a proxy for the unobservable fundamental (e.g. customer trades in FX markets). We do so by exploiting novel data on exchange rate scapegoats from surveys of a broad set of investors, as well as proxies of unobservable fundamentals based on FX order flow. Exchange rate scapegoats stem from monthly surveys of 40-60 financial market participants, who are asked to rate on a quantitative scale the importance of six key variables (short-term interest rates, long-term interest rates, growth, inflation, current account, equity flows) as drivers of a country's exchange rate *vis-a-vis* its reference currency.[3] This survey data is available over a 9-year period (2001-2009) for a panel of currencies of advanced and emerging economies. Thus, the data allows us to extract quantitative scapegoat measures for each of these six fundamentals over time and across currencies. We match this survey data with a novel dataset on FX order flow as a proxy of unobservable factors driving exchange rates. The order flow data are proprietary customer transactions from one of the major players in the FX market in terms of market share, namely UBS. The empirical estimations are conducted for 12 currencies (6 of advanced and 6 of emerging economies) individually over this 9-year period, using data at monthly frequency.

We present and test two main hypotheses of the scapegoat theory of exchange rates. The first hypothesis inherent in the theory is that the inclusion of scapegoats (surveys) improves the power of fundamentals in explaining exchange rate movements. We test this hypothesis by examining two specifications of the scapegoat model: one based on constant parameters following Bacchetta and van Wincoop (2011), and (a more realistic) one based on time-varying parameters as in the earlier version of Bacchetta and van Wincoop (2009). We test these two specifications of the scapegoat model against two alternative benchmark exchange rate models, one based on constant parameters and one based

[2]In other words, in these papers Bacchetta and van Wincoop carry out simulations assuming a model of determination of the exchange rate and showing that allowing for scapegoat effects enables them to match the moments of exchange rates and fundamentals data. Our paper may be seen as a companion paper to their scapegoat theory and their calibration exercises in that we test empirically, rather than calibrate, the scapegoat model by using data on FX scapegoats.

[3]Specifically, with the exception of the current account all variables are measured as differentials relative to the country of the reference currency. The reference currency is mostly the US dollar.

on time-varying parameters with Bayesian updating for the macroeconomic variables. Moreover, we use three criteria for the comparison of in-sample model performance across models – one based on the adjusted R^2, a second on an information criterion, and a third on market-timing (directional accuracy) tests. The empirical results show that the scapegoat model with time-varying parameters performs significantly better than the benchmark models, and does so across all three performance criteria. Moreover, the magnitude of the improvement in the performance of the scapegoat model over the benchmark models is substantial. For instance, the adjusted R^2 increases from about 11 percent for the time-varying parameter model without scapegoats to, on average across currencies, 27 percent with scapegoats. The hit ratio of correctly explained directional FX changes rises from about 59 percent for the benchmark models to about 70 percent for the scapegoat model with time-varying parameters across the 12 currencies. We also find that the scapegoat model with constant parameters performs satisfactorily. It generally outperforms its respective benchmark model based on constant parameters, but more surprisingly it also yields a better performance than the more complex model with time-varying parameters in a few cases. This may suggest that the use of scapegoat variables *per se* is sufficient to capture the unstable relationship between fundamentals and exchange rates, at least for some currencies.[4]

More generally, the results show that the improvement in the in-sample explanatory power of the scapegoat model does not only stem from the inclusion of the order flow variable, but also from the inclusion of the scapegoat parameters themselves. This finding is relevant because it suggests that while order flow is important in accounting for currency movements, the scapegoat parameters have an additional, sizeable explanatory power. In fact, the joint role of order flow and scapegoat parameters is a necessary condition for the scapegoat effect to arise. Again, these findings are robust across currencies as well as across macro fundamentals as scapegoats.

The second hypothesis of the scapegoat theory relates to the determinants of the scapegoat factors themselves, and the question about which macroeconomic fundamental becomes a scapegoat, and at which point in time. Bacchetta and van Wincoop's scapegoat theory states that a macro fundamental becomes a scapegoat if there is a sizeable shock to unobservable fundamentals, and at the same time the size of the deviation of the macro fundamental from its equilibrium is large and theoretically consistent with the observed direction of change in the exchange rate. We indeed find empirical support for this hypothesis. In fact, a macroeconomic fundamental is picked and identified by market participants as a scapegoat at times when (i) the unobservable fundamental experiences a large shock, (ii) the fundamental tends to be out of sync with its own longer-term equilibrium (e.g. experiences abnormal values) and (iii) moves in a direction that is consistent with the observed

[4] Put another way, this result suggests that even if the parameters are constant themselves, the expectations of the parameters can change significantly over time generating a scapegoat effect.

movements in the exchange rate.

Taken together, these two pieces of empirical evidence provide strong support in favor of the scapegoat theory of exchange rates. The findings of the various tests are mutually consistent and suggest that the high degree of instability in the relationship between exchange rates and fundamentals is to a significant extent explained by the presence of scapegoats. In other words, in their attempt to gauge what factors may drive exchange rates market participants have a tendency to single out individual macro variables, which tend to be those that are out of sync with their own longer term equilibrium or experience abnormal values, and in particular at times when exchange rate movements are also large. Overall, these findings have important implications for exchange rate modelling, suggesting that a more accurate understanding of exchange rates requires taking into account the role of scapegoat factors, and their time-varying nature.

The rest of the paper is organized as follows. Section 2 outlines the main elements of Bacchetta and van Wincoop's scapegoat theory of exchange rates, and describes its testable empirical implications. Section 3 presents the data used for the empirical analysis, focusing in particular on the measurement of exchange rate scapegoats, and also discusses the empirical methodology underlying our estimations. The empirical findings are then presented in Section 4, going through the two hypotheses outlined above. Section 5 concludes.

2 Scapegoat theory and hypotheses

The essence of the scapegoat theory of exchange rates is that some macroeconomic factors receive an unusually large weight and thus are made scapegoats of exchange rate movements. Such episodes can happen when investors do not know the true model of exchange rates or the true parameters of the model, and when some of the drivers of exchange rate fluctuations are unobservable.[5] In particular, the weight or scapegoat role of a macroeconomic variable is higher when both the role of the unobservable for currency movements is larger, and the macroeconomic fundamental shows large variation which is consistent with the observed movement in the exchange rate. Such "rational confusion" arises because agents make inference on the true parameter only conditioning on observable fundamentals and exchange rate movements at times when the exchange rate is instead driven by unobservables (e.g. large customer order flows). Thus, when exchange rates move strongly in response to changes in the unobservables, it is rational for agents to blame factors that they can actually observe, and more precisely those macro fundamentals that are out of sync from their longer term equilibrium values.

This scapegoat effect, or rational confusion, can generate an unstable relationship between

[5] In this paper the words agents and investors are used interchangeably.

exchange rates and macro fundamentals. More precisely, the relationship between the exchange rate and fundamentals is determined mainly by the expectation of the structural parameters and not by the structural parameters themselves, and such expectations can exhibit large short-term fluctuations and thus generate scapegoat effects. Next, we describe such effects, following two related models developed by Bacchetta and van Wincoop (2009, 2011). We then introduce our main hypotheses for the empirical test of the scapegoat model of exchange rates. Finally, we motivate and present two fundamental-based exchange rate models which benchmark the scapegoat model.

2.1 The scapegoat model of exchange rates

Bacchetta and van Wincoop describe the scapegoat effect in a series of papers (2004, 2006, 2009, 2011). These papers differ for a number of reasons, although they have the same central theme. For example, Bacchetta and van Wincoop (2004, 2006) assume that agents have heterogeneous information, whereas Bacchetta and van Wincoop (2009, 2011) develop a dynamic model where the exchange rate is forward looking and depends on expectations of future fundamentals. Bacchetta and van Wincoop (2009) examine the case where parameters are unknown and *time-varying*, whereas Bacchetta and van Wincoop (2011) show that the scapegoat effect can arise also with unknown and *constant* parameters. In practise, there are many ways in which parameter uncertainty can be generated. What is crucial to generate a scapegoat effect, however, is the uncertainty of structural parameters attached to fundamentals, combined with the role of unobserved fundamentals: put simply, agents do not know the coefficients of the model and do not observe one of the fundamentals.

To a large extent, the different models of Bacchetta and van Wincoop share similar empirical implications. Hence, our empirical test can be seen more generally as a test of the scapegoat effect, which is central to all of the above papers, although we follow closely Bacchetta and van Wincoop (2009, 2011) in what follows. We start by presenting their key equation describing the scapegoat effect when parameters are constant but unknown. Then, we move to describing the more general case with time-varying parameters. Starting with a standard formulation of the exchange rate as the present value of future fundamentals, in the vein of Engel and West (2005), and using first differences, Bacchetta and van Wincoop (2011) derive the following equation:

$$\Delta s_t \cong \mathbf{f}_t'((1-\lambda)\boldsymbol{\beta} + \lambda E_t\boldsymbol{\beta}) + (1-\lambda)b_t, \tag{1}$$

where s_t is the log nominal exchange rate (expressed as the foreign price of the domestic currency), $\mathbf{f}_t = (f_{1,t}, f_{2,t}, \ldots, f_{N,t})'$ is a vector of N observed macro fundamentals (expressed in first differences), $\boldsymbol{\beta} = (\beta_1, \beta_2, \ldots, \beta_N)'$ is the vector of time-varying true structural parameters, $E_t\boldsymbol{\beta}$ is the vector of expected structural parameters, b_t is the unobserved fundamental, and λ is the discount factor. Thus, the true structural parameters $\boldsymbol{\beta}$ are constant but are unknown to investors, who learn over time about $\boldsymbol{\beta}$ through observing the exchange rate and the macro fundamentals. Precisely, each period t they observe the signal $\mathbf{f}_t\boldsymbol{\beta}+ b_t$. However, both the parameters $\boldsymbol{\beta}$ and the fundamental b_t are unknown to them. As a result, although they can eventually learn about the structural parameters, this can only happen *slowly* over time.

Equation (1) also shows that the fundamentals $\mathbf{f}_t$ are multiplied by a weighted average of actual and expected parameters. However, higher weights are attached to the expected values of the parameters rather than the actual values, since the discount factor λ is smaller than but close to unity (see Engel and West, 2005; Sarno and Sojli, 2009).[6] Moreover, even though the parameters themselves are constant, the expectations of the parameters can change significantly over time. Precisely, the impact of macro fundamentals on the exchange rate in the scapegoat model can be formulated as:

$$\frac{\partial \Delta s_t}{\partial f_{n,t}} \cong (1-\lambda)\beta_n + \lambda E_t\beta_n + \lambda \mathbf{f}_t' \frac{\partial E_t \boldsymbol{\beta}}{\partial f_{n,t}}. \tag{2}$$

Interestingly, the derivative of the exchange rate with respect to the fundamentals not only depends on the expectation of the structural parameters but also on the derivative of the structural parameters with respect to the fundamental. The latter term reflects a transitory effect which can generate high-frequency fluctuations. Such fluctuations would complement the short to medium term deviations already generated by variations in the expectation of the structural parameters. As a result, the uncertainty about the level of the parameters can determine transitory and persistent fluctuations in the level of the exchange rate. In turn, these fluctuations can induce instability in the relationship between exchange rates and macro fundamentals.

In short, Bacchetta and van Wincoop (2011) show that the scapegoat effect can exist even if the true structural parameters are constant.[7] However, in this model agents eventually learn the true value of the parameters. By contrast, in an earlier version of the model, Bacchetta and van Wincoop (2009) made the more realistic assumption that structural parameters vary over time. For this reason, we now introduce their original specification:

$$\Delta s_t = \mathbf{f}_t'((1-\lambda)\boldsymbol{\beta}_t + \lambda E_t\boldsymbol{\beta}_t) + (1-\lambda)b_t + \lambda \sum_{i=1}^{T} \mathbf{f}_{t-i}' \left(E_t\boldsymbol{\beta}_{t-i} - E_{t-1}\boldsymbol{\beta}_{t-i} \right), \tag{3}$$

where $\boldsymbol{\beta}_t = (\beta_{1,t}, \beta_{2,t}, \ldots, \beta_{N,t})'$ is the vector of time-varying true structural parameters, and $E_t\boldsymbol{\beta}_t = (E_t\beta_{1,t}, E_t\beta_{2,t}, \ldots, E_t\beta_{N,t})'$ is the vector of expected parameters at time t. The true structural

[6] More precisely, just as a fundamental may at times receive a larger weight in investors' trading decisions over the short-term, it may at other times receive too little weight. The model by Bacchetta and van Wincoop (2011) entails that in the long-run investors know the true structural parameters, which should imply that these long-run structural parameters should match the average scapegoat parameters.

[7] Another simplification in their model set-up is the exclusion of risk premia. They show that the inclusion of risk premia does not materially alter the findings about the importance of scapegoats.

parameters $\boldsymbol{\beta}_t$ now vary over time but are again unknown to investors. While investors may know the value of these structural parameters over the long-run, they may not know their value and time variation in the short to medium term. For this reason, some observable macro fundamental may at times be given an "excessive" weight by investors, in the sense that the fundamental is given more weight over the short-term than the longer-term structural relationship of the fundamental with the exchange rate entails. This fundamental then becomes a natural scapegoat and influences the trading strategies of investors. Therefore, in equation (3), the expectations of structural parameters directly determine changes in the exchange rate.

