FINANCIAL CRISES, NONLINEAR DYNAMICS AND MACROECONOMIC ISSUES IN CURRENCY MARKETS

By

Dooyeon Cho

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

Economics

2011

Abstract

FINANCIAL CRISES, NONLINEAR DYNAMICS AND MACROECONOMIC ISSUES IN CURRENCY MARKETS

By

Dooyeon Cho

This dissertation consists of three chapters on international financial crises, nonlinear dynamics and macroeconomic issues in currency markets. The first chapter examines the mechanisms behind output drops across a sample of 23 international financial crises. While three generations of models have studied the causes of financial crises, less is known about the mechanisms by which crises lead to output drops. One unresolved question is whether the mechanisms behind output drops are similar across episodes. To address this question, we apply the Business Cycle Accounting (BCA) methodology by Chari et al. (2007) to a sample of crises. While the efficiency wedge is invariably the most important one, the relevance of the labor and investment wedges varies depending on the size of the output drop and the severity of banking problems–as measured by bank closures, nonperforming loans and credit flows. Typically, in cases with smaller output drops and milder banking crises, the labor wedge tends to be more important than the investment wedge. The opposite is true in cases, such as those in East Asia in 1997/98, with larger output drops and severe banking problems.

The second chapter explores the interaction between exchange rate volatility and fun-

damentals by examining the role of trade intensity in the reversion of exchange rates to long-run equilibrium values. While exchange rates remain mostly unpredictable, researchers have been able to link currency fluctuations to some fundamentals such as interest rates, Taylor rule fundamentals, and relative PPP. In an effort to add to this literature, in this paper we present evidence of a link between trade intensity and exchange rate dynamics. We first establish a negative effect of trade intensity on exchange rate volatility via panel regressions using distance as an instrument to correct for endogeneity. We also run a nonlinear model of mean reversion to compute half-lives of deviations of bilateral exchange rates from relative PPP, and find these half-lives to be significantly lower high trade intensity currency pairs. This finding does not appear to be driven by Central Bank intervention. In an application, we show that our findings can be used to improve the performance of currency trading strategies, by allowing the thresholds beyond which a currency is considered overvalued to depend on trade intensity.

The last chapter provides an extensive analysis for both nonlinear and long memory characteristics as well as mean reverting behavior of real exchange rates. This paper estimates a fractionally integrated, nonlinear autoregressive *ESTAR* (*FI-NLAR-ESTAR*) model for strongly dependent processes developed by Baillie and Kapetanios (2008). While the linear fractionally integrated model appears to fail to detect mean reversion in real exchange rates, the nonlinear long memory model is found to be more supportive of significant empirical evidence for the presence of slow mean reversion in real exchange rates for all of the currencies considered in this study over the recent float. The results suggest that a model that is capable of representing both nonlinear and long memory characteristics may help identifying mean reversion in real exchange rates.

ACKNOWLEDGMENTS

This dissertation would not have been possible without the guidance and the help of several individuals who in one way or another contributed and extended their valuable assistance in the preparation and completion of this study. First, my utmost gratitude goes to my main advisor, Richard T. Baillie for his patience and steadfast encouragement to complete this study. I am truly indebted and grateful to my another advisor, Antonio Doblas-Madrid, whose encouragement, supervision and support from the preliminary to the concluding level enabled me to develop the subjects. They have inspired me so that I could overcome all the obstacles in the completion of this research work. I would like to express my deepest gratitude to both advisors for guiding my research for the past several years, helping me to develop my background in both Economics and Finance, and allowing me the opportunity to write papers together for publication. I could never have reached the depths of this dissertation without their insightful advice. Besides my advisors, I would like to sincerely thank the faculty members, Raoul Minetti and Kirt C. Butler. Regarding my research work, they helped me by generously providing their insights and suggestions.

I would like to thank my fellow graduate students for sharing their enthusiasm and comments for my work: Jieun Chang, Kang-Hung Chang, Sanders Chang, Guojun Chen, Byung-Cheol Kim, Jaesoo Kim, Sang-Hyun Kim, Do Won Kwak, Sanglim Lee, Gabriele Lepori, Seunghwa Rho, Valentin Verdier, and Wei-Siang Wang.

Last but not least, I would like to express my gratitude to my parents and elder brother, Sungyeon (Joe) Cho for their unwavering love and support through the good and bad times.

Contents

List of Tables

List of Figures

Chapter 1

Business Cycle Accounting for International Financial Crises: The Link Between Banks and the Investment Wedge

1.1 Introduction

Over the last three decades, international financial crises have struck in countries as diverse as Argentina, Korea, Turkey and Finland. Typical symptoms of crises have been large real depreciations, current account reversals (or sudden stops), difficulties in the banking sector and, in some cases, sovereign default. On the real side of the economy, crises have typically led to dramatic declines in output and employment. It is precisely because of these severe real effects, that international financial crises are a topic of perennial interest for academic economists and policymakers alike.

Economists have developed an extensive literature examining the causes of crises, as recurrent waves of financial disasters have led to the subsequent development of different generations of models. Latin American crises in the 1970s and 1980s motivated first generation models (e.g., Krugman (1979), Flood and Garber (1984)), highlighting the incompatibility of fixed exchange rates with monetized fiscal deficits. The European ERM crisis of 1992/93 and Mexico's 1994/95 episode led to second generation theories (e.g., Obstfeld (1994), Cole and Kehoe (1996), (2000)), emphasizing multiple equilibria and self-fulfilling prophecies. And after the Asian crisis of 1997/98, third generation models (e.g., Burnside et al. (2001), Schneider and Tornell (2004)) tended to stress the role of government guarantees and currency mismatches in private sector balance sheets. However, as Calvo (2000) noted, while all three generations have provided valuable insights into how and when crises are possible, they have had less to say about the mechanisms through which crises lead to output drops. In all three generations, typically, the objective is to determine conditions under which markets can force governments to abandon currency pegs and/or default, *assuming* that the abandonment/default has adverse real effects. This assumption is often made because it is difficult to generate output drops endogenously. In fact, in many environments, crises may raise output, as real depreciations improve net exports.

The literature seeking to identify mechanisms by which crises lead to output drops is relatively more recent and less extensive. Regarding output drops in specific episodes, to our knowledge, the cases that have been most extensively studied are Mexico in 1994/95 and Korea in 1997/98. In the context of the "Tequila" crisis, Meza (2008) finds that changes in fiscal policy account for about 20 percent of the output drop in Mexico in 1995, while Kehoe and Ruhl (2009) find that reallocation from nontradable to tradable sectors explains the evolution of the real exchange rate and trade flows, but not the drop in output and total factor productivity (TFP). In the case of Korea's 1997/98 crisis, Benjamin and Meza (2009) develop a model of sectoral reallocation which takes into account the effect of high interest rates on firms' working capital, and show that the model accounts for about half of the decline in GDP and TFP.

In this paper, instead of studying the role of specific frictions in a given episode, our approach is to perform an exploratory analysis of output drops throughout a sample of crises. We employ the Business Cycle Accounting (BCA) methodology developed by Chari, Kehoe and McGrattan (2007) (CKM henceforth). BCA decomposes output fluctuations into fluctuations due to changes in an efficiency wedge, which captures changes in TFP, a labor wedge, which captures labor-market distortions, an investment wedge, capturing investment-market distortions, and a government consumption wedge, capturing government purchases plus net exports. After estimating the processes governing all wedges, we use simulations where some wedges vary and others are held constant to discern which kinds of distortions play the most important role accounting for observed fluctuations. Thus, BCA provides a priori guidance for economists seeking to explicitly model frictions. One important question that this analysis will help us answer is to what extent crises are alike. That is, if a similar combination of wedges accounts well for the data in all (or most) episodes, it may be possible to develop one single model of output drops with general applicability. On the other hand, it could be that different crises, or clusters of crises, are driven by different sets of distortions. In that case, much like in the aforementioned three generations, it may be preferable to develop multiple models, tailored to different varieties of crises.

To construct our sample, we start from the list of episodes compiled by Kaminsky (2006). After dropping some cases due to data limitations, we are left with the following 23 episodes, involving 13 countries: Argentina (1981, 1985, 1989, 1994, 2001), Brazil (1987, 1991, 1999), Chile (1982, 1994), Finland (1991), Indonesia (1997), Israel (1983), Korea (1997), Malaysia (1997), Mexico (1982, 1994), Philippines (1983, 1997), Sweden (1992), Thailand (1997), and Turkey (1994, 2000). Note that this sample offers variation along several potentially interesting dimensions. First, the sample includes crises of the 1980s, which are generally explained by first-generation models, and crises of the 1990s and 2000s, which do not conform to first-generation crisis models. The sample also offers wide variation along other dimensions, such as the size of the output drop and speed of recovery, rates of inflation, the geographical location of the crisis, and the severity of banking crises.

After applying the BCA methodology to all cases and examining the results, some patterns emerge. Across the sample, the efficiency wedge plays the leading role in accounting for the drop, often explaining well over half of it. The labor wedge follows, explaining on average about 20 percent of the drop, and the investment wedge comes third, accounting on average for circa 14 percent of the drop. Finally, the government consumption wedge plays a negligible role. In light of previous studies, these average percentages are not surprising. More novel is our finding that, behind these average percentages, there exist wide variations between episodes. These variations are fairly systematic along some dimensions. First, the percentages of the drop explained by the efficiency and investment wedges are positively correlated with crisis severity (i.e., these wedges explain larger percentages of the drops in crises with larger drops), whereas the percentage explained by the labor wedge is negatively correlated with severity. On the other hand, in the three years after the crisis year—defined as the year of the biggest output drop—we find that the efficiency wedge contributes most to recoveries, while the labor wedge, and even more so the investment wedge, are typically very persistent. That is, on average, the labor wedge contributes to the drop in output in the crisis year, and barely contributes to growth in the following three years, while the investment wedge tends to depress output not only in the crisis year, but also in the following three years. Regarding correlations, the contributions of the efficiency and investment wedges to the recoveries are markedly positively correlated with the size of the recovery, while the contribution of the labor wedge to the recovery is essentially uncorrelated with the size of the recovery. Perhaps the most salient stylized fact that holds in our sample is a relationship between the investment wedge and several measures of banking crisis severity. These measures include the fraction of banks closed relative to the total number of banks, the share of nonperforming loans (NPLs) at the peak of the crisis, and the change in real bank credit to the private sector. Finally, we also examine other factors, such as inflation, and the time and geographical location of the crisis. We find that the importance of the investment wedge, the size of the output drop, and the severity of banking problems appear to be particularly pronounced in East Asian crisis episodes when compared to Latin and European crises. To a lesser extent (and due to considerable overlap), the same differences arise when comparing crises of the 1980s to those after 1990. Finally, we find no relationship between the relative importance of different wedges and other variables, such as inflation rates.

As a robustness check, we re-run the BCA analysis in our sample allowing for variable capital utilization, and find that, relative to the baseline case, the importance of the efficiency wedge falls and the importance of the labor and investment wedges increases, although the efficiency wedge continues to explain the largest fraction of the drops, followed by the labor and investment wedges. Overall, our results remain qualitatively unaltered. That is, the correlations with crisis severity remain positive for the efficiency and investment wedges and negative for the labor wedge, and the contribution of the investment wedge continues to be correlated with our measures of banking crisis severity.