2.2 Empirical scapegoat models

We now turn to stating the empirical hypotheses to test this scapegoat theory. Our first research hypothesis is that scapegoat effects are empirically powerful in explaining exchange rate movements. In order to test this hypothesis, we estimate the following two empirical scapegoat models of exchange rates. The first is the empirical counterpart to equation (1):

$$CP - SCA : \Delta s_t = \mathbf{f}_t'\boldsymbol{\beta} + (\boldsymbol{\tau}_t\mathbf{f}_t)'\boldsymbol{\gamma} + \delta x_t + u_t, \tag{4}$$

where $\boldsymbol{\tau}_t$ is the vector of scapegoat parameters $E_t\boldsymbol{\beta}$. We identify the latter by using survey data, and the theoretical unobserved fundamental b_t is proxied by FX order flow x_t; the measurement of both $\boldsymbol{\tau}_t$ and x_t is described in detail in Section 3. The second model we estimate is the empirical counterpart to equation (3):

$$TVP - SCA : \Delta s_t = \mathbf{f}_t'\boldsymbol{\beta}_t + (\boldsymbol{\tau}_t\mathbf{f}_t)'\boldsymbol{\gamma} + \delta x_t + u_t, \tag{5}$$

where the structural parameters are now time-varying, and $\boldsymbol{\tau}_t$ denotes the vector of scapegoat parameter $E_t\boldsymbol{\beta}_t$. It is also apparent that the last term in equation (3), which captures the change in the expectations of past parameters interacted with past fundamentals, is missing from equation (5). This term is dropped as data on current and lagged expectations of past parameters are hard to measure empirically, and may also be of second-order importance relative to the current scapegoat parameter.[8]

In order to gauge the effect of fundamentals on exchange rates, we need to determine the evolution over time of the underlying structural relationship between exchange rates and fundamentals. Investors may know the process that determines the evolution of $\boldsymbol{\beta}_t$, even if the actual levels of the

[8]Hence the empirical model we take to the data is a simplified version of the scapegoat model, as we neglect the additional channel whereby current fundamentals lead to changes in the expectation of both current and past parameters. Thus, if the hypothesis holds for our simplified empirical model it should hold even if we were to include the last term.

structural parameters are unknown to them. We consider the case where each structural parameter $\beta_{n,t}$ evolves as a driftless random walk:

$$\beta_{n,t} = \beta_{n,t-1} + v_{n,t}. \quad (6)$$

This is a widely used process in the empirical literature on modelling time-varying parameters (e.g. see Cogley and Sargent, 2002; Primiceri, 2005; Rossi, 2005), and is also used in Bacchetta and van Wincoop (2009). We assume homoskedastic errors and uncorrelated factors, so that $\mathbf{v}_t$ is a vector of normally distributed error terms with zero mean and diagonal covariance matrix $\mathbf{Q}$. Both these assumptions can be easily relaxed, and are not crucial to our analysis.[9]

As to our null hypothesis, we expect $\boldsymbol{\gamma}$ to be statistically significantly different from zero and correctly signed. Of course, for some variables the interpretation of the sign is not clear-cut (e.g. equity flows). Moreover, we may expect the parameters $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}$ to be consistent with each others. We also expect the order flow parameter δ to be negative, implying that when the buying pressure for the foreign currency increases the domestic currency depreciates (Evans and Lyons, 2002; Bacchetta and van Wincoop, 2004, 2006, 2009, 2011). More generally, the test of the scapegoat model of exchange rates rests on the comparison of the empirical estimation of models (4) and (5) with some benchmark models, using appropriate metrics of evaluation.

The second main hypothesis of the scapegoat theory relates to the determinants of the scapegoat parameter $\tau_{n,t}$ itself. What determines the evolution of this parameter? When does a macro fundamental become a scapegoat? The papers by Bacchetta and van Wincoop (2009, 2011) show that a particular macro fundamental is more likely to become a scapegoat when there are large shocks to the unobservable b_t *and* this fundamental is out of sync with its longer term equilibrium value. We formulate an empirical test for this hypothesis in the empirical work discussed below.

2.3 Exchange rate models to benchmark the scapegoat model

An important issue is how to benchmark the scapegoat models, i.e. with which alternative models to compare their explanatory power. One natural candidate is a basic macro model with constant and known parameters. Such fundamental-based exchange rate model is consistent with the notion that the exchange rate is given by the present value of current and expected future fundamentals (Mark,

[9] In Bacchetta and van Wincoop (2009) the expectations of structural parameters are more volatile than the actual underlying true parameters, and the two can diverge for reasonably long periods due to the scapegoat effects. However, in the long run, the two are equal so it needs to hold that they have equal unconditional means ($E\overline{\beta} = E\overline{\tau}$). To be consistent with the scapegoat theory, this condition needs to hold also in the estimation. In the first draft of this paper, we imposed such condition by standardizing the surveys τ_t to have a mean of zero, as this is already the case for β_t. This standardization was useful in making the estimated model theoretically consistent, but it came at a cost as the time-varying parameters were defined in deviation from their long-run mean and, more importantly, it was not possible to interpret either the magnitude or the sign in a meaningful way. So, in this version we decided not to adopt such standardization. Instead, we only standardize the surveys so that they have unit variance.

1995; Engel and West, 2005; Engle, Mark and West, 2008). This model can be easily rewritten in first differences, so that changes in the exchange rate Δs_t depend on changes in the fundamentals $\mathbf{f}_t$:

$$CP - MACRO : \Delta s_t = \mathbf{f}_t'\boldsymbol{\beta} + u_t. \tag{7}$$

The model in equation (7) is a logical benchmark for the constant-parameter scapegoat model, $CP - SCA$, given in equation (4). However, there is overwhelming evidence of parameter instability in empirical exchange rate models (Rossi, 2005). This instability may be rationalized on a number of grounds, including policy regime changes, instabilities in the money demand or purchasing-power-parity equations, or also agents' heterogeneity leading to different responses to macroeconomic developments over time (e.g. see Schinasi and Swamy, 1989; Rossi, 2005, 2006). An alternative explanation is that frequent shifts in the parameters can result when models, which optimally use the information in the fundamentals, experience large and frequent changes in structural parameters (Sarno and Valente, 2009). For these reasons a second potential benchmark is a model that accounts for parameter instability. We therefore use a second benchmark specification that allows for time-varying parameters, and which constitutes the benchmark for the scapegoat model with time-varying parameters, $TVP - SCA$ given in equation (5):

$$TVP - MACRO : \Delta s_t = \mathbf{f}_t'\boldsymbol{\beta}_t + u_t. \tag{8}$$

Note that both benchmark models in equations (7) and (8) assume that parameters are known to the investors. However, the latter model also allows parameters to vary over time, and the unstable relationship between exchange rates and fundamentals is generated by parameters being volatile. In contrast, Bacchetta and van Wincoop (2009) originally assumed that the investors cannot observe directly the (shocks to the) structural parameters $\boldsymbol{\beta}_t$. Agents observe the signal $\mathbf{f}_t'\boldsymbol{\beta}_t + b_t$ through the change in the exchange rate, but because the order flow is unobservable to them the only extra piece of information they have is $\mathbf{f}_t$. As a result, large changes in the unobservable combined with large changes in the observed fundamental can easily alter agents' expectations. Thus, agents can naturally change their expectations of the structural parameters even if $\boldsymbol{\beta}_t$ were actually zero.[10]

3 Data and econometric methodology

This section starts by outlining the data, and specifically how we measure FX scapegoats as well as order flow and macro fundamentals. We then proceed by discussing our empirical methodology.

[10] For example, assume that the unobservable $b_t > 0$ and $f_{n,t} > 0$, but $\beta_{n,t}$ is 0 so that the true parameter did not change. It follows that agents naturally increase their expectation of $\beta_{n,t}$, since they are confused by $f_{n,t}$ being greater than zero. The scapegoat effect arises from this rational confusion.

3.1 Data on scapegoats and fundamentals

We employ a novel dataset to measure when and which fundamentals are used as scapegoats for exchange rate movements by financial market participants. The aim is to extract a quantitative measure of the importance that investors attach to different macroeconomic fundamentals to explain exchange rates at a particular point in time.

The data is based on surveys of 40-60 FX market participants from major financial institutions (mostly asset managers) conducted monthly by Consensus Economics. These market participants reside in many different locations globally, though the majority is located in the US, the UK and other advanced economies. The participants are asked to "rank the current importance of a range of different factors in determining exchange rate movements" for each of a broad set of currencies bilaterally *vis-a-vis* a reference currency, which is mostly the US dollar and *vis-a-vis* the euro for some European currencies. For the euro, Japanese yen and UK pound, the exchange rates considered are *vis-a-vis* the US dollar.

More precisely, participants are asked to rank six key macroeconomic factors on a scale from 0 (no influence) to 10 (very strong influence). The six key variables are short-term interest rates, long-term interest rates, growth, inflation, trade/current account, and equity flows. The survey explicitly stresses that the weights should be for the variables relative to those of the country of the reference currency.[11]

Consensus Economics conducts the surveys monthly with the same financial market participants, so that the change in participants is relatively small. However, Consensus Economics conducts several surveys on exchange rates with these market participants (such as about short-term forecasts, longer-term forecasts, expected trading ranges, and market uncertainty), and alternates across these surveys over the months. This means that the surveys about FX scapegoats is conducted only between every 3 to 6 months, though at regular intervals over the years. We interpolate the data for missing months so as to arrive at a dataset with monthly observations. The data are interpolated by means of a simple Kalman filter, as described in Appendix A. The advantage of using the Kalman filter is that it only uses information available to the investor at any point in time.[12]

Overall, the survey data on FX scapegoats are available over a 9-year period (2001-2009) and

[11] Moreover, survey participants are invited at each survey round to add additional factors that they see as important drivers of the exchange rate. We do no include these additional factors, both because few of these are mentioned sufficiently often to generate a time series for a particular currency, and also because some are hard to measure. For instance, additional factors mentioned are political conflicts, fear of interventions by central banks, and house prices. Of course, the six macro fundamentals at our disposal only comprise a subset of potentially relevant fundamentals, and indeed Andersen, Bollerslev, Diebold and Vega (2003) document that the set of macroeconomic news that affects the conditional mean of the exchange rate is quite broad. Nevertheless, the set of variables in the survey are all standard in the theoretical and empirical literature on exchange rate determination.

[12] Nevertheless, we also experimented with a simpler linear interpolation. The results were qualitatively and quantitatively similar, so our results are robust to the technique used to interpolate the survey.

a large panel of currencies of advanced and emerging economies. We reduce our country sample to those 12 currencies for which we have survey data for the full 9-year period, 6 being currencies of advanced countries (Australian dollar, Canadian dollar, euro, Japanese yen, Swiss franc, and UK pound) and 6 emerging market, or EM, currencies (Czech koruna, Mexican peso, Polish zloty, South African rand, Singaporean dollar, and Korean won). Another important criterion for the selection of EM currencies is that these six are among the most freely floating EM currencies, though all may have experienced periods of interventions by their monetary authorities.

Table 1 shows summary statistics about the scapegoat surveys for the 12 currencies in our sample. A first interesting fact is that the six macro variables have mostly similar means and standard deviations across all 12 currencies and over time. A somewhat higher mean is recorded for short-term interest rates, and a somewhat lower mean for inflation as scapegoat. However, there are some revealing differences across currencies, in particular between advanced and EM currencies. For instance, inflation has never been the single most important scapegoat for advanced countries' currencies over the past decade, which seems reasonable given that inflation and inflation differentials have been relatively stable in the industrialized world over this period. Short-term interest rates have been the dominant scapegoat for advanced currencies relatively more frequently, whereas for EM currencies growth differentials and the current account have been more frequently considered by investors as the main scapegoats. Figure 1 also shows the time variations of the scapegoat factors for some advanced and EM currencies, which is useful to illustrate how the weights investors attach to macro fundamentals can change substantially over time, and the main scapegoat changes fairly frequently.

We match the monthly scapegoat data with the actual macroeconomic fundamentals for these six variables. To obtain monthly data, we use the trade balance instead of the current account, and use interpolated monthly GDP growth figures. The data source for all macro series is the IMF's *International Financial Statistics*. To be as consistent as possible with the surveys, actual macroeconomic fundamentals are calculated relative to those of the country of the reference currency. As to the scaling of the scapegoat variables, we scale each scapegoat variable for each currency so that its mean and standard deviation are identical to those of the underlying actual macroeconomic variable. Table 2 offers summary statistics for the actual macro fundamentals with all variables, except the current account, being measured relative to the reference currency.

A final point concerns the exchange rate data. Given the survey questions, we use nominal bilateral exchange rate changes *vis-a-vis* the reference currency, in the benchmark specification using changes over the past month. As we know the precise day when the surveys were conducted, these exchange rate changes are calculated relative to the market closing of the previous business day.

3.2 Data on order flow

The other important data for the empirical test of the scapegoat theory of exchange rates is on order flow. Our rationale is as follows. Bacchetta and van Wincoop's papers stress the key role of unobservables, in particular unobservable trades, as drivers of exchange rates. It is hence important to try and capture such unobservables for two reasons. First, to test whether unobservables as captured and proxied by order flow exert a significant effect on monthly exchange rate changes; and second, it is important to control for unobservables in order to test whether scapegoats exert an additional effect on exchange rates.[13]

We use a comprehensive proprietary dataset of order flow for all 12 currencies in our sample over the entire 2001-2009 period. These order flow series are bilateral *vis-a-vis* the reference currency. The source of the data is UBS, and these data are not made public by UBS, constituting therefore a genuine unobservable for investors in the FX market. To match the order flow data to the scapegoat data, we calculate the cumulative monthly order flow, aggregating daily order flow data, on the business day previous to the latest scapegoat survey and over the previous month.

Note that we have available order flow from different types of customers for the advanced economies, but not for EM economies. Therefore we use total order flow for EM currencies, whereas we use (the sum of) hedge funds and asset managers order flow for advanced countries. This is because the order flow of sophisticated investors is more likely to capture the unobservable shock in the theory of Bacchetta and van Wincoop. Moreover, we suspect that total order flow in EM economies is vastly dominated by sophisticated investors, so that the use of total order flow seems appropriate. Table 3 provides some summary statistics of the order flow series for each of the 12 currencies in our sample, indicating that order flow does fluctuate considerably over time.

The FX microstructure approach has surged since Evans and Lyons (2002) first documented that order flow explains a substantial proportion of the fluctuations in major exchange rates, a result that stands in contrast with decades of failure to find a satisfactory empirical macroeconomic model of exchange rate behavior. Evans and Lyons (2005) subsequently show that order flow contains predictive power and outperforms a random walk in an out-of-sample forecasting exercise using conventional statistical criteria. Similarly, Rime, Sarno and Sojli (2010) find that order flow models generate substantial economic gains to an investor in a dynamic asset allocation setting. The explanatory and forecasting power of order flow has been mainly linked to macroeconomic news (e.g. Dominguez and Panthaki, 2006; Berger *et al.*, 2008; Love and Payne, 2008; Evans and Lyons, 2008), changes in expectations about the macroeconomy (Rime, Sarno and Sojli, 2010), and signals on the current state of the economy (Evans and Lyons 2005, 2006).

[13] Order flow, the net of buyer- and seller-initiated transactions, is employed to capture price-relevant information that is revealed through trade (see Evans and Lyons, 2002).