Regarding previous literature, our finding that the efficiency, labor, and investment wedges, in this order, play the most important roles explaining output is consistent with the findings of related studies. In fact, the roles of the efficiency and labor wedges have been highlighted by CKM, Ahearne et al. (2006), Kersting (2008), Cociuba and Ueberfeldt (2008) and Lama (2011), for, respectively, the United States, Ireland, the U.K., Canada, and six Latin American countries. On the other hand, our findings point to two arguments against dismissing the investment wedge as a tertiary, relatively unimportant force. First, the investment wedge tends to be persistent, in the sense that it typically continues to contribute to output drops several years after the crisis. Second, the relevance of the investment wedge is greater in more severe crises and in crises with deep banking problems. These characteristics are typical of the wave of crises that hit East-Asia in 1997-98. Regarding our findings on the investment wedge, the study that most relates to ours is Chakraborty (2009)'s BCA analysis of Japan in the 1990s, which found the efficiency and investment wedges to be most relevant, with the labor wedge playing a smaller role. Moreover, this study relates the investment wedge to a well-known feature of Japan's economy during this period, the lack of lending by so-called 'zombie banks'.

In sum, our results suggest that researchers interested in modeling output drops in the aftermath of crises may be well advised to use different frictions, depending on the severity of banking sector difficulties. In cases with relatively mild banking crises, frictions that translate into the productivity and labor wedges are most likely to drive the bulk of the economic activity. On the other hand, in episodes where banking crises—as measured by the share of nonperforming loans and the prevalence of bank closures—are more severe, the efficiency and investment wedges are likely to explain most of the movement in macroeconomic aggregates.

The rest of the paper is organized as follows. In Section 1.2, we introduce the model and describe the measurement and accounting procedure. In Section 1.3, we describe our data. In Section 1.4, we present and discuss results. In Section 1.5, we re-run our analysis allowing for variable capital utilization, and in Section 1.6, we conclude.

1.2 The model and business cycle accounting procedure

1.2.1 The model

Following CKM, here, we sketch the model and accounting procedure. The model is a standard neoclassical growth model. Every period t, the economy is hit by one of a finite number of events s_t. The history of realized events up to period t is denoted by $s^t = (s_0, ..., s_t)$. The initial realization of the event s_0 is exogenously given. As of period 0, $\pi_t\left(s^t\right)$ denotes the probability of any particular history s^t. The economy has four stochastic variables which depend on s^t: the efficiency wedge $A_t\left(s^t\right)$, which acts like time-varying productivity; the labor wedge $1-\tau_{lt}\left(s^t\right)$, which is akin to a time-varying tax on labor income;

the investment wedge $1/\left[1+\tau_{xt}\left(s^t\right)\right]$, which has the same effect as a time-varying tax on investment, and the government consumption wedge $g_t\left(s^t\right)$, which resembles government expenditure.[1]

The population N_t is assumed to grow at the constant rate γ_n . The representative consumer chooses per capita consumption $c_t\left(s^t\right)$ and per capita labor $l_t\left(s^t\right)$ to maximize

$$\sum_{t=0}^{\infty}\sum_{s^t}\beta^t\pi_t\left(s^t\right)U\left(c_t\left(s^t\right),l_t\left(s^t\right)\right)N_t, \tag{1.1}$$

where $\beta\in(0,1)$ is a discount factor. Utility maximization is subject to the budget constraint

$$\begin{aligned} & c_t\left(s^t\right)+\left[1+\tau_{xt}\left(s^t\right)\right]\left[(1+\gamma_n)\,k_{t+1}\left(s^t\right)-(1-\delta)\,k_t\left(s^{t-1}\right)\right] \\ = \; & \left[1-\tau_{lt}\left(s^t\right)\right]w_t\left(s^t\right)l_t\left(s^t\right)+r_t\left(s^t\right)k_t\left(s^{t-1}\right)+T_t\left(s^t\right), \end{aligned} \tag{1.2}$$

where $k_t\left(s^{t-1}\right)$, $\left[(1+\gamma_n)\,k_{t+1}\left(s^t\right)-(1-\delta)\,k_t\left(s^{t-1}\right)\right]$, and $T_t\left(s^t\right)$ are, respectively, per capita capital, per capita investment and per capita lump-sum taxes/transfers. The wage rate and rental rate on capital are denoted, respectively, by $w_t\left(s^t\right)$ and $r_t\left(s^t\right)$, and δ is the rate at which capital depreciates.

Every period t, firms choose per capita capital $k_t\left(s^{t-1}\right)$ and per capita labor $l_t\left(s^t\right)$ to maximize profits

$$A_t\left(s^t\right)F\left(k_t\left(s^{t-1}\right),(1+\gamma)^t\,l_t\left(s^t\right)\right)-r_t\left(s^t\right)k_t\left(s^{t-1}\right)-w_t\left(s^t\right)l_t\left(s^t\right), \tag{1.3}$$

where γ denotes the constant rate of labor-augmenting technical progress.

[1] Several modifications of the BCA model, which incorporate additional wedges, have been developed, often with the objective of tailoring the procedure to developing economies. Despite the merits of the extensions, we have chosen to stick to the baseline BCA model because, in our judgment, it remains the most standard and commonly used version. By employing the well-known original version, we hope that it will be easier to compare our findings with those of existing and future studies. Moreover, some countries in our sample, e.g., Finland, are developed countries.