3.3 Econometric methodology

In Bacchetta and van Wincoop (2009, 2011), the scapegoat models not only include macro factors with loadings that either vary over time or are constant, but also the expectation of future parameters and unobserved fundamentals. For convenience, we repeat equation (5) for our empirical version of the scapegoat model with time-varying parameters

$$TVP - SCA : \Delta s_t = \mathbf{f}_t' \boldsymbol{\beta}_t + (\boldsymbol{\tau}_t \mathbf{f}_t)' \boldsymbol{\gamma} + \delta x_t + u_t, \tag{9}$$

where τ_t denotes the survey (scapegoat) parameters, which capture the expectation of future parameters and weights the information in the macro factors; and x_t is order flow, which proxies for the unobservable fundamentals. In the estimation, all variables are separately standardized in such a way that they have zero mean and unit variance.[14]

From an econometric point of view our empirical scapegoat model consists of estimating a model with both time-varying parameters ($\boldsymbol{\beta}_t$) and time-invariant parameters ($\boldsymbol{\gamma}$ and δ). We perform a Bayesian estimation of the parameters of the empirical exchange rate models in this paper, following e.g. Kim and Nelson (1999) and Cogley and Sargent (2002). The use of Bayesian estimation methods in this context is particularly appropriate for at least two reasons. First, it allows us to account for uncertainty surrounding parameter estimates in the model, which is important given our relatively small number of observations. Second, it allows us to make no assumption about the order of integration of the variables in the model. This is relevant since, while exchange rate returns are clearly stationary, the fundamentals are persistent, and this is known to complicate statistical inference in empirical exchange rate regressions.

We use the Gibbs sampler to simulate draws from the posterior distribution. The Gibbs sampler, which belongs to the family of Markov Chain Monte Carlo (MCMC) methods, decomposes the original estimation problem into (tractable) independent ones. In this way we can sample iteratively from the conditional densities of the parameters blocks. Precisely, all parameters are drawn sequentially from their full conditional posterior distribution. For the constant-parameters linear models, we simply draw the hyperparameters conditional on the data. By contrast, in the models with time-varying parameters there are two main steps. First, we draw a history of states conditional on the data and the hyperparameters using the Carter and Kohn (1994) simulation smoother. Then, we draw the hyperparameters, conditional on the data and the states. By repeatedly simulating from the known conditional distribution of each block in turn, we get samples of draws. These draws, beyond a burn-in period, are treated as variates from the target posterior distribution. More precisely,

[14] The surveys are simply standardized by dividing by their standard deviation, so that they always take positive values. This standardization is adopted as it simplifies the interpretation of the results.

for the time-varying parameter models we perform 80,000 replications of which the first 40,000 are burned-in, and we save 1 every 10 draws of the last 40,000 replications of the chain so that the draws are independent.

The priors used in this paper are diffuse, and their distributions are chosen for convenience following a number of papers (e.g. Koop, 2003; Kim and Nelson, 1999; Cogley and Sargent, 2002; Primiceri, 2005). For example, it is convenient to assume that the initial states for the time-varying coefficients, and the hyperparameters, are independent of each other. The priors for the covariances of the state innovations are assumed to be distributed as inverse-Wishart so that also the posterior has an inverse-Wishart distribution. Similarly, assuming an inverse-Gamma distribution for the measurement innovations implies that the posterior is distributed as an inverse-Gamma. In the scapegoat model, the constant parameters are drawn from a normal distribution given that the prior is also assumed to be normal. The priors for the initial states of the time-varying coefficients are assumed to be normally distributed. Finally, the Bayesian linear regression algorithm implements a simple MCMC assuming an independent inverse Gamma-Normal prior distribution (for details see Kim and Nelson, 1999). The MCMC algorithm for each of the estimated models is described in more detail in Appendix B.

4 Empirical results

We now turn to the empirical results. Our focus is on the empirical model specifications outlined above, with the six macro fundamentals available in the scapegoat survey data: growth, inflation, short-term interest rate, long-term interest rate, current account, and equity flows. All these variables, except the current account, are computed as differential with respect to the domestic variable, e.g. for the short-term interest rate $f_{i_{ST},t} = i^*_{ST} - i_{ST}$, where (*) denotes the foreign country.

Before turning to the empirical results, it is important to explain how we choose the observed fundamentals. We use three fundamentals per regression. Ideally, we would like to use all the six macro fundamentals, so that each of the six observable variables has a chance of being selected as the scapegoat by investors. However, the use of too many fundamentals would make the estimation unfeasible (in particular when the parameters are time-varying). Thus, we restrict our attention to only three fundamentals, which are allowed to be country specific. We use a general-to-specific method to select the set of three fundamentals, for each exchange rate. Precisely, we regress Δs_t on the second term of equation (5):

$$\Delta s_t = \gamma_1 \tau_{1,t} f_{1,t} + \ldots + \gamma_6 \tau_{6,t} f_{6,t} + u_t, \tag{10}$$

and we exclude the variable associated with the lowest t-statistic. We repeat the same procedure sequentially until we end up with the three most relevant (statistically significant) macro variables, for each exchange rate. In short, we use regression (10) to pre-screen the scapegoats and reduce the number of potential scapegoats from six to three in order to make the subsequent estimation feasible and reduce estimation error.

Table 4 summarizes the estimates of the model with constant parameters ($CP - MACRO$ in equation (7)). The table contains point estimates and one-standard deviation Bayesian confidence intervals (in squared brackets). However, from Table 4 we can also see the set of variables selected by our general-to-specific method for each country. Growth differentials, short term interest rate differentials, and equity flows differentials are selected for most of the industrialized countries, whereas the current account is only chosen for the euro and the Swiss franc, and inflation is chosen only for the yen. By contrast, interest rate, growth and equity flows differentials, are particularly important for EM economies.

We proceed column-by-column, thus interpreting the coefficient of each macro fundamental in turn. We find that growth has the expected negative and significant coefficient for the Canadian dollar, the Singaporean dollar, the yen and the South Korean won, so that the currency of the faster growing country appreciates. We also find that the Polish zloty rises when the inflation differential falls, as its purchasing power increases relative to the US dollar, but this effect is not statistically significant. By contrast, the yen and Singaporean dollar appreciate when inflation rises. Moreover, we find the traditional forward bias since the loading on the short-term interest rate differential is always lower than unity. Also, the sign of the loading on the long rate differential is mostly negative for industrialized economies, and positive for EM economies with the only exception of the Mexican peso. A current account deficit is associated with a weaker currency for the euro, the South African rand and the South Korean won, but it takes a counterintuitive positive sign for the Swiss franc. Finally, with the only exception of the UK pound, we find that as equity inflows in the domestic country rise relative to the inflows in the foreign country, the domestic currency appreciates.

Table 5 presents the estimates of the time-invariant coefficients ($\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ and δ) of the scapegoat model with constant parameters ($CP - SCA$ in equation (4)).[15] If the expectation of the structural parameters matters for the exchange rate due to scapegoat effects, $\boldsymbol{\gamma}$ must be statistically different from zero. Also, γ_n should intensify the effect of the true parameter β_n so that it should take the same sign as the structural parameter. Overall, we find that $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}$ are strongly significant over both the country and variable dimensions, and that the $\boldsymbol{\gamma}$ coefficients intensify the effect of the $\boldsymbol{\beta}$ coefficients (i.e. they have the same sign). These results are generally consistent with the benchmark macro model with constant parameters. However, we now find with no exception that

[15] Estimations of the time-varying parameters benchmark model ($TVP - MACRO$) are not reported, but it is worth noting that the parameters, though allowed to switch sign over the sample period, in general show little time-variation, displaying a persistent behavior.

higher growth is associated with an appreciating exchange rate, and a current account deficit with a weaker currency.[16]

Another important finding is the existence of a close link between monthly exchange rate movements and order flow, so that net buying pressure for the foreign currency is associated with a depreciation of the domestic currency. This result confirms that unobservable fundamentals, proxied by order flow, exert a significant effect on exchange rates. This is a necessary condition for the scapegoat effect to exist, as outlined in Section 2.

Table 6 presents the estimates of the time-invariant parameters (γ and δ) of the scapegoat model with time-varying parameters ($TVP - SCA$ in equation (5)). For scapegoat effects to exist, also in this case γ and δ should be jointly statistically different from zero. We find that the γ coefficients are generally significant over both the country and variable dimensions. Most importantly, for all industrialized countries, at least two out of the three γ coefficients are significant. Also, for EM economies at least one of the γ coefficients is significant, but for the Polish zloty and the Singaporean dollar all three γs are significant, and in two cases for the South Korean won.[17] Moreover, the existence of a close link between monthly exchange rate movements and order flow is confirmed. Thus, we again conclude that there is evidence in support of the basic predictions of the scapegoat model.

4.1 In-sample fit of scapegoat model

The first hypothesis of the scapegoat theory, as formulated in Section 2, is that scapegoat effects are empirically powerful in explaining exchange rate movements. This requires that the scapegoat models (with constant and time-varying parameters) perform satisfactorily in fitting exchange rate fluctuations, and outperform the two benchmark exchange rate models, i.e. the constant parameter model and the time-varying parameters model without scapegoat effects given in equations (7) and (8). In this sub-section, we present evidence on the statistical performance of the scapegoat models relative to the benchmark models, using three criteria – the (adjusted) R^2, an information criterion, and market timing tests.

Specifically, Table 7 contains the R^2, both adjusted and non-adjusted, the Akaike information criterion (AIC), and two tests of market timing. In general, the adjusted-R^2 increases when we replace the benchmark specification for constant parameters with the specification for time-varying parameters. More importantly, the explained variances of the scapegoat models, $CP - SCA$ and $TVP - SCA$, are much larger than the respective benchmark models, e.g. the $CP - SCA$ model

[16] Another minor difference with Table 4 is that for the Czech koruna a positive long-term interest rate differential is associated with an appreciating currency.

[17] It is worth noting that few γs take an opposite sign to the γs of Table 5. However, a few of these differing γs in Table 6 are not statistically different from zero.

performs much better than the respective $CP-MACRO$ benchmark model (with the only exception of the Swiss franc and the UK pound). For some currencies the order of improvement is remarkable: by means of the scapegoat models, we move from explaining little of the variance of the exchange rate changes to explaining a much larger proportion (e.g. for the euro and the yen where the R^2s for $TVP - SCA$ are 39% and 47% respectively). Moreover, the scapegoat model with time-varying parameters, $TVP - SCA$ is generally associated with R^2s at least as large as the scapegoat model with constant parameters, $CP - SCA$, with the only exception of two EM currencies, namely the Czech koruna and the Mexican peso.

As for the information criterion, Table 7 provides two pieces of information: the residual sum of squares and the AIC. The residual sum of squares is common to the AIC and the Bayes information criterion (not reported), whereas the two criteria differ in how they penalize for the use of extra variables. It holds that the lower the residual sum of squares or the AIC, the better is the performance of the model. The AIC confirms the results of the R^2 for all industrialized countries' currencies except the Australian dollar. By contrast, for some EM currencies the scapegoat model with constant parameters is not as good as the respective benchmark model with constant parameters. But the scapegoat model with time-varying parameters still outperforms all the other models, and the gain relative to the benchmark model with time-varying parameters is often very large. In sum, the information criterion confirms that allowing for scapegoat effects leads to superior empirical models of the exchange rate.

To complete the model-fit analysis, we consider a set of tests for market timing ability of the competing models, including the 'hit' ratio (HR). The latter is calculated as the proportion of times the sign of the fitted value correctly matches the one of the realized change in the exchange rate. We also employ the test statistic proposed by Henriksson and Merton (1981). The HM test is asymptotically equivalent to a one-tailed test on the significance of the slope coefficient in the following regression:

$$I_{\left\{\Delta s_t>0\right\}} = \varphi_0^{HM} + \varphi_1^{HM} I_{\left\{\widetilde{\Delta s_t}>0\right\}} + \varepsilon_t \tag{11}$$

where Δs_t, $\widetilde{\Delta s_t}$ denote the realized and fitted exchange rate returns, respectively; and $I_{\{.\}}$ is the indicator function that takes the value of 1 when its argument is true and 0 otherwise. A positive and significant φ_1^{HM} provides evidence of market timing. Overall, a fairly clear-cut result emerges from calculating the hit ratio and the HM test. The analysis of the hit ratio statistics shows that for all currencies except the Swiss franc the scapegoat model with time-varying parameters performs better than the other models - i.e. the hit ratios of the scapegoat model are the highest. What varies across currencies is the pecking order of the remaining models. In particular, the scapegoat model with constant parameters outperforms the benchmark model with time-varying parameters only in a few cases (e.g. for the euro and the Japanese yen), but it does outperform the respective benchmark model with constant parameters. These findings, in terms of pecking order, are largely corroborated by the results of the regression-based market timing test. For all industrialized countries' currencies, the φ_1^{HM} coefficient for the time-varying models displays evidence of market timing, i.e. the estimates of φ_1^{HM} are statistically positive. This result also holds for EM currencies, with the exception of the Mexican peso. In contrast, the evidence in favor of market timing for the constant parameters models is weak.[18] We thus conclude that the scapegoat model with time-varying parameters, $TVP - SCA$ has the highest market timing ability, and the scapegoat models tend to outperform their respective benchmark models over all metrics considered.

Figure 2 provides a visual comparison of the (unconditional) adjusted R^2s. However, differently from Table 6, we try to shed light on the drivers of the superior performance of the scapegoat model. Specifically, we look at the two components that differentiate the scapegoat model with time-varying parameters ($TVP - SCA$) from the time-varying parameters model ($TVP - MACRO$), i.e. the order flow and the pure scapegoat term. So, in addition to the $TVP - MACRO$ and $TVP - SCA$ models described above, we consider a variation of the scapegoat specification, where δ (in equation (5)) is set to zero. In essence, by comparing two specifications of the scapegoat model (with and without order flows) we are able to isolate the marginal contribution of order flow and scapegoats to the goodness of fit of the model. Figure 2 suggests that the relative contribution of order flow varies across countries. For example, order flow and the scapegoat terms are roughly equally important for the euro and the Singaporean dollar. The contribution of the scapegoat term prevails e.g. for the Swiss franc, the UK pound and the South Korean won. By contrast, order flow is particularly important for the Canadian dollar and the Japanese yen. However, generally Figure 2 indicates that the scapegoats themselves are an important, or in some cases even dominant, cause for the improved model fit of the scapegoat model for the majority of currencies.

To further refine the results, we now turn to assessing how the relative contributions of macro factors (loadings on the time-varying parameters), order flow and scapegoat variables evolve over time. Figure 3 presents the rolling adjusted-R^2 for the benchmark model with time-varying parameters, and two specifications of the scapegoat model: the restricted specification where δ is set to zero and the full specification where δ is estimated. Thus, in Figure 3 the top area ($TVP - SCA$) reflects the marginal contribution of order flow, whereas the middle area ($TVP - SCA$ no order flow) reflects the marginal contribution of the scapegoat effect. We report the analysis for two industrialized and two EM currencies as examples. Overall, it is apparent that the relative contribution of each

[18] However, there are still more cases of a positive and significant φ_1^{HM} for the scapegoat model with constant parameters than for the respective benchmark model.

component varies over time and across countries.

To highlight one specific example, for the Canadian dollar order flow was particularly important around the last quarter of 2002. However, abstracting from this episode, the time-varying parameters benchmark model performs surprisingly well, in particular until the first quarter of 2004. Around the first quarter of 2003, the contribution of each component was roughly equal. Then, the contribution of the scapegoat effect faded away, whereas the contribution of order flow and, to a lesser extent, macro factors picked up during the recent crisis. Moreover, the scapegoat effect experienced a sharp and short-lived increase towards the end of the sample when order flow, becoming increasingly important, may have generated rational confusion. By contrast, as far as the euro is concerned, the contribution of macro factors is negligible if compared to order flow and scapegoat variables. The contribution of the scapegoat effect was high throughout the sample, but even higher during the first and last two years, whereas order flow was very important in the middle of the sample. Moreover, at the beginning of the sample there was evidence of a clear scapegoat effect, as the large contribution of order flow was associated with an even larger contribution of the scapegoat variables, and the contribution of the macro factors was almost nil.

For the South African rand, the role of macro factors was remarkable throughout the sample, although it became less important over time. By contrast, the scapegoat effect was weak over the central part of the sample. However, in early 2003 and towards the end of the sample, the rising role of order flow is notable, and this may have generated episodes of rational confusion. That said, the two episodes differ from each other. For example, the sudden rise of the scapegoat effect at the end of the sample follows a period when order flow has been consistently important. Differently from the other currencies, for the Korean won the scapegoat effect is particularly important for the entire sample, although the scapegoat effect takes its highest values over the first part of the sample. It is plausible that investors may have found it rational to blame observable macro fundamentals, in particular over the central years of the sample, when unobservable order flow was also particularly important. In fact, for an episode of rational confusion, or scapegoat effect, to exist it should be associated with episodes when order flow was also important. In sum, also this graphical analysis provides evidence in favor of the importance of scapegoat effects, although these effects vary over time and across countries.

4.2 When does a fundamental become a scapegoat?

We now turn to the second hypothesis of the scapegoat theory as formulated in Section 2. Our test investigates whether or not the scapegoat parameter $\tau_{n,t}$ is related to the joint evolution of macro fundamentals and unobservable fundamentals. This is an important question as episodes of rational confusion can only arise, according to the theory, when there are large shocks to the unobservable. During these episodes it becomes rational for agents to blame factors they can actually observe. However, among those observable factors, investors will tend to blame those macroeconomic fundamentals that are out of sync with their longer term equilibrium value. So, there is a scapegoat effect only if *both* the macro fundamental and the unobservable are large. However, such contingency, though necessary, is not sufficient *per se*. The deviation of the macro factor not only has to be large, but also theoretically consistent with the change in the exchange rate. For instance, take output growth as example. Higher output growth should lead to an appreciation of the exchange rate. Now imagine that as a result of large order flow there is a sharp appreciation of the domestic currency. At the same time domestic output growth happens to be very negative. Clearly, output growth cannot explain the appreciation. There would have to be strong positive output growth to explain the appreciation. The theory implies that in this case output growth cannot be the scapegoat of the exchange rate.

For this reason, we first check whether on average large changes in a macro fundamental, at times when order flow also displays large shocks, are theoretically consistent with directional changes in the exchange rate. Our test is based on the following panel regression of the exchange rate on order flow interacted with a macro factor:

$$\Delta s_t = \alpha_0 + \alpha_1 \left(-x_t \times f_{n,t}\right) I_{\left\{f_{n,t}^q, x_t^q\right\}} + u_t. \tag{12}$$

We estimate the regression separately for each of the six macro fundamentals. Order flow is taken with the minus sign so that the expected sign of the parameter α_1 should be the one we would expect from regressing the exchange rate on the fundamental.[19] Order flow and the fundamental are selected for different quantiles, and we select in turn the top 20, 30 and 40 percent of observations. However, a particular observation is selected only if both the fundamental and order flow fall in their respective quantiles. Thus, $I_{\left\{f_{n,t}^q, x_t^q\right\}}$ takes the value of 1 if $f_{n,t}$ and x_t are respectively in their top q percent of observations. This means that both the fundamental and order flow have experienced a sufficiently large shock at time t. As mentioned above, this is a necessary condition for the fundamental to become a scapegoat. Moreover, to some extent, the sign of the regression is also important, as it informs us whether the movement of the exchange rate is theoretically consistent with the movement in order flow and the fundamental.[20]

Table 8 shows that the estimates largely support the scapegoat theory, as the sign of the regres-

[19] Assume that the fundamental has a positive average impact on the exchange rate. Order flow has a negative impact. In this case negative order flow combined with a positive fundamental (or positive order flow with a negative fundamental) should make the variable a scapegoat. So we simply regress the exchange rate on minus the product of order flow times the fundamental. Therefore, the sign of the regression should be the same as we expect from regressing the exchange rate on the fundamental.

[20] That said, we are aware that different theories may sometimes conflict over the sign to attach to a particular variable.

sion is generally theoretically consistent. For example, output growth and the current account have the expected negative sign so that positive output growth and a current account surplus are both associated with an appreciation of the exchange rate, when there is also net buying pressure for the currency. These results are robust to the quantile considered. Moreover, we find that the short-term interest rate differential is consistent with the forward bias (though the coefficient is now negative, and hence more extreme than in Tables 5 and 6), and higher long-term interest rates are associated with a small depreciation of the exchange rate.

So far we have only tested the first leg of our second hypothesis. We can now turn to the second part of the test, where we show that the survey weight indeed rises (i.e. a variable becomes a scapegoat) when large changes to the fundamental are associated with a large shock to the unobservable. In particular, what follows relates the scapegoat weight of a macro variable to the absolute value of the interaction between the macro factor itself and order flow. For simplicity, we assume that only one macro factor is a scapegoat at any one point in time. Take again the example of output growth: we only select those observations for which market participants attach a high weight to output growth relative to the other macro fundamentals. Therefore, the use of the indicator function excludes those observations for which output growth is not selected as a scapegoat by the investor, i.e. when the value of the survey on output growth is relatively low. This is a reasonable assumption consistent with the original work of Bacchetta and van Wincoop (2004) and with the anecdotal evidence that the FX market concentrates on one issue at a time. Thus, our empirical test is based on the following panel regression:

$$\tau_{n,t} = \zeta_0 + \zeta_1 \left| x_t \times f_{n,t} \right| I_{\{\tau_{n,t} > \tau_{j,t}\}} I_{\{f^q_{n,t}, x^q_t\}} + \varepsilon_t, \tag{13}$$

where the indicator function $I_{\{f^q_{n,t}, x^q_t\}}$, consistent with Table 8, takes the value of 1 if at time t both $f_{n,t}$ and x_t are in the top q percent of observations, whereas $I_{\{\tau_{n,t} > \tau_{j,t}\}}$ takes the value of 1 if the survey on the macro factor n exceeds the values of the remaining two macro factors $j \neq n$ at each time t. Thus, we repeat the regression separately for each of the six macro fundamentals, and each of the quantiles. Equation (13) closely follows Bacchetta and van Wincoop (2009, 2011), in that in their model the expectation of the structural parameter at time t is determined by the weighted average of time $t-1$ expectation of the structural parameter and the structural parameter itself, plus a term similar to our $(x_t \times f_{n,t})$. This last term is key in their model, as it reflects the scapegoat effect.[21]

Table 9 presents the regression results. We find that the parameters (ζ_1) take the expected positive sign for all fundamentals and quantiles. This result suggests that $\tau_{n,t}$ is indeed the scapegoat

[21] The weighted average instead reflects the rather slow speed of learning, as agents attach higher weight to the past expectation of the structural parameter than the structural parameter itself.

parameter as it consistently increases when both macro fundamentals and order flows become large in absolute value. Table 9 also shows that this statistical relation is strong for all fundamentals, with R^2s ranging from 22 to 78 percent. Moreover, the *t*-statistic increases as we move from the top 20 percent of observations to the top 40 percent. In sum, taken together, the two legs of our test give strong support to the scapegoat theory, indicating not only that scapegoat effects are powerful in enhancing the empirical performance of exchange rate models, but also that these effects arise when large unobservable shocks move the exchange rate and the scapegoat experiences a large value, consistent with the theory.

5 Conclusions

Investors have a tendency to pick individual economic fundamentals as scapegoats for exchange rate movements. There is indeed ample anecdotal evidence that financial market participants blame individual fundamentals for exchange rate movements, with such blame often shifting rapidly across different fundamentals over time. This fact has been conceptualized in a series of seminal papers by Bacchetta and van Wincoop (2004, 2009, 2011). The main insight from the scapegoat theory of exchange rates is that investors face uncertainties in the form of unobservables driving exchange rates as well as about the true effect of observable fundamentals. When exchange rates move strongly in response to changes in unobservables, it is rational for investors to blame factors that they can actually observe, and more precisely those macro fundamentals that are out of sync with their longer term equilibrium values.

The present paper constitutes the first empirical test of the scapegoat theory of exchange rates. In our empirical analysis we exploit novel data on exchange rate scapegoats from surveys, as well as proxies of unobservable fundamentals based on proprietary FX order flow. Exchange rate scapegoats stem from monthly surveys of 40-60 financial market participants, who are asked to rate on a quantitative scale the importance of a number of macro factors as drivers of a country's exchange rate *vis-a-vis* its reference currency. We match this survey data with a dataset on FX order flow as a proxy of unobservable factors driving exchange rates. Overall, we test the scapegoat theory over a sample of 12 currencies, equally split between industrialized and emerging countries, over the 2001-2009 period.

We find strong empirical support for two key hypotheses derived from the scapegoat theory of exchange rates. First, we estimate two versions of the scapegoat model: one based on constant parameters, and a more general one based on time-varying parameters. The scapegoat model with time-varying parameters performs very well in explaining exchange rate movements, showing a significantly improved performance relative to benchmark models that do not allow for scapegoat effects.

This finding is robust across three different performance criteria, as well as across currencies and over time. Importantly, the improvement in the explanatory power of the scapegoat model does not only stem from the inclusion of the order flow variable, but also from the inclusion of the scapegoat parameters themselves. This finding is relevant because it suggests that while order flow is important in accounting for currency movements, the scapegoat parameters have an additional, sizeable explanatory power. Moreover, the simple scapegoat model with constant parameters also does a relatively good job. It generally outperforms the benchmark macro model with constant parameters, and in a few cases also the benchmark model with time-varying parameters. These results are robust not only for currencies of industrialized economies but also for those of several emerging markets.

Second, we find that a macroeconomic fundamental is picked and identified by market participants as a scapegoat in periods when it is strongly out of sync from its own longer-term equilibrium and at the same time the unobservable fundamental is large. We also show that large changes in the fundamental, at times when the unobservable displays large shocks, are generally consistent with the direction of changes in the exchange rate. This result is particularly strong for variables such as output growth and the current account, for which the direction of their impact on the exchange rate is theoretically not controversial.

Taken together, our results provide strong support in favor of the scapegoat theory of exchange rates, and clearly suggest that expectations of structural parameters, and their interaction with unobservables, are important for improving our understanding of exchange rate fluctuations.

A Appendix: Interpolating Survey Data

This section describes how we interpolate the original survey data by means of the Kalman filter.[22] Our objective is to construct a monthly time series, using as an input the Consensus Economics survey (see Section 3.1), which is conducted only between 3 to 6 months.

The model can be written in state space form such that the survey data are the observed data and the interpolated monthly surveys are the unobservable state variables. The measurement equation is

$$Y_t = s_t \quad \text{if } \mathrm{Y_t} \text{ is available} \tag{A.1}$$

where Y_t denotes the observed survey and s_t the interpolated survey. We also assume that the measurement error is equal to zero, so that we impose that the interpolated survey perfectly matches the observed survey. Moreover, such measurement equation only 'exists' for those times t for which the survey is available.

To complete the state space we need to define the transition equation, and we assume that the interpolated survey evolves as a driftless random walk

$$s_t = s_{t-1} + u_t \tag{A.2}$$

where the transition error u_t is normally distributed with zero mean and standard deviation σ_u.

We now illustrate the Kalman Filter, and specify below the relevant prediction equations, the likelihood contribution, and the updating equations.

Prediction

$$s_{t|t-1} = s_{t-1|t-1} \tag{A.3}$$

$$P_{t|t-1} = P_{t-1|t-1} + \sigma_u^2 \tag{A.4}$$

Likelihood Contribution

$$\xi_t = \left(Y_t - s_{t|t-1}\right) I_{\{\mathrm{Y}_t \neq 0\}} \tag{A.5}$$

$$F_t = P_{t|t-1} \tag{A.6}$$

$$\ln L_t = -0.5 \left(\ln |F_t| + \xi_t' F_t^{-1} \xi_t\right) \tag{A.7}$$

where $I_{\{\mathrm{Y}_t \neq 0\}}$ is the indicator function which takes the value of 1 if the survey is available and 0 otherwise.

Updating

$$K_t = P_{t|t-1} + F_t^{-1} \tag{A.8}$$

$$s_{t|t} = s_{t|t-1} + K_t \xi_t \tag{A.9}$$

$$P_{t|t} = P_{t|t-1} - K_t P_{t|t-1} \tag{A.10}$$

[22] The method draws on the literature on term structure models, where survey data are widely used (e.g. Kim and Orphanides, 2004), and more generally on Harvey (1989).

We use the filtered estimate of the state variable $\left(s_{t|t}\right)$ as our interpolated survey, which we define as τ_t throughout the paper. Therefore, the interpolated survey τ_t only uses the information available up to time t, which is within the information set of the agent. In contrast, by using the smoothed estimates $\left(s_{t|T}\right)$ we would otherwise use future information, which is not available to the agent at the time when expectations are formed.

B Appendix: Bayesian MCMC estimation

This section of the appendix describes the estimation of the constant parameter model, time-varying parameters model, and scapegoat model. We perform a Bayesian estimation of the parameters of the empirical exchange rate models, following Kim and Nelson (1999) and Cogley and Sargent (2002, 2005), among others.