Equilibrium in the economy is fully described by

$$c_t\left(s^t\right) + \left[(1+\gamma_n)\, k_{t+1}\left(s^t\right) - (1-\delta)\, k_t\left(s^{t-1}\right)\right] + g_t\left(s^t\right) = y_t\left(s^t\right), \tag{1.4}$$

$$y_t\left(s^t\right) = A_t\left(s^t\right) F\left(k_t\left(s^{t-1}\right), (1+\gamma)^t\, l_t\left(s^t\right)\right), \tag{1.5}$$

$$-\frac{U_{lt}\left(s^t\right)}{U_{ct}\left(s^t\right)} = \left[1-\tau_{lt}(s^t)\right] A_t\left(s^t\right)(1+\gamma)^t F_{lt}, \tag{1.6}$$

and

$$\begin{aligned} U_{ct}\left(s^t\right)\left[1+\tau_{xt}\left(s^t\right)\right] &= \beta \sum_{s^{t+1}} \pi_t\left(s^{t+1}\middle| s^t\right) U_{ct+1}\left(s^{t+1}\right) \\ &\quad \times \left\{A_{t+1}\left(s^{t+1}\right) F_{kt+1}\left(s^{t+1}\right) + (1-\delta)\left[1+\tau_{xt+1}\left(s^{t+1}\right)\right]\right\}, \end{aligned} \tag{1.7}$$

where U_{ct} and U_{lt} denote the first derivatives of the utility function with respect to consumption and labor and similarly, F_{lt} and F_{kt} denote the first derivatives of the production function with respect to labor and capital. Equation (1.4) is the feasibility constraint of the economy. Equation (1.5) is the production function. Equation (1.6) states that in equilibrium, the marginal rate of substitution between consumption and leisure equals the marginal product of labor, distorted by $\tau_{lt}(s^t)$. And finally, equation (1.7) is an intertemporal Euler equation, distorted by $\tau_{xt}\left(s^t\right)$ and $\tau_{xt+1}\left(s^{t+1}\right)$.

As CKM and Chakraborty (2009) emphasize, the wedges or frictions represent all possible distortions that can enter the first order conditions. Taxes can be thought of as the typical wedges. For example, the labor wedge can be any kind of friction that distorts the relationship between the marginal product of labor and the marginal rate of substitution between consumption and leisure. These frictions may arise from a variety of sources, such as taxes, monopoly power by unions or firms, sticky wages or sticky prices. CKM generalize these results by illustrating the mapping, and showing that explicitly modeled frictions amap into wedges in this prototype economy.[2] For example, input-financing frictions map into efficiency wedges, investment-financing frictions into investment wedges, and fluctuations in net exports in an open economy map into government consumption wedges. Also, sticky wedges and monetary shocks map into labor wedges.

Consequently, by construction, the model exactly reproduces the data on output, labor, investment, and consumption when all four wedges are jointly fed into the model.

1.2.2 The business cycle accounting procedure

How to measure the wedges

As in CKM, we assume that the mapping from the event s_t to all the wedges is one to one and onto. The accounting procedure is to conduct experiments that isolate the marginal effect of each wedge as well as the marginal effects of combinations of the wedges on aggregate variables. For example, in conducting the experiment that isolates the marginal effect of the investment wedge, we hold all other wedges fixed at some constant levels in all periods.

To implement the accounting procedure, we assume that the production function has the Cobb-Douglas form

$$F(k,l) = k^{\alpha} l^{1-\alpha}, \tag{1.8}$$

where α is the capital share and the utility function is of the form

$$U(c,l) = \log c + \psi \log(1-l), \tag{1.9}$$

[2] CKM demonstrate the mapping from detailed economies with frictions to prototype economies with wedges. They also deal with the mapping of financial frictions to investment wedges. They focus on the financial frictions in the Bernanke et al. (1999) model and abstract from the monetary features of that model (For more details, see pages 828-834 in CKM).

where ψ denotes the time allocation parameter. We borrow parameter values from the business cycle literature. Concretely, in Table 1.1, we describe our sources and numerical values for each country. We then use these values together with the data to derive the steady state value of the wedges.

To measure the wedges, note that the efficiency wedge A_t and the labor wedge τ_{lt} can be directly calculated from equations (1.5) and (1.6) without computing the equilibrium of the model. Also, following CKM, we measure the government wedge g_t directly from the data as the sum of government spending and net exports.[3] Measuring the investment wedge τ_{xt} is not as straightforward. Since the Euler equation (1.7) involves expectations over time, and agents' optimal decision rules depend on the stochastic process driving the wedges, measuring this wedge requires that we compute the equilibrium of the model.

To estimate the stochastic process for the state, we follow CKM and specify a VAR(1) process for the four dimensional state $s_t = (\log A_t, \tau_{lt}, \tau_{xt}, \log g_t)$. The process has the form

$$s_{t+1} = P_0 + P s_t + Q \varepsilon_{t+1}, \tag{1.10}$$

where the shock is independent and identically distributed over time and is distributed normally with mean zero and covariance matrix V. The estimate of V is positive semi-definite, because we estimate the lower triangular matrix Q, where $V = QQ'$. The matrix Q has no structural interpretation. We use a standard maximum likelihood procedure to estimate the parameters P_0, P and V of the VAR(1) process for the wedges.[4] To do so, we

[3] Meza (2008) adds net exports to investment rather than government spending since he analyzes the role of actual fiscal policy.

[4] As the yearly-data analysis in CKM, we impose the additional restriction that the covariance between the shocks to the government consumption wedge and those to all other wedges is zero. In other words, we assume that the government consumption wedge is uncorrelated with all other wedges for the structure of the matrix.

use the log-linear decision rules of the prototype economy along with data on output, labor, investment, and the sum of government spending and net exports. Specifically, we use the log-linear method when we derive estimates of the process for the wedges and for computing equilibria.

We assume that the economy is in the steady state in pre-crisis year t, where the crisis year $t+1$ is defined as the year with the greatest output drop. We solve the model using log-linearization and the method of undetermined coefficients. The model is expressed in state-space form as follows

$$\begin{aligned} X_{t+1} &= AX_t + B\epsilon_{t+1} \\ Y_t &= CX_t + w_t, \end{aligned} \tag{1.11}$$

where $X_t = [\log \hat{k}_t, \log z_t, \tau_{lt}, \tau_{xt}, \log \hat{g}_t, 1]'$, $z_t = A_t/(1+\gamma)^t$, $Y_t = [\log \hat{y}_t, \log \hat{x}_t, \log l_t, \log \hat{g}_t]'$, and $w_t = Dw_{t-1} + \eta_t$. The matrix A summarizes coefficients linking X_t to X_{t+1}, including the coefficients in matrices P and P_0 from the above process and the coefficients linking X_t to $\hat{k}_{t+1}$ (found via log-linearization and the method of undetermined coefficients). The matrix B summarizes variance-covariance parameters, including Q from the VAR(1) process above. Finally, C summarizes the coefficients linking X_t to Y_t (found via log-linearization and the method of undetermined coefficients), and elements of D are the parameters governing serial correlation of the measurement error. We assume that $E\left(\eta_t \eta_t'\right) = 0_{4\text{x}4}$ and $E\left(\epsilon_t \eta_s'\right) = 0$ for all periods t and s.

The log-likelihood function to be maximized is given by

$$L(\Theta) = \sum_{t=0}^{T-1} \left\{ \log |\Omega_t| + \text{trace}\left(\Omega_t^{-1} u_t u_t'\right) - \log |\partial f(Z_t, \Theta) / \partial Z_t| \right\}, \tag{1.12}$$

where the parameters to be estimated are in vector Θ, u_t is the innovation vector, and Ω_t is its covariance. The last term in (1.12) is nonzero if the elements of Y are not the raw series but depend on the raw series Z plus the parameter vector. Following CKM, for the results reported, we fix parameters of preferences, production, and growth and estimate the processes for the wedges. The parameters to be estimated are elements of P_0, P and Q. The log-likelihood function above is obtained using the Kalman filter, which generates one-period-ahead predictions compared to the actual data. The differences between the actual data and the predictions generated by the filter enter into the log-likelihood function. Once we have estimated P_0, P and V, we can find the realized values of the wedges. (For more technical details, see Appendices of Chari et al. (2006).)

Evaluating the contribution of each wedge

Having measured realized values for the four wedges, we now implement the simulations that allow us to determine the extent to which output fluctuations can be attributed to each wedge. For each episode, we let t and $t+1$ denote, respectively, the pre-crisis and the crisis year. To determine the relevance of a given wedge, we simulate the model letting that wedge vary only up to the pre-crisis year t, and holding that wedge fixed at its pre-crisis level from time $t+1$ onwards, so as to nullify the effect of changes in that specific wedge.[5] For instance, to compute the share of the drop due to the efficiency wedge, we conduct a simulation in which we feed into the model the full series for the labor, investment, and government consumption wedges, together with a truncated efficiency wedge, which equals

[5] Meza (2008) constructs counterfactual wedges that eliminate the effect of changes in fiscal policy. He solves the fiscal policy model to find the relation between wedges and fiscal policy variables.

the realized wedge for years up to the pre-crisis year t but is held constant at its year-t level from the crisis year $t+1$ onwards. Using the same method, we evaluate the importance of the labor, investment, and government consumption wedges, accordingly.

We feed the truncated wedge along with the other wedges into the model. The greater the difference between the actual and the predicted output drop, the greater the importance of the truncated wedge. For brevity, we will not report results with the truncated government consumption wedge since, in our sample, as well as in previous studies, there is virtually no difference between the output path in the data and the output path predicted by the model that ignores changes in this wedge from the crisis year onward.

1.3 Data

To build our sample, we begin with the list of crises compiled by Kaminsky (2006). After dropping cases due to data limitations, 13 countries and 23 crisis episodes remained in our sample. The countries, pre-crisis years, and output drops observed in these crises are displayed in Table 1.2. The crises occurred mostly during the 1980s and 1990s, and some in the early 2000s, and involved the following countries: Argentina, Brazil, Chile, Finland, Indonesia, Israel, Korea, Malaysia, Mexico, Philippines, Sweden, Thailand, and Turkey. The crises were on average quite severe. In fact, the average output drop between the pre-crisis year t and the crisis year $t+1$ is approximately 8 percent. In Table 1.4, we show, along with the percentage drops in output, the percentage drops in employment and investment, for each crisis in the sample. The average drop in employment, at 3.2%, is smaller than the drop in output. Investment, on the other hand, is much more volatile than output, and registers an average drop of about 25%.

Most of our data are from the *International Financial Statistics* (*IFS*). The only series that are not from this source are working age population (i.e., population aged 15-64), total employment, and hours worked, which are collected from the *International Labour Office* (*ILO*) *LABORSTA* database. The years for which we have found data are shown in Table 1.3. With the exception of Turkey, for which data start in 1988, for all other countries, the first year is 1980. The last year differs by country, varying between 2005 and 2007.