B.1 The linear regression algorithm (CP-MACRO and CP-SCA)

This subsection deals with the estimation of the constant parameter models $CP - MACRO$ and $CP - SCA$. Let us consider the following linear regression model

$$\Delta s_t = \mathbf{X}_t' \boldsymbol{\theta} + u_t, \tag{B.1}$$

where s_t is the log of the nominal exchange rate (defined as the foreign price of domestic currency), $\boldsymbol{\theta} = (\theta_1, \theta_2, , \ldots, \theta_K)'$ is a K vector coefficients, $\mathbf{X}_t = (X_{1,t}, X_{2,t}, , \ldots, X_{K,t})'$ is a K vector of regressors a time t, and u_t is a disturbance term normally distributed with 0 mean and constant variance σ^2. We need to estimate the set of the conditional mean hyperparameters ($\boldsymbol{\theta}$) and the constant variance hyperparameter (σ^2). We define the following priors: for θ we assume a Normal prior $\mathrm{N}(\theta_0, V_0)$, where $\boldsymbol{\theta}_0 = \mathbf{0}_K$ and $\mathbf{V}_0 = \mathbf{I}_{KK}$; for σ^2 we assume an inverse Gamma prior $\mathrm{IG}(\frac{d_0^2}{2}, \frac{v0}{2})$ with shape and scale parameters $v_0 = 1$ and $d_0^2 = 1$, respectively. The Gibbs algorithm consists of the following simple steps:

1. Initialize σ^2.
2. Sample $\boldsymbol{\theta}$ from $p\left(\boldsymbol{\theta}|\sigma^2, \boldsymbol{\Delta}\mathbf{s}^T, \mathbf{X}^T\right) = N(\boldsymbol{\theta}_1, \mathbf{V}_1)$, where $\mathbf{V}_1 = \left(\mathbf{V}_0^{-1} + \sigma^{-2}\mathbf{X}\mathbf{X}'\right)^{-1}$ and $\boldsymbol{\theta}_1 = \mathbf{V}_1\left(\mathbf{V}_0^{-1}\boldsymbol{\theta}_0 + \sigma^{-2}\mathbf{X}\Delta s'\right)$.
3. Sample σ^2 from $p\left(\sigma^2|\theta, \boldsymbol{\Delta}\mathbf{s}^T, \mathbf{X}^T\right) = IG\left(\frac{d_1^2}{2}, \frac{v_1}{2}\right)$, where $v_1 = v_0 + T$ and $d_1^2 = d_0^2 + \sum_{t=1}^{T} \left(\Delta s_t - \mathbf{X}_t'\boldsymbol{\theta}\right)^2$.
4. Go to step 2 and iterate 40,000 times beyond a burn-in of 20,000 iterations.

In the $CP - MACRO$ model $\mathbf{X}_t = [\mathbf{f}_t]$ and $\boldsymbol{\theta} = [\boldsymbol{\beta}]$, where $\mathbf{f}_t$ denotes a 3×1 vector of macro fundamentals. By contrast, in the $CP - SCA$ model $\mathbf{X}_t = [\mathbf{f}_t; \boldsymbol{\tau}\mathbf{f}_t; x_t]$ and $\boldsymbol{\theta} = [\boldsymbol{\beta}; \gamma; \delta]$, where $\mathbf{f}_t$ is a 3×1 vector of macro fundamentals, $\boldsymbol{\tau}_t\mathbf{f}_t$ is a 3×1 vector of scapegoat parameters $\boldsymbol{\tau}_t$ (surveys) times their respective macro fundamentals $\mathbf{f}_t$, x_t is the unobservable fundamental (order flow) and $\boldsymbol{\theta}$ is the K vector of coefficients. Therefore, in the $CP - SCA$ model $K = 7$.

B.2 Time-varying parameters algorithm (TVP-MACRO)

A model with time-varying parameters displays a non-linear state space representation. The measurement equation is

$$\Delta s_t = \mathbf{f}_t' \boldsymbol{\beta}_t + u_t, \tag{B.2}$$

where the conditional $\boldsymbol{\beta}_t$ parameters are now time-varying. To close the model we need to specify the transition equation which describes the law of motion of the parameters. We treat the parameters as a hidden state vector which evolves as a multivariate driftless random walk

$$\boldsymbol{\beta}_t = \boldsymbol{\beta}_{t-1} + \mathbf{v}_t, \tag{B.3}$$

where $\mathbf{v}_t$ is an i.i.d. Gaussian process with mean $\mathbf{0}$ and covariance $\mathbf{Q}$. We assume that the innovations, $(u_t, \mathbf{v}_t)$, are identically and independently distributed normal random variables with mean 0 and covariance matrix

$$E_t \begin{bmatrix} u_t \\ \mathbf{v}_t \end{bmatrix} [u_t \ \mathbf{v}_t] = \mathbf{V} = \begin{pmatrix} \sigma^2 & 0 \\ 0 & \mathbf{Q} \end{pmatrix}, \tag{B.4}$$

where σ^2 is the variance for the measurement innovation and $\mathbf{Q}$ is the covariance matrix for the state innovations. We assume that the innovations are not correlated. In particular, not only the cross-covariance matrix is equal to 0, but also the $\mathbf{Q}$ matrix takes a diagonal form. These assumptions can easily be relaxed but are not crucial to our analysis.

What follows outlines the Gibbs sampler algorithm we use to simulate a sample from the joint posterior $p\left(\sigma^2, \mathbf{Q}, \boldsymbol{\beta}^T \mid \mathbf{y}^T\right)$, where the vectors

$$\mathbf{y}^T = [y_1, \ldots, y_T] \tag{B.5}$$

and

$$\boldsymbol{\beta}^T = [\beta_1, \ldots, \beta_T] \tag{B.6}$$

represent the history of the data $\mathbf{y}^T = [\Delta s^T,\ \mathbf{f}^T]$, and states $\boldsymbol{\beta}^T$, up to time T. Thus, the Gibbs sampler consists of sampling conditionally from three blocks, of which two relate to the hyperparameters $(\sigma^2, \mathbf{Q})$, and the remaining one to the latent parameters $\boldsymbol{\beta}^T$. Next we describe each of the steps in turn.

Gibbs Step 1: States given hyperparameters

The model is linear with a conditional Gaussian state space representation, so that the joint posterior density of β^T is simply

$$p\left(\boldsymbol{\beta}^T | \sigma^2, \mathbf{Q}, \mathbf{y}^T\right) = p\left(\boldsymbol{\beta}_T | \sigma^2, \mathbf{Q}, \mathbf{y}^T\right) \prod_{t=1}^{T-1} p\left(\boldsymbol{\beta}_t | \boldsymbol{\beta}_{t+1}, \sigma^2, \mathbf{Q}, \mathbf{y}^t\right). \tag{B.7}$$

The conditional posterior of $\boldsymbol{\beta}^T$ can be obtained through a forward run of the Kalman filter followed by the one of the simulation smoother as in e.g. Carter and Kohn (1994) or Chib and Greenberg (1995). Given $\boldsymbol{\beta}_{0|0}$ and $\mathbf{R}_{0|0}$, the Kalman Filter forward recursion are

$$
\begin{aligned}
\mathbf{K}_t &= \mathbf{R}_{t|t-1}\mathbf{f}_t'(\mathbf{f}_t\mathbf{R}_{t|t-1}\mathbf{f}_t' + \sigma^2)^{-1} \\
\boldsymbol{\beta}_{t|t} &= \boldsymbol{\beta}_{t-1|t-1} + \mathbf{K}_t(\Delta s_t - \mathbf{f}_t'\boldsymbol{\beta}_{t-1|t-1}) \\
\mathbf{R}_{t|t-1} &= \mathbf{R}_{t-1|t-1} + \mathbf{Q} \\
\mathbf{R}_{t|t} &= \mathbf{R}_{t|t-1} - \mathbf{K}_t\mathbf{f}_t\mathbf{R}_{t|t-1}
\end{aligned} \tag{B.8}
$$

where $\boldsymbol{\beta}_{t|t} \equiv E(\boldsymbol{\beta}_t|\sigma^2, \mathbf{Q}, \mathbf{y}^t)$, $\mathbf{R}_{t|t-1} \equiv Var(\boldsymbol{\beta}_t|\sigma^2, \mathbf{Q}, \mathbf{y}^{t-1})$ and $R_{t|t} \equiv Var(\boldsymbol{\beta}_t|\sigma^2, \mathbf{Q}, \mathbf{y}^{t-1})$ are the mean and, respectively, the predicted and smoothed variance-covariance matrices.

The last forward recursion delivers $p\left(\boldsymbol{\beta}_T|\sigma^2, \mathbf{Q}, \mathbf{y}^T\right) = N(\boldsymbol{\beta}_{T|T}, \mathbf{R}_{T|T})$, the first term of the joint posterior (B.7). The simulation smoother instead provides the updated estimates of the conditional means and variances, $\boldsymbol{\beta}_{t|t+1} \equiv E(\boldsymbol{\beta}_t|\boldsymbol{\beta}_{t+1}, \sigma^2, \mathbf{Q}, \mathbf{y}^t)$ and $R_{t|t} \equiv Var(\boldsymbol{\beta}_t|\boldsymbol{\beta}_{t+1,}\sigma^2, \mathbf{Q}, \mathbf{y}^t)$, respectively. Specifically:

$$
\begin{aligned}
\boldsymbol{\beta}_{t|t+1} &= \boldsymbol{\beta}_{t|t} + \mathbf{R}_{t|t}\mathbf{R}_{t+1|t}^{-1}(\boldsymbol{\beta}_{t+1}^d - \boldsymbol{\beta}_{t|t}) \\
\mathbf{R}_{t|t+1} &= \mathbf{R}_{t|t} - \mathbf{R}_{t|t}\mathbf{R}_{t+1|t}^{-1}\mathbf{R}_{t|t}
\end{aligned} \tag{B.9}
$$

fully determine the remaining densities of equation (B.7),

$$
p\left(\boldsymbol{\beta}_t|\boldsymbol{\beta}_{t+1}, \sigma^2, \mathbf{Q}, \mathbf{y}^t\right) = N(\boldsymbol{\beta}_{t|t+1}, \mathbf{R}_{t|t+1}) \tag{B.10}
$$

To obtain an entire sample of the latent parameters $\boldsymbol{\beta}^T$, the simulation smoother works as follows. First, draw $\boldsymbol{\beta}_T^d$ from $N(\boldsymbol{\beta}_{T|T}, \mathbf{R}_{T|T})$, then compute $\mathbf{R}_{T-1|T}$ and $\boldsymbol{\beta}_{T-1|T}$ using $\boldsymbol{\beta}_T^d$. Second, draw $\boldsymbol{\beta}_{T-1}^d$ from $N(\boldsymbol{\beta}_{T-1|T}, \mathbf{R}_{T-1|T})$, and so forth. Finally, draw $\boldsymbol{\beta}_1^d$ from $N(\boldsymbol{\beta}_{1|2}, \mathbf{R}_{1|2})$.

Gibbs Step 2: Hyperparameter σ^2 given states

Conditional on $\boldsymbol{\beta}^T$ and $\mathbf{y}^T$, the innovations of the measurement equation are observable so that the conditional density of σ^2 is independent from $\mathbf{Q}$. When an inverse Gamma prior is combined with a Gaussian likelihood, the posterior has also an inverse Gamma density

$$
p\left(\sigma^2|\boldsymbol{\beta}^T, \mathbf{y}^T\right) = IG(\frac{S_1}{2}, \frac{\nu_1}{2}) \tag{B.11}
$$

with scale and shape parameters

$$
\begin{aligned}
&S_1 = S_0 + \sum_{t=1}^{T}(\Delta s_t - \mathbf{f}_t'\boldsymbol{\beta}_t)^2 \\
&\nu_1 = \nu_0 + T
\end{aligned}
$$

where the priors are $S_0 = 1$ and $\nu_0 = 1$.

Gibbs Step 3: Hyperparameter Q given states

We now focus on drawing the variance-covariance matrix of the coefficients' innovations $\mathbf{v}_t$, $\mathbf{Q}$. Conditional on a realization of $\boldsymbol{\beta}^T$, the innovations $\mathbf{v}_t$ are observable. Moreover, because $\mathbf{v}_t$ is independent of the other shocks of the model u_t, then σ is redundant to draw $\mathbf{Q}$. Given an inverse-Wishart prior for $\mathbf{Q}$ and a normal likelihood, the posterior of $\mathbf{Q}$ has itself an inverse-Wishard distribution

$$
p\left(\mathbf{Q}|\boldsymbol{\beta}^T, \mathbf{y}^T\right) = IW\left(\mathbf{Q}_1^{-1}, z_1\right) \tag{B.12}
$$

with scale and degrees-of-freedom parameters

$$\mathbf{Q}_1 = \mathbf{Q}_0 + \sum_{t=1}^{T} \left(\boldsymbol{\beta}_t - \boldsymbol{\beta}_{t-1}\right)\left(\boldsymbol{\beta}_t - \boldsymbol{\beta}_{t-1}\right)'$$
$$z_1 = z_0 + T.$$

Under the assumption of uncorrelated states we set the off-diagonal elements of $\mathbf{Q}^d$ to 0.[23]

We iterate over the three steps above for a number of iterations sufficient to ensure convergence of the chain to the ergodic distribution. Precisely, we perform 80,000 replications of which the first 40,000 are burned-in, and we save 1 every 10 draws of the last 40,000 replications of the chain.

B.3 The scapegoat model (TVP-SCA)

In Bacchetta and van Wincoop (2009), the scapegoat model not only includes macro factors with loadings that vary over time (as in our benchmark $TVP-MACRO$), but also the expectation of future parameters and unobserved fundamentals. Our empirical version of the scapegoat model of Bacchetta and van Wincoop (2009) is the following

$$\Delta s_t = \mathbf{f}_t'\boldsymbol{\beta}_t + (\boldsymbol{\tau}_t\mathbf{f}_t)'\boldsymbol{\gamma} + \delta x_t + u_t, \tag{B.13}$$

where $\boldsymbol{\tau}_t$ denotes the surveys which capture the expectation of future parameters and weights the information in the macro factors. In addition, x_t is the order flow, which proxies for the unobservable fundamental.

From an econometric point of view, our empirical scapegoat model consists of estimating a model with both time-varying parameters ($\boldsymbol{\beta}_t$) and time-invariant parameters ($\boldsymbol{\gamma}$ and δ). This means that we need to modify the time-varying parameters algorithm described above. In particular, the conditional distribution of the variance of the measurement error also depends on $\boldsymbol{\gamma}$ and δ so that the scale matrix now becomes $S_1 = S_0 + \sum_{t=1}^{T}(\Delta s_t - \mathbf{f}_t'\boldsymbol{\beta}_t - (\boldsymbol{\tau}_t\mathbf{f}_t)'\boldsymbol{\gamma} - \delta x_t)^2$. Similarly, the joint posterior density of the states will also depend on $\boldsymbol{\gamma}$ and δ. Thus, in the forward Kalman recursion we modify the filtered value of the state at time t such that $\boldsymbol{\beta}_{t|t} = \boldsymbol{\beta}_{t-1|t-1} + \mathbf{K}_t(\Delta s_t - \mathbf{f}_t'\boldsymbol{\beta}_{t-1|t-1} - (\boldsymbol{\tau}_t\mathbf{f}_t)'\boldsymbol{\gamma} - \delta x_t)$.

More importantly, an additional step in the Gibbs sampler is required to draw $\boldsymbol{\gamma}$ and δ. Conditional on the previous draw of the states, we can rewrite the original scapegoat model as

$$\Delta\widetilde{s}_t = \Delta s_t - \mathbf{f}_t'\boldsymbol{\beta}_t = \mathbf{z}_t'\mathbf{A} + u_t, \tag{B.14}$$

where $\mathbf{z}_t = [\boldsymbol{\tau}_t\mathbf{f}_t; x_t]$ and $\mathbf{A} = [\boldsymbol{\gamma}; \delta]$ are vectors of independent variables and parameters, respectively, each of dimension (4×1). Now, drawing $\mathbf{A}$ is equivalent to the problem of drawing the conditional mean parameters in a linear regression model (see above). We assume a Normal prior distribution, with $\mathbf{a}_0 = \mathbf{0}_4$ and $\mathbf{V}_{A,0} = \mathbf{I}_{4,4}$, so that the posterior is also Normal

$$p\left(\mathbf{A}|\sigma^2, \mathbf{y}^T, \boldsymbol{\beta}^T\right) = N\left(\mathbf{a}_1, \mathbf{V}_{A,1}\right), \tag{B.15}$$

where $\mathbf{V}_{A,1} = \left(\mathbf{V}_{A,0}^{-1} + \sigma^{-2}\mathbf{z}\mathbf{z}'\right)^{-1}$ and $\mathbf{a}_1 = \mathbf{V}_{A,1}\left(\mathbf{V}_{A,0}^{-1}\mathbf{a}_0 + \sigma^{-2}\mathbf{z}\Delta\widetilde{s}\right)$.

[23] An alternative would be to work with the full conditional density equation by equation assuming an inverse Gamma for each element of the diagonal of Q, so that also the posterior has an inverse Gamma density. The two methods are equivalent.

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Table 1
Surveys Summary Statistics

Panel A: All currencies

	ΔGrowth	ΔInflation	ΔRate ST	ΔRate LT	CA	ΔEquity
Obs	1224	1224	1224	1224	1224	1224
Obs: scape	246	22	660	59	157	246
Obs: (%) scape	12.3	1.8	53.9	4.8	12.8	20.1
Mean	5	3.9	6.0	4.9	5.0	5.0
Std. Dev.	1.2	1.1	1.4	1.0	1.2	1.2
Min	1.5	1.1	1.7	1.3	1.3	1
Max	8.2	8.0	9.0	8.0	8.8	8.3

Panel B: Industrialized Economies

	ΔGrowth	ΔInflation	ΔRate ST	ΔRate LT	CA	ΔEquity
Obs	612	612	612	612	612	612
Obs: scape	40	0	387	32	58	121
Obs: (%) scape	6.5	0.0	63.2	5.2	9.5	19.8
Mean	4.9	3.6	6.1	5.1	4.6	4.9
Std. Dev.	1.1	0.8	1.5	1.0	1.2	1.1
Min	2.0	1.1	1.7	1.9	1.3	2.0
Max	8.2	6.3	9.0	8.0	7.4	8.0

Panel C: Emerging Market Economies

	ΔGrowth	ΔInflation	ΔRate ST	ΔRate LT	CA	ΔEquity
Obs	612	612	612	612	612	612
Obs: scape	111	22	273	27	99	125
Obs: (%) scape	18.1	3.6	44.6	4.4	16.2	20.4
Mean	5.1	4.3	5.9	4.8	5.3	5.1
Std. Dev.	1.3	1.3	1.2	1.0	1.1	1.3
Min	1.5	1.5	2.3	1.3	2.0	1.0
Max	8.1	8.0	8.7	7.8	8.8	8.3

The table presents descriptive statistics for the survey data on exchange rates. "Obs: scape" and "Obs: scape (%)" indicate how many times a variable was the main scapegoat out of the six variables considered, and the percentage share of all observations for which it was the main scapegoat, respectively. The dataset covers the interpolated monthly surveys from March 2001 to August 2009.

Table 2
Macro Fundamentals Summary Statistics

Panel A: All currencies

	ΔGrowth	ΔInflation	ΔRate ST	ΔRate LT	CA	ΔEquity
Obs	1224	1224	1224	1224	1224	1224
Mean	0.75	0.20	1.42	0.82	5.51	-1.80
Std. Dev.	2.52	2.31	3.24	2.47	7.34	6.57
Min	-10.22	-5.14	-5.20	-4.15	-10.83	-38.23
Max	11.01	10.98	14.39	10.40	35.22	33.24

Panel B: Industrialized Economies

	ΔGrowth	ΔInflation	ΔRate ST	ΔRate LT	CA	ΔEquity
Obs	612	612	612	612	612	612
Mean	-0.13	-0.67	0.10	-0.39	5.53	-1.19
Std. Dev.	1.58	1.44	2.17	1.49	4.19	8.01
Min	-8.71	-5.14	-5.20	-4.15	-2.22	-38.23
Max	3.24	3.59	5.27	2.65	16.66	33.24

Panel C: Emerging Market Economies

	ΔGrowth	ΔInflation	ΔRate ST	ΔRate LT	CA	ΔEquity
Obs	612	612	612	612	612	612
Mean	1.64	1.06	2.74	2.04	5.50	-2.42
Std. Dev.	2.94	2.67	5.59	2.65	9.51	4.62
Min	-10.22	-4.09	-2.93	-3.54	-10.83	-19.80
Max	11.01	10.98	14.39	10.40	35.22	8.64

The table presents descriptive statistics for the following macro fundamentals: growth, inflation, short-term interest rates, long-term interest rates, current account, and equity flows. All these variables, except the current account, are computed as differential with respect to the domestic variable, e.g. as for the short term interest rate ΔRate ST= $i^*_{ST} - i_{ST}$, where $(*)$ denotes the foreign country. The dataset covers the period from March 2001 to August 2009.

Table 3
Exchange Rates and Order Flows Summary Statistics

Panel A: Industrialized Economies

	Mean	St. Dev	Min	Max	Mean	St. Dev	Min	Max
	AUD/USD				CAD/USD			
Δs	-0.39	4.22	-11.25	23.48	-0.25	2.82	-6.34	10.80
x	-0.11	0.91	-4.40	1.54	0.02	0.90	-3.08	4.76
	EUR/USD				JPY/USD			
Δs	-0.43	2.90	-6.93	6.39	-0.16	3.20	-7.60	7.39
x	-0.21	3.06	-8.39	13.39	0.44	2.17	-6.26	7.09
	CHF/EUR				GPB/USD			
Δs	0.01	1.26	-4.50	3.92	-0.05	2.92	-7.41	8.70
x	0.26	1.63	-4.79	11.77	-0.13	3.10	-21.45	17.66

Panel B: Emerging Market Economies

	Mean	St. Dev	Min	Max	Mean	StDev	Min	Max
	CZK/EUR				MXN/USD			
Δs	-0.27	1.77	-4.042	6.44	0.39	3.44	-13.33	22.19
x	0.00	0.11	-0.65	0.43	-0.06	0.21	-0.98	0.50
	PLN/EUR				ZAR/USD			
Δs	-0.22	3.49	-7.32	13.06	0.14	5.22	-13.97	14.68
x	-0.03	0.18	-0.86	0.67	0.00	0.40	-1.46	1.35
	SGD/USD				SKO/USD			
Δs	-0.21	1.57	-4.37	4.61	0.06	3.82	-13.11	19.01
x	-0.01	0.45	-2.74	2.10	-0.08	0.34	-1.34	0.94

The table presents descriptive statistics for monthly exchange rate returns (Δs) and order flow (x) for each of the 12 currencies. The order flow data is the cumulative monthly order flow, based on daily order flow data, on the business day previous to the latest scapegoat survey and over the previous month. Order flow is measured in billion of dollars. The dataset covers the period from March 2001 to August 2009.

Table 4
Constant Parameters Macro Model (CP-MACRO)

Panel A: Industrialized Economies

	ΔGrowth	ΔInflation	ΔRate ST	ΔRate LT	CA	ΔEquity
AUD/USD	-	-	0.250**	-0.218**	-	-0.185**
	-	-	[0.145;0.357]	[-0.323;-0.114]	-	[-0.273;-0.095]
CAD/USD	-0.288**	-	0.181**	-	-	-0.351**
	[-0.384;-0.191]	-	[0.082;0.278]	-	-	[-0.460;-0.246]
EUR/USD	-	-	0.296**	-0.394**	-0.276**	-
	-	-	[0.179;0.414]	[-0.528;-0.268]	[-0.370;-0.184]	-
JPY/USD	-0.123**	-0.114*	-	-0.048	-	-
	[-0.226;-0.024]	[-0.232;0.001]	-	[-0.151;0.053]	-	-
CHF/EUR	0.055*	-	-	-	0.262**	-0.081*
	[-0.035;0.145]	-	-	-	[0.169;0.353]	[-0.172;0.004]
GPB/USD	0.127**	-	0.039	-	-	0.143**
	[0.019;0.239]	-	[-0.074;0.147]	-	-	[0.055;0.230]

Panel B: Emerging Market Economies

	ΔGrowth	ΔInflation	ΔRate ST	ΔRate LT	CA	ΔEquity
CZK/EUR	-	-	0.051	0.004	-	−0.338**
	-	-	[-0.063;0.162]	[-0.113;0.123]	-	[-0.437;-0.234]
MXD/USD	-	-	0.296**	-0.195**	-	-0.141**
	-	-	[0.167;0.426]	[-0.328;-0.071]	-	[-0.232;-0.054]
PLN/USD	-0.023	0.017	-	-	-	-0.145**
	[-0.124;0.075]	[-0.073;0.104]	-	-	-	[-0.238;-0.054]
ZAR/USD	-	-	-0.357**	0.466**	-0.334**	-
	-	-	[-0.466;-0.239]	[0.321;0.599]	[-0.438;-0.232]	-
SGD/USD	-0.201**	-0.263**	-	0.308**	-	-
	[-0.294;-0.113]	[-0.380;-0.151]	-	[0.193;0.417]	-	-
KRW/USD	-0.259**	-	0.199**	-	-0.388**	-
	[-0.349;-0.168]	-	[0.111;0.284]	-	[-0.485;-0.294]	-

The table presents the estimated loadings of the exchange rate empirical model with constant parameters ($CP - MACRO$)

$$\Delta s_t = \beta_1 f_{1,t} + \beta_2 f_{2,t} + \beta_3 f_{3,t} + u_t,$$

where Δs_t is the monthly exchange rate return (if s_t increases the domestic exchange rate - either the USD or the EUR - appreciates). The sample period spans from March 2001 to August 2009. We use three macro factors per country. The selection criterion for the macro factors consists of a general-to-specific method, whereby we regress Δs_t on the survey ($\tau_{i,t}$) times the respective macro factor ($f_{i,t}$)

$$\Delta s_t = \alpha_1 \tau_{1,t} f_{1,t} + \alpha_2 \tau_{2,t} f_{2,t} + \alpha_3 \tau_{3,t} f_{3,t} + u_t$$

and we select the three macro factors corresponding to the αs that display the highest t-statistics, using the selection procedure described in Section 4. Note that all variables, except the surveys, are standardized by subtracting the mean and dividing by their standard deviation. $\boldsymbol{\tau}$s are standardized so that they have unit variance. One-standard deviation confidence intervals are reported in brackets. (*) and (**) indicate that the (27-68) and (16-84) intervals, respectively, do not contain 0.

Table 5
Constant Parameters Scapegoat Model (CP-SCA)

Panel A: Industrialized Economies

	ΔGrowth	ΔInflation	ΔRate ST	ΔRate LT	CA	ΔEquity	Orderflow
AUD/USD							
β	-	-	0.03**	-0.08**	-	-0.08**	-
	-	-	[0.02;0.05]	[-0.16;-0.01]	-	[-0.14;-0.02]	-
γ	-	-	0.09**	-0.04**	-	-0.03**	-0.11**
	-	-	[0.06;0.11]	[-0.06;-0.02]	-	[-0.06;-0.01]	[-0.19;-0.04]
CAD/USD							
β	-0.17**	-	0.05**	-	-	-0.10**	-
	[-0.28;-0.05]	-	[0.01;0.10]	-	-	[-0.20; -0.02]	-
γ	-0.02**	-	0.04**	-	-	-0.05**	-0.36**
	[-0.04;-0.01]	-	[0.01;0.06]	-	-	[-0.09;-0.01]	[-0.45;-0.27]
EUR/USD							
β	-	-	0.09**	-0.12**	-0.13**	-	-
	-	-	[0.01;0.18]	[-0.24;-0.02]	[-0.24;-0.03]	-	-
γ	-	-	0.07**	-0.05**	-0.03**	-	-0.33**
	-	-	[0.02;0.13]	[-0.08;-0.01]	[-0.05;-0.01]	-	[-0.42;-0.23]
JPY/USD							
β	-0.09**	-0.03*	-	-0.05**	-	-	-
	[-0.16;-0.02]	[-0.12;0.05]	-	[-0.10;-0.01]	-	-	-
γ	-0.02**	-0.02*	-	-0.06**	-	-	-0.38**
	[-0.04;-0.01]	[-0.05;0.02]	-	[-0.10;-0.02]	-	-	[-0.47;-0.28]
CHF/EUR							
β	-0.06**	-	-	-	−0.03**	-0.04**	-
	[-0.10;-0.01]	-	-	-	[-0.06;0.00]	[-0.10;0.00]	-
γ	-0.01**	-	-	-	-0.01**	-0.03**	-0.11**
	[-0.03;0.00]	-	-	-	[-0.02;0.00]	[-0.06;0.00]	[-0.19;-0.03]
GPB/USD							
β	-0.07**	-	0.05**	-	-	0.05**	-
	[-0.13;-0.01]	-	[0.00;0.11]	-	-	[0.01;0.11]	-
γ	-0.01**	-	0.03**	-	-	0.03**	-0.16**
	[-0.01;0.00]	-	[0.00;0.06]	-	-	[0.01;0.07]	[-0.25;-0.07]

Panel B: Emerging Market Economies							
	ΔGrowth	ΔInflation	ΔRate ST	ΔRate LT	CA	ΔEquity	Orderflow
CZK/EUR							
β	-	-	0.05**	-0.07**	-	-0.13**	-
	-	-	[0.05;0.05]	[-0.13;-0.01]	-	[-0.22;-0.03]	-
γ	-	-	0.16**	-0.11**	-	-0.05**	-0.22**
	-	-	[0.17;0.17]	[-0.16;-0.05]	-	[-0.09;-0.01]	[-0.32;-0.11]
MXD/USD							
β	-	-	0.10**	-0.09**	-	-0.06**	-
	-	-	[0.02;0.19]	[-0.18;-0.01]	-	[-0.11;-0.01]	-
γ	-	-	0.07**	-0.05**	-	-0.03**	-0.12**
	-	-	[0.02;0.12]	[-0.08;-0.02]	-	[-0.06;-0.01]	[-0.21;-0.04]
PLN/USD							
β	-0.08**	0.03*	-	-	-	-0.07**	-
	[-0.14;-0.02]	[-0.01;0.08]	-	-	-	[-0.13;-0.01]	-
γ	-0.02**	0.03*	-	-	-	-0.07**	-0.14**
	[-0.04;-0.01]	[0.00;0.06]	-	-	-	[-0.12;-0.02]	[-0.23;-0.05]
ZAR/USD							
β	-	-	-0.11**	0.18**	-0.20**	-	-
	-	-	[-0.22;-0.02]	[0.03;0.33]	[-0.34;-0.05]	-	-
γ	-	-	-0.05**	0.04**	-0.03**	-	-0.33**
	-	-	[-0.10;-0.01]	[0.01;0.07]	[-0.06;-0.01]	-	[-0.43;-0.23]
SGD/USD							
β	-0.12**	-0.06*	-	0.05	-	-	-
	[-0.21;-0.03]	[-0.15;0.01]	-	[-0.05;0.16]	-	-	-
γ	-0.02**	-0.02*	-	0.01	-	-	-0.33**
	[-0.03;0.00]	[-0.06;0.01]	-	[-0.03;0.04]	-	-	[-0.43;-0.23]
KRW/USD							
β	-0.17**	-	0.09**	-	-0.27**	-	-
	[-0.28;-0.05]	-	[0.01;0.18]	-	[-0.41;-0.11]	-	-
γ	-0.02**	-	0.05**	-	-0.04**	-	-0.23**
	[-0.04;-0.01]	-	[0.01;0.09]	-	[-0.07;-0.01]	-	[-0.33;-0.13]

The table presents the estimates for the coefficients ($\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ and δ) of the scapegoat model ($CP - SCA$):

$$\Delta s_t = \mathbf{f}_t'\boldsymbol{\beta} + (\boldsymbol{\tau}_t\mathbf{f}_t)'\boldsymbol{\gamma} + \delta x_t + u_t.$$

Note that all variables, except the surveys, are standardized by subtracting the mean and dividing by their standard deviation. $\boldsymbol{\tau}$s are standardized so that they have unit variance. One-standard deviation confidence intervals are reported in brackets. (*) and (**) indicate that the (27-68) and (16-84) intervals, respectively, do not contain 0.