The series for per capita output (y), per capita investment (x), per capita labor input (l), per capita government consumption (g) and per capita consumption (c) are constructed as follows. Per capita output (y) is the sum of nominal GDP, deflated using the GDP deflator and dividing by population aged 15-64. In the case of Mexico, we added services from, and depreciation of, consumer durables to GDP. We were not able to find this information for other countries. We also omitted sales taxes, since they are small and unavailable for most countries. The series for per capita investment (x) is given by gross fixed investment (plus personal consumption expenditures on durables in the case of Mexico), deflated and divided by population aged 15-64. Using both the law of motion for capital and the perpetual inventory method, we calculate the series for per capita capital stock (k). To construct the series for the per capita labor input (l), we multiply annual hours worked per employed person by total employment, and divide the result by population aged 15-64. Since the value obtained is total hours worked per year, we divide it by the number of weeks per year (50) and the endowment of total hours per week (100). As mentioned earlier, the series for per capita government consumption (g) is the sum of government spending and net exports of goods and services, which, again, is deflated and divided by working-age population. By equation (1.4), the series for per capita consumption (c) is simply obtained by subtracting per capita investment (x) and per capita government consumption (g) from per capita output (y).

Regarding data on banking crises, our sources are the following. Data on percentages of banks closed and shares of nonperforming loans over total loans come from Laeven and Valencia (2008) and Reinhart and Rogoff (2009). We gathered data on credit extended from the World Bank's series "Domestic Credit Provided by Banking Sector (% of GDP)". We multiplied this series by nominal GDP (from *IFS*) to obtain nominal domestic credit provided by the banking sector, and deflated this series using the CPI series (also from *IFS*) to finally obtain real domestic credit.

1.4 Results

The output paths and realized values for the efficiency, labor, and investment wedges for all countries are depicted in Figure 1.1. Already at first glance, it quickly becomes apparent that there is a much stronger association between output and the efficiency wedge than between output and the labor or investment wedge. This holds not only in crisis years—most of which stand out visually due to the large output drops—but typically through the sample period. In Figure 1.2, we show the paths of output, investment, and labor for all countries. Every graph shows the data together with the results from three simulations, each including all wedges except for respectively, the efficiency, labor, and investment wedge. Clearly, some wedges play a much more important role in some episodes than in others, with the labor wedge, for example, playing an important role in Argentina in 2001, and the investment wedge playing a key role, for example, in Malaysia in 1997.

To quantify the importance of a given wedge for a given episode, our primary measure is the percentage contribution to the output drop in the crisis year. We compute this percentage by performing the following calculations, which are similar to the calculations in Meza (2008). Let $y_{i,t}$ and $y_{i,t+1}$ denote country i's real (detrended) per capita output in, respectively, the pre-crisis year t and the crisis year $t+1$, and let $d_{i,t} = (y_{i,t} - y_{i,t+1})/y_{i,t}$ be the corresponding percentage output drop. Next, for each wedge $w \in \{\text{Efficiency, Labor, Investment}\}$, we take output values from a simulation where we feed into the model realized values of wedges other than w, and let w vary only up to pre-crisis year t, holding it fixed at its year-t level in later years. We let $\widetilde{y}_{i,t+1}(w)$ denote the year-$t+1$ (detrended) per-capita output generated by this simulation, and $\widetilde{d}_{i,t}(w) = (y_{i,t} - \widetilde{y}_{i,t+1}(w))/y_{i,t}$ denote the simulated percentage drop. Finally, we define $\Phi_{i,t}(w)$, the contribution of wedge w to the output drop in country i between years t and $t+1$ as

$$\Phi_{i,t}(w) = \frac{d_{i,t} - \widetilde{d}_{i,t}(w)}{d_{i,t}}. \tag{1.13}$$

To interpret this measure, it is useful to look at Figure 1.3. As we can see in the top panel, when the efficiency wedge is held constant, output falls by about 7 percentage points, whereas in the data, it falls by about 12 points. The difference of approximately 5 points, about 40%, is the amount attributable to the efficiency wedge. Doing this for all wedges and crises, we obtain the contributions shown in Table 1.5. Not surprisingly, the efficiency wedge is usually largest, whereas the contributions of the labor and investment wedges vary widely between episodes. On average, the efficiency wedge accounts for 62.2% of the decline of output, the labor wedge, 21.7%, and the investment wedge for 14%.[6]

[6] It is worth noting that there is a high correlation (0.58 for labor and 0.47 for investment)

Three remarks are in order. First, although the average contribution of the investment wedge—as measured by $\Phi_{i,t}(w)$—is lower than that of the labor wedge, we must keep in mind that this is an unweighted average, which assigns the same weight to each episode regardless of severity. As we will see shortly, since the importance of the labor and investment wedges is respectively, negatively and positively correlated with the size of the output drop, a severity-weighted average would lower the average importance of the labor wedge and raise that of the investment wedge. Second, there are instances where the contribution of a given wedge is negative (e.g., the labor wedge in Indonesia in 1997). In these cases, the wedge completely misses the evolution of output, leading to an expansion instead of a contraction. The third remark is that, by construction, the sum of the fractions explained by different wedges need not equal one.

We also examine the effect of the wedges in the post-crisis years $t+1$ to $t+4$. Given that, over these three years, output recovers in some cases and falls or stagnates in others, we cannot use an analog version of $\Phi_{i,t}(w)$ to measure the wedge's contributions. This would be problematic given the difficulty in interpreting signs, and the fact that in several cases, output at $t+1$ is very similar to output at $t+4$, which would make the denominator close to zero. In these cases, wedge contributions would be very large numbers, which would skew averages. To avoid these issues, we define an alternative measure as follows. For country i and wedge $w \in \{$ Efficiency, Labor, Investment$\}$ the contribution to the recovery is given by

$$\varkappa_{i,t+1}(w) = [\widetilde{y}_{i,t+1}(w) - y_{i,t+1}] - [\widetilde{y}_{i,t+4}(w) - y_{i,t+4}]. \tag{1.14}$$

between the contributions of the labor and investment wedges, given in Table 1.5, and the drops in labor and ivestment given in Table 1.4. Thus, although the reported measures of contributions focus on output, the importance of the labor and investment wedges are informative about the evolution of labor and investment.