Table 6
Time-varying Parameters Scapegoat Model (TVP-SCA)

Panel A: Industrialized Economies

	ΔGrowth	ΔInflation	ΔRate ST	ΔRate LT	CA	ΔEquity	Orderflow
AUD/USD							
γ	-	-	0.02	-0.19**	-	-0.17**	-0.10**
	-	-	[-0.10;0.14]	[-0.28;-0.11]	-	[-0.26;-0.08]	[-0.17;-0.03]
CAD/USD							
γ	-0.05**	-	-0.07*	-	-	0.03	-0.36**
	[-0.09;-0.01]	-	[-0.18;0.04]	-	-	[-0.06;0.13]	[-0.45;-0.27]
EUR/USD							
γ	-	-	-0.01	-0.32**	-0.60**	-	-0.46**
	-	-	[-0.15;0.13]	[-0.46;-0.18]	[-0.75;-0.45]	-	[-0.55;-0.37]
JPY/USD							
γ	-0.13**	0.20**	-	-0.01	-	-	-0.43**
	[-0.21;-0.04]	[0.04;0.34]	-	[-0.18;0.16]	-	-	[-0.53;-0.33]
CHF/EUR							
γ	-0.03**	-	-	-	-0.07**	-0.01	-0.14**
	[-0.05;-0.01]	-	-	-	[-0.12;-0.01]	[-0.07;0.06]	[-0.22;-0.05]
GPB/USD							
γ	-0.16**	-	0.06	-	-	-0.07*	-0.12**
	[-0.24;-0.08]	-	[-0.06;0.19]	-	-	[-0.15;0.00]	[-0.20;-0.04]

Panel B: Emerging Market Economies

	ΔGrowth	ΔInflation	ΔRate ST	ΔRate LT	CA	ΔEquity	Orderflow
CZK/EUR							
γ	-	-	-0.02	-0.22**	-	-0.03	-0.20**
	-	-	[-0.16;0.11]	[-0.36;-0.08]	-	[-0.13;0.08]	[-0.29;-0.10]
MXD/USD							
γ	-	-	0.02	-0.11**	-	0.01	-0.15**
	-	-	[-0.08;0.12]	[-0.17;-0.04]	-	[-0.08;0.11]	[-0.24;-0.05]
PLN/USD							
γ	-0.16**	0.19**	-	-	-	-0.06*	-0.20**
	[-0.26;-0.06]	[0.05;0.33]	-	-	-	[-0.18;0.05]	[-0.30;-0.10]
ZAR/USD							
γ	-	-	-0.03	-0.03	-0.07**	-	-0.37**
	-	-	[-0.18;0.12]	[-0.12;0.06]	[-0.12;-0.02]	-	[-0.47;-0.28]
SGD/USD							
γ	-0.04**	0.50**	-	-0.61**	-	-	-0.26**
	[-0.08;-0.01]	[0.32;0.67]	-	[-0.73;-0.49]	-	-	[-0.37;-0.16]
KRW/USD							
γ	-0.06**	-	0.07	-	-0.05**	-	-0.25**
	[-0.12;-0.01]	-	[-0.06;0.19]	-	[-0.09;-0.01]	-	[-0.35;-0.16]

The table presents the estimates for the time-invariant coefficients ($\boldsymbol{\gamma}$ and δ) of the scapegoat model:

$$\begin{aligned} \Delta s_t &= \mathbf{f}_t'\boldsymbol{\beta}_t + (\boldsymbol{\tau}_t\mathbf{f}_t)'\boldsymbol{\gamma} + \delta x_t + u_t \\ \boldsymbol{\beta}_t &= \boldsymbol{\beta}_{t-1} + \mathbf{v}_t. \end{aligned}$$

This model is also defined as $TVP-SCA$, whereas $TVP-MACRO$ (not reported) is the benchmark model where $\boldsymbol{\gamma}$ and δ are set to 0. Note that all variables, except the surveys, are standardized by subtracting the mean and dividing by their standard deviation. $\boldsymbol{\tau}$s are standardized so that they have unit variance. One-standard deviation confidence intervals are reported in brackets. (*) and (**) indicate that the (27-68) and (16-84) intervals, respectively, do not contain 0.

Table 7
In-sample Model Performance

Panel A: Industrialized Economies

	Expl. Variance		Information Criteria		Market-timing tests	
	R^2(%)	R^2adj(%)	log(SSR/T)	AIC	HR(%)	HM
AUD/USD						
CP-MACRO	7.6	4.8	-0.09	-0.03	54.9	0.10
TVP-MACRO	17.2	14.7	-0.32	-0.26	62.7	0.26^{***}
CP-SCA	26.1	20.6	0.00	0.13	50.0	0.00
TVP-SCA	26.0	20.6	-0.45	-0.31	64.7	0.30^{***}
CAD/USD						
CP-MACRO	8.7	5.9	-0.10	-0.04	53.9	0.08
TVP -MACRO	16.4	13.8	-0.34	-0.28	64.7	0.30^{***}
CP-SCA	25.3	19.8	-0.23	-0.09	55.9	0.12
TVP-SCA	39.0	34.5	-0.65	-0.51	75.5	0.51^{***}
EUR/USD						
CP-MACRO	6.5	3.6	-0.08	-0.02	58.8	0.18^{**}
TVP-MACRO	8.4	5.6	-0.23	-0.17	61.8	0.26^{***}
CP-SCA	20.9	15.1	-0.18	-0.05	70.6	0.41^{***}
TVP-SCA	46.9	42.9	-0.86	-0.72	75.5	0.52^{***}
JPY/USD						
CP-MACRO	1.6	-1.4	-0.03	0.03	56.9	0.14
TVP-MACRO	5.1	2.2	-0.14	-0.08	57.8	0.16^{*}
CP-SCA	21.4	15.6	-0.15	-0.01	68.6	0.37^{***}
TVP-SCA	31.2	26.1	-0.54	-0.40	78.4	0.57^{***}
CHF/EUR						
CP-MACRO	7.2	4.4	-0.08	-0.03	63.7	0.27^{***}
TVP-MACRO	10.1	7.4	-0.20	-0.14	60.8	0.21^{***}
CP-SCA	5.6	0.0	0.05	0.19	53.9	0.07
TVP-SCA	18.7	12.7	-0.40	-0.26	59.8	0.20^{**}
GPB/USD						
CP-MACRO	5.7	2.9	-0.07	-0.01	49.0	-0.02
TVP-MACRO	21.9	19.5	-0.38	-0.32	61.8	0.25^{***}
CP-SCA	8.6	1.9	-0.06	0.08	54.9	0.10
TVP-SCA	30.8	25.7	-0.54	-0.41	69.6	0.41^{***}

In-sample Model Performance

Panel B: Emerging Market Economies

	Expl. Variance		Information Criteria		Market-timing tests	
	R^2(%)	R^2adj(%)	log(SSR/T)	AIC	HR(%)	HM
CZK/EUR						
CP-MACRO	10.8	8.1	-0.13	-0.07	56.9	0.14
TVP-MACRO	17.5	15.0	-0.27	-0.21	60.8	0.22^{**}
CP-SCA	30.7	25.6	0.02	0.16	52.9	0.06
TVP-SCA	26.0	20.5	-0.41	-0.28	65.7	0.31^{***}
MXD/USD						
CP-MACRO	3.9	1.0	-0.05	0.01	49.0	-0.01
TVP-MACRO	7.5	4.7	-0.15	-0.09	53.9	0.06
CP-SCA	15.8	9.6	-0.03	0.10	46.1	-0.07
TVP-SCA	13.4	7.0	-0.25	-0.11	61.8	0.22^{**}
PLN/USD						
CP-MACRO	2.0	-1.0	-0.03	0.03	49.0	-0.02
TVP-MACRO	16.0	13.5	-0.29	-0.23	60.8	0.24^{**}
CP-SCA	9.1	2.4	-0.02	0.12	55.9	0.12
TVP-SCA	24.3	18.7	-0.41	-0.27	64.7	0.30^{***}
ZAR/USD						
CP-MACRO	7.4	4.6	-0.09	-0.03	57.8	0.16^{*}
TVP-MACRO	9.4	6.7	-0.16	-0.11	63.7	0.28^{***}
CP-SCA	21.2	15.4	-0.19	-0.06	60.8	0.22^{**}
TVP-SCA	30.2	25.1	-0.51	-0.37	71.6	0.43^{***}
SGD/USD						
CP-MACRO	7.6	4.8	-0.09	-0.03	62.7	0.25^{***}
TVP-MACRO	11.5	8.8	-0.17	-0.11	71.6	0.43^{***}
CP-SCA	17.5	11.4	-0.18	-0.04	73.5	0.47^{***}
TVP-SCA	36.9	32.3	-0.45	-0.32	73.5	0.47^{***}
KRW/USD						
CP-MACRO	14.3	11.7	-0.17	-0.11	59.8	0.20^{*}
TVP-MACRO	26.4	24.2	-0.56	-0.50	64.7	0.32^{***}
CP-SCA	23.0	17.3	-0.19	-0.06	60.8	0.22^{**}
TVP-SCA	58.6	55.6	-1.20	-1.07	74.5	0.51^{***}

The table provides several measures of model fit such as measures of explained variance, information criteria and market timing. As for the information criteria, ln(RSS/T) is common to both the AIC and BIC (not reported), whereas the two differ in the way they penalize for the extra parameters. The HM test is a one-tailed test on the significance of the slope coefficient in the following regression:

$$I_{\left\{\Delta s_t > 0\right\}} = \varphi_0^{HM} + \varphi_1^{HM} I_{\left\{\widetilde{\Delta s_t} > 0\right\}} + \varepsilon_t,$$

where Δs_t and $\widetilde{\Delta s_t}$ denote the realized and fitted exchange rate returns, and I is the indicator function equal to unity when its argument is true and 0 otherwise. A positive and significant φ_1^{HM} provides evidence of market timing. Precisely, we report under HM $\widehat{\varphi_1}$ and in parentheses its standard error calculated using Newey-West (1987).

Table 8

Exchange Rates, Order Flows and Macro Factors

	ΔGrowth			ΔInflation			ΔRate ST		
q	20%	30%	40%	20%	30%	40%	20%	30%	40%
α_0	-0.31	-0.20	-0.11	-0.09	-0.17	-0.01	0.08	0.06	-0.03
t-stat	(-1.14)	(-1.08)	(-0.93)	(-0.26)	(-0.77)	(-0.08)	(0.61)	(0.75)	(-0.39)
α_1	-0.17	-0.17	-0.13	0.00	-0.01	0.00	-0.04	-0.09	-0.09
t-stat	(-2.09)	(-2.60)	(-2.23)	(-0.03)	(-0.21)	(-0.01)	(-0.91)	(-2.43)	(-2.73)
R^2(%)	14	11	4	0	0	0	3	4	4
R^2adj(%)	11	9	3	-5	-2	-2	1	3	3
N_I	31	57	111	22	40	59	52	106	165

	ΔRate LT			CA			ΔEquity		
q	20%	30%	40%	20%	30%	40%	20%	30%	40%
α_0	0.01	-0.03	-0.06	0.33	0.34	0.12	0.17	0.10	0.02
t-stat	(0.04)	(-0.24)	(-0.62)	(1.00)	(1.81)	(0.95)	(0.72)	(0.70)	(0.17)
α_1	0.08	0.06	0.04	-0.17	-0.17	-0.11	0.00	0.00	0.00
t-stat	(1.86)	(1.63)	(1.25)	(-1.75)	(-2.46)	(-2.02)	(0.00)	(-0.07)	(-0.06)
R^2(%)	11	4	1	10	10	4	0	0	0
R^2adj(%)	8	3	1	6	8	2	-2	-1	0
N_I	34	76	135	24	43	83	45	85	149

The table presents the regression of the exchange rate return on the order flow times the macro factor:

$$\Delta s_t = \alpha_0 + \alpha_1 \left(-x_t \times f_{n,t}\right) I_{\left\{f^q_{n,t}, x^q_t\right\}} + u_t.$$

The order flow is taken with the minus sign so that the expected sign should be the one we would expect from regressing the exchange rate return on the fundamental. The order flow and the fundamental are selected for different quantiles ranging from 20 to 40 percent. Precisely, we sort each variable in absolute value and we take the largest 20, 30 and 40 percent of the observations, and the observation is selected only if in that period both the fundamental and order flow are included in their respective quantiles. N_I denotes the number of times the fundamental times order flow is selected for each quantile. Thus, $I_{\left\{f^q_{n,t}, x^q_t\right\}}$ takes the value of 1 if at time t both $f_{n,t}$ and x_t are in the top q percent of observations. This means that both the fundamental and order flow have experienced a sufficiently large shock. The regression is estimated using robust estimation; by default, the Matlab algorithm uses iteratively re-weighted least squares with a bisquare weighting function.