This measure simply captures whether the gap between the predicted and actual outputs shrinks over the course of the post-crisis years $t+1$ to $t+4$. Once more, Figure 1.3 is helpful to interpret the measure. In the top panel, we can see that the gap between simulated and actual outputs does not shrink, but instead grows slightly, over the course of the years $t+1$ to $t+4$. Hence, the contribution of the efficiency wedge to recovery would be slightly negative. Calculating $\varkappa_{i,t+1}(w)$ in this fashion for all episodes and wedges, we obtain Table 1.6. As we can see, the efficiency wedge contributes most to recoveries, on average about 3.4 percentage points, whereas the labor wedge's average contribution to recoveries is positive, but close to zero, and the investment wedge's contribution averages minus 0.4 points.

1.4.1 Wedges and Observables

Our sample includes crisis episodes that are heterogeneous along a number of observable dimensions, including the severity of the crisis, the degree of problems in the banking sector, the time and geographical location of the crisis, inflation rates, and so on. This variability may be useful in order to uncover associations between particular observables and the contributions of the three wedges. In turn, these associations could provide hints as to what mechanisms or frictions underlie the distortions measured by the wedges.

In this section, we report the most salient associations between the relative contributions of different wedges and other observable variables. First, we discuss the correlations between the contributions of wedges and the size of the output drop. Second, we document a correlation between the importance of the investment wedge and several measures of banking crisis severity. This association is arguably the most intriguing, since it points to specific frictions that may be related to the wedges. Finally, we discuss other correlates, such as rates of inflation, the geographical location of the crisis, and the time of the crisis.

Size of the Output Drop The association between crisis severity and the contribution of each wedge is depicted in Figure 1.4. Clearly, there is a positive relationship between the size of the output drop and the contribution of the efficiency and investment wedges, and a negative relationship between the output drop and the contribution of the labor wedge. Table 1.7 (a), which shows correlations between output drop and the contribution of each wedge, conveys the same message. The efficiency and investment wedges play more important roles in more severe crises, while the relative importance of the labor wedge is negatively correlated with severity.

A similar picture emerges when we consider the contributions of different wedges to recoveries (or stagnations) in post-crisis years. The contributions of the wedges—as defined by $\varkappa_{i,t+1}(w)$—correlate with the size of the recovery, measured as $y_{i,t+4} - y_{i,t+1}$ as follows. The efficiency and investment wedges display strong positive correlations (0.73 and 0.67, respectively), while the labor wedge has a small negative correlation coefficient -0.05. That is, the contributions of the efficiency and investment wedges to the recoveries tend to be greater for episodes with better post-crisis performance.

Severity of Banking Crises Perhaps the most striking association between our findings and observables is the existence of a correlation between the percentage contribution of the investment wedge to output drops and various measures of banking crisis severity. Using the database compiled by Laeven and Valencia (2008), and supplementing with information from Reinhart and Rogoff (2009), we compiled information, for each crisis, on the fraction of all banks closed, as well as on the fraction of nonperforming loans (NPLs) at the peak of the crisis. This information, along with some qualitative comments, is summarized in Table 1.8.

To illustrate the relationship between banking and the investment wedge, in Figure 1.5, we compare Brazil in 1987, a crisis with relatively mild banking problems to Indonesia in 1997, a crisis with more serious banking problems. In the graph, it is clear that the contribution of the investment wedge is greater in the latter. While we deliberately chose these two crises for illustrative purposes, the message from the comparison holds more generally. As can be seen in Table 1.7, panel (b), the ratio of banks closed to the total number of banks correlates positively with investment wedge's contribution to the output drop. The ratio is essentially uncorrelated with the contribution of the efficiency wedge, and somewhat negatively correlated with the contribution of the labor wedge. This measure of banking crisis severity, however, does not adjust for the size of the closed institutions, and may therefore misrepresent the aggregate significance of the crisis. To address this issue, we also examine a different measure of severity, the share of nonperforming loans throughout the banking sector at the peak of the crisis. As displayed in Table 1.7, panel (b), using this measure yields a similar pattern of correlations. The correlation with the efficiency wedge turns negative, but remains very small, the correlation with the investment wedge remains positive, and increases, and the correlation with the labor wedge remains negative.

Finally, we examine the flow of bank credit to the private sector in the crisis year, as well as in the three following years. While the series from the World Bank (see the Data Section above) is available as a percentage of GDP, multiplying the series by nominal GDP, and deflating using the CPI, we construct a series for the flow of real credit from the banking system to the private sector. As displayed in Table 1.7, panel (b), the percentage drop in real credit is positively correlated with the contribution of the investment wedge to the output drop. The sign is positive, regardless of whether we consider the drop of credit between years t and $t+1$, t and $t+2$, t and $t+3$, or t and $t+4$.

In sum, a variety of measures consistently point to a relationship, which seems plausible intuitively, between banking crisis severity and the investment wedge.

Other Correlates: Inflation, Time, Geographical Location We also explored several additional variables and experimented with various subsampling criteria in search of patterns. Specifically, we considered inflation, geography, and whether the crisis took place before or after 1990.