Table 9

Surveys, Order Flows and Macro Factors

q	ΔGrowth 20%	ΔGrowth 30%	ΔGrowth 40%	ΔInflation 20%	ΔInflation 30%	ΔInflation 40%	ΔRate ST 20%	ΔRate ST 30%	ΔRate ST 40%
ζ_0	0.02	0.01	-0.10	-0.12	0.03	-0.10	0.03	0.12	0.13
t-stat	(0.12)	(0.08)	(-0.94)	(-0.51)	(0.18)	(-0.92)	(0.22)	(1.40)	(1.86)
ζ_1	0.30	0.36	0.47	0.18	0.23	0.32	0.27	0.28	0.31
t-stat	(3.41)	(4.31)	(5.94)	(2.32)	(3.32)	(5.11)	(4.80)	(5.45)	(6.57)
R^2(%)	30	25	26	20	21	28	34	24	22
$R^2{}_{N_{II}}$(%)	67	49	47	26	33	36	78	64	62
R^2adj(%)	28	24	25	16	19	26	33	23	21
$R^2{}_{N_{II}}$adj(%)	66	48	47	22	31	35	78	64	61
N_I	31	57	111	22	40	59	52	106	165
N_{II}	11	29	49	6	10	14	24	45	70

q	ΔRate LT 20%	ΔRate LT 30%	ΔRate LT 40%	CA 20%	CA 30%	CA 40%	ΔEquity 20%	ΔEquity 30%	ΔEquity 40%
ζ_0	0.11	-0.04	-0.04	-0.60	-0.62	-0.42	-0.66	-0.58	-0.44
t-stat	(0.60)	(-0.35)	(-0.50)	(-2.36)	(-4.41)	(-4.05)	(-5.43)	(-6.03)	(-5.92)
ζ_1	0.14	0.29	0.43	0.59	0.71	0.59	0.53	0.61	0.62
t-stat	(1.79)	(3.84)	(6.73)	(2.76)	(5.06)	(6.32)	(4.32)	(4.85)	(5.75)
R^2(%)	9	17	25	30	39	31	31	23	19
$R^2{}_{N_{II}}$(%)	37	36	44	55	64	40	71	39	33
R^2adj(%)	6	16	24	27	38	30	29	22	19
$R^2{}_{N_{II}}$adj(%)	35	35	43	52	63	39	71	39	33
N_I	34	76	135	24	43	83	45	85	149
N_{II}	10	30	54	4	8	23	9	17	38

The table displays the results for the six panel regressions of the survey ($\tau_{n,t}$) on the absolute value of the correspondent macro factor ($f_{n,t}$) times the order flow (x_t) times the indicator functions $\left(I_{\{\tau_{n,t}>\tau_{j,t}\}}\right)$ and $\left(I_{\{f^q_{n,t},x^q_t\}}\right)$. The latter takes the value of 1 if the survey on the macro factor n exceeds the values of the other two macro factors $j \neq n$ at each time t. For a generic survey $\tau_{n,t}$ we estimate

$$\tau_{n,t} = \zeta_0 + \zeta_1 \left|x_t \times f_{n,t}\right| I_{\{f^q_{n,t},x^q_t\}} I_{\{\tau_{n,t}>\tau_{j,t}\}} + \varepsilon_t,$$

where n is an index of macro variable and t is an index of time. For each of the six regressions, a country macro variable is included or not according to whether it was previously selected in Table 4 using the general-to-specific criterion. For example, for $n = \Delta$Growth we only use CAD, EUR, JPY, CHF, GBP, and ZAR. Similarly to Table 8, N_I denotes the number of times the fundamental times order flow is selected for each quantile. In addition, within these N_I observations, N_{II} denotes the number of times the fundamental n exceeds the values of the other two macro factors $j \neq n$. And R^2_Nadj is the adjusted R^2 computed over the N_{II} observations. The regression is estimated using robust estimation; by default, the Matlab algorithm uses iteratively re-weighted least squares with a bisquare weighting function.

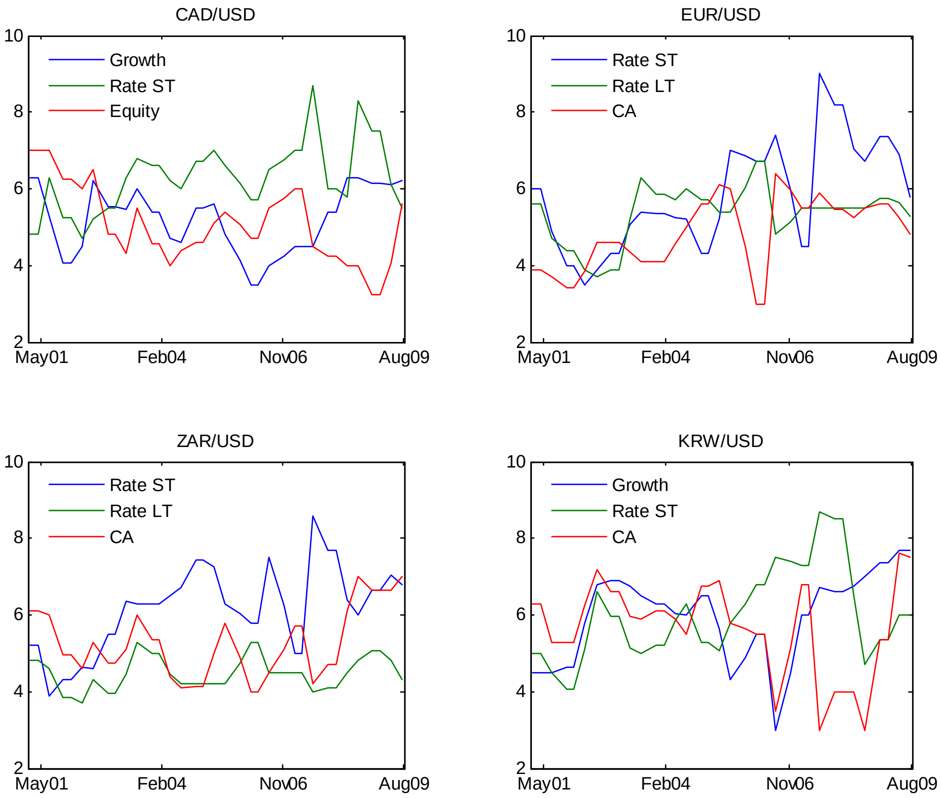

Figure 1
Selected scapegoat variables

The figures show the exchange rate surveys selected by our general-to-specific criterion for four currencies: Canadian dollar, euro, South African rand and Korean won. The sample spans the period from March 2001 to August 2009.

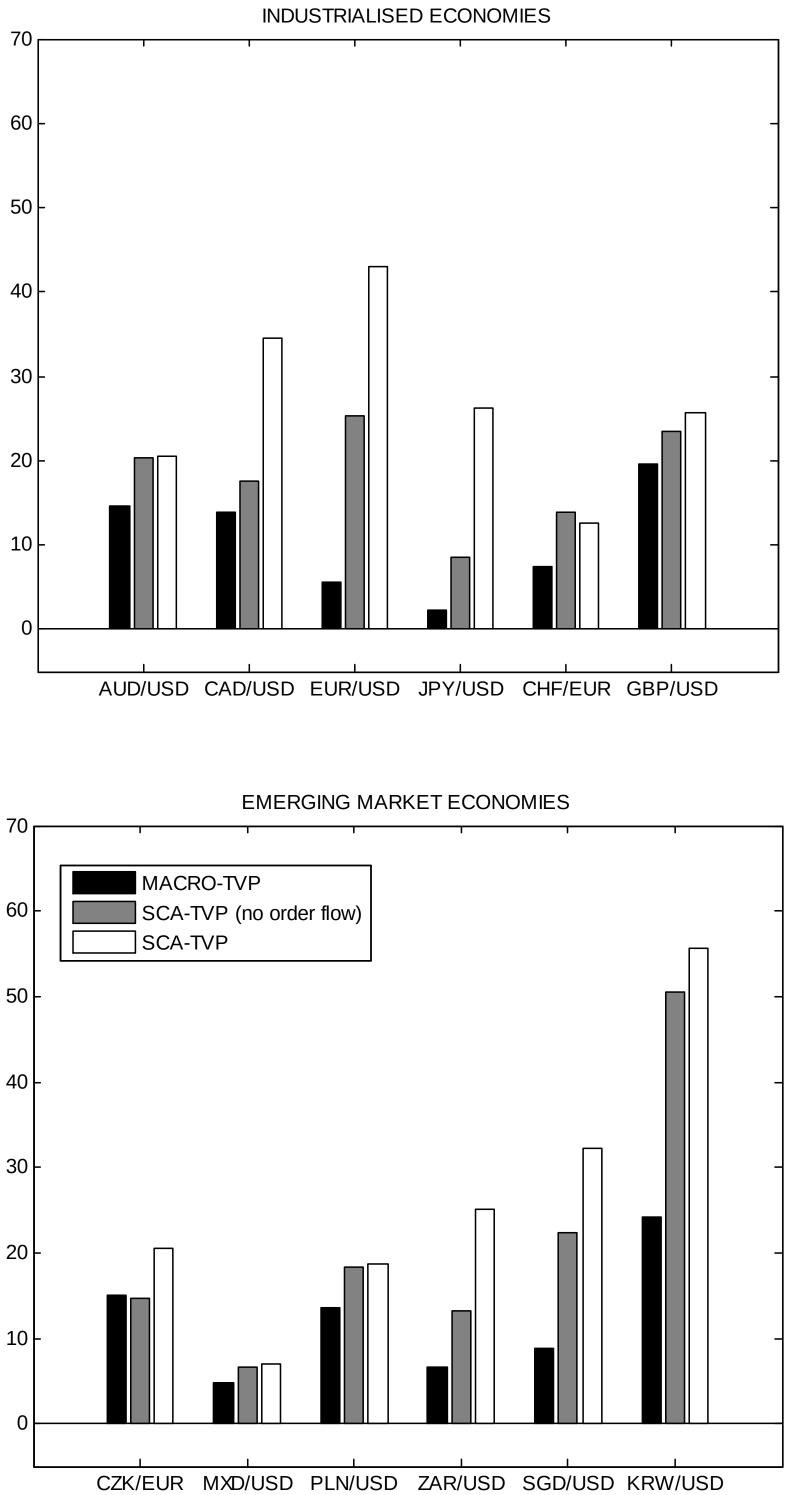

Figure 2
Unconditional adjusted-$\mathbf{R}^2$

The figures show the percentage adjusted-R^2 for the benchmark model with time-varying parameters ($TVP - MACRO$), and two specifications of the scapegoat model with time-varying parameters: the full specification where δ is estimated ($TVP - SCA$) and the restricted specification where δ is set to zero ($TVP - SCA$ with no order flow). The first panel refers to the industrialized countries, whereas the second to emerging market economies.

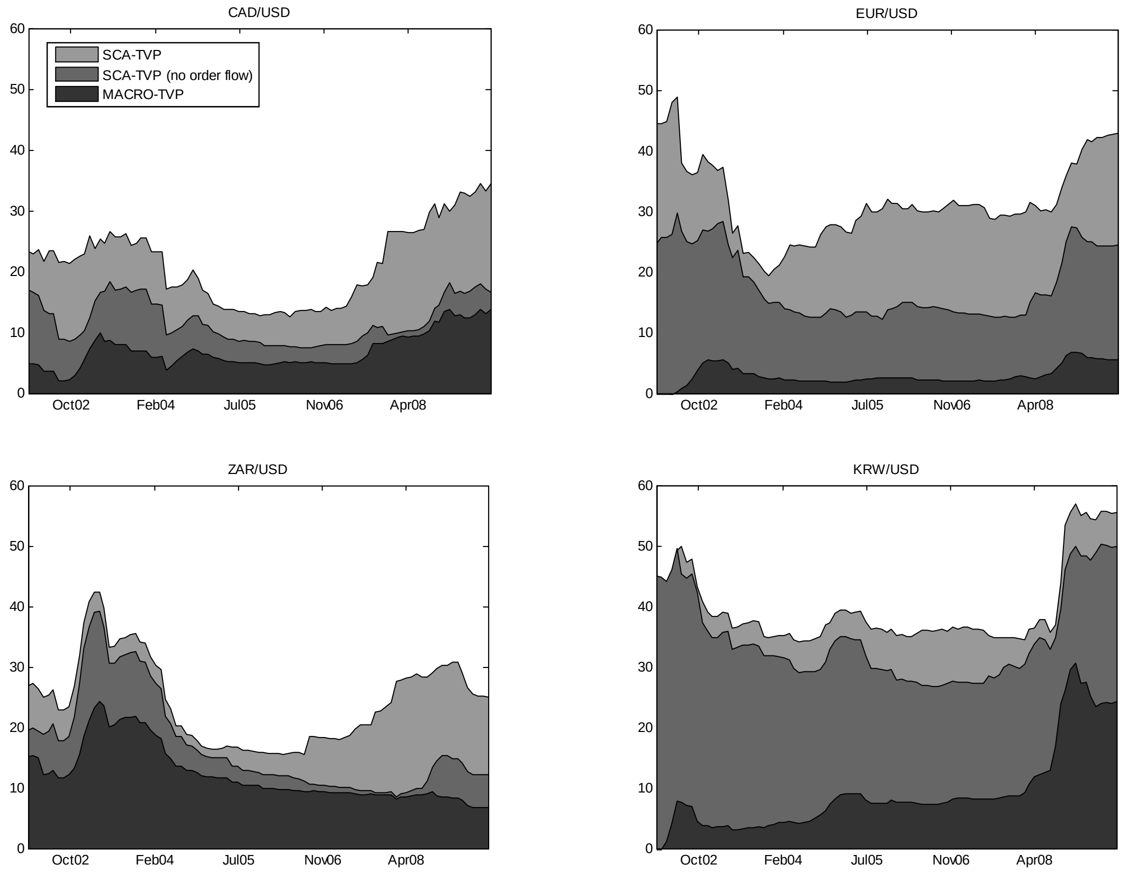

Figure 3
Rolling adjusted-R^2

The figure shows the rolling percentage adjusted R^2 for the benchmark model with time-varying parameters ($TVP - MACRO$), and two specifications of the scapegoat model: the full specification where δ is estimated ($TVP - SCA$) and the restricted specification where δ is set to zero ($TVP - SCA$ with no order flow). The sample spans from February 2002 to August 2009 and covers the Canadian dollar (CAD), euro (EUR), South African rand (ZAR) and Korean won (KRW).