We found no significant correlation between the rate of inflation during the crisis year and the contributions of different wedges to the output drop. Despite the often-heard argument that inflation distorts investment decisions by increasing the uncertainty faced by lenders, we actually find a small negative correlation between the inflation rate and the contribution of the investment wedge to the output drop. Associations with the contributions of the efficiency and labor wedges are also very weak.

A much stronger pattern emerges when one examines results depending on the geographical location of the crisis. In Asian crises (meaning, for our purposes, Korea, Indonesia, Malaysia, the Philippines, and Thailand), the efficiency wedge accounts for 51.6% of the decline in output, the labor wedge for 14.5%, and the investment wedge for 39.2%, on average. For the remaining crises, i.e., in Latin American and European crises (including Turkey as European), the efficiency wedge accounts for 66% of the decline of output, the labor wedge for 24.2%, and the investment wedge, on average, for 6.6%. The importance of the investment wedge is not only higher on average for Asian countries, but also very strongly correlated with severity. Table 1.7 (c) displays correlations between the percentage output drop and each wedge's contribution for both subsamples. In Asian crises, the contribution of the efficiency and investment wedges is highly correlated with severity, while the contribution of the labor wedge correlates negatively with severity. In European and Latin American crises, the contributions of the efficiency and labor wedges are mildly positively correlated with severity, and the contribution of the investment wedge is mildly negatively correlated with severity. Although these findings regarding the geographical location of the crisis are rather pronounced, they are more difficult to interpret than our findings on banking crisis severity.

Finally, we compared crises of the 1980s to crises of the 1990s and 2000s. Due to our sample size, however, this exercise overlaps to a substantial degree with breaking up the sample between Asian and non-Asian crises. Thus, we find a more important role for the investment wedge in post-1990 crises and a more important role for the labor wedge in the crises of the 1980s.

1.5 Wedges with alternative specification: Variable capital utilization

In this section, following CKM, we consider an alternative specification of the technology allowing for variable instead of fixed capital utilization. This specification of the technology is due to Kydland and Prescott (1988) and Hornstein and Prescott (1993). We assume that the production function is now

$$y = A\,(kh)^{\alpha}\,(nh)^{1-\alpha}\,, \tag{1.15}$$

where n is the number of workers employed and h is the length (or hours) of the workweek. Labor input is given by $l = nh$.

We assume that the number of workers n is constant and that all the variation in labor is from the workweek h. Under the assumption of variable capital utilization, the services of capital kh are proportional to the product of the stock k and the labor input l. So, variations in the labor input induce variations in the flow of capital services. The capital utilization rate is proportional to the labor input l, and the efficiency wedge is proportional to y/k^{α}.

This change of specification results in nontrivial changes in measured wedges. The output paths and realized values for the efficiency, labor, and investment wedges with variable capital utilization for all countries are depicted in Figure 1.6. Not surprisingly, relative to the baseline case, the importance of the efficiency wedge falls and the contributions of the labor and investment wedges increase. Nevertheless, the efficiency wedge continues to explain the largest fraction of the drops. Moreover, variable capital utilization does not qualitatively alter our overall findings. In Tables 1.9 and 1.10, we report the contributions to output drops and recoveries, respectively, while Table 1.11 is an analog of Table 1.7, and thus displays correlations between wedge contributions and observables. The wedges shown in Table 1.9 correlate with the size of the output drop in the same way as the wedges in Table 1.5, that is, positively for efficiency and investment, and negatively for labor. Similarly, the messages from Tables 1.10 and 1.11 coincide with those from Tables 1.6 and 1.7, respectively. In particular, in Table 1.11, (panel (b)) the contribution of the investment wedge to the output drop continues to be correlated with our measures of banking crisis severity.

1.6 Conclusion

Using the 'Business Cycle Accounting' methodology developed by Chari, Kehoe and McGrattan (2007), we study output drops across a sample of 23 international financial crises. Throughout the sample, the efficiency wedge is consistently the most important wedge in terms of its ability to explain the output drop, followed by the labor and investment wedges. We also find that the importance of different wedges varies widely across episodes. The importance of the efficiency and investment wedges correlates positively with severity, as well as with bank closures. By contrast, the labor wedge is relatively more relevant in less severe crises, and in crises with milder banking problems. Moreover, the investment wedge tends to be persistent, in the sense that it tends to cause output to decline for several years after the crisis.

By uncovering some stylized facts, this study points to some directions for future research. Our main findings regarding banking crises and the investment wedge suggest a need for crisis models that explicitly incorporate a banking sector as a crucial intermediary for investment. Another direction for future research is to investigate whether there are institutional or other differences (beyond banking crisis severity) that may account for the different results obtained for Asian versus non-Asian countries. Perhaps some hints may be found in Cargill and Parker (2002), who argue that, when compared to their Western counterparts, East Asian financial systems are more heavily intermediated by banks, place more emphasis on state-bank-firm relationships, and are extremely reluctant to impose bankruptcy, especially on large borrowers.

Table 1.1. Benchmark Model Parameter Values

Country	Parameter Values					
	Technology progress rate (γ_z)	Population growth rate (γ_n)	Discount factor (β)	Dep. rate of capital (δ)	Time allocation parameter (ψ)	Capital share (α)
Argentina	0	0.016	0.920	0.050	2.33	0.400
Brazil	0	0.020	0.900	0.070	3.93	0.400
Chile	0.020	0.015	0.980	0.050	3.36	0.300
Finland	0.024	0	0.980	0.050	2.24	0.350
Indonesia	0.024	0.023	0.960	0.050	2.24	0.350
Israel	0.015	0.025	0.950	0.050	2.24	0.350
Korea	0.053	0.015	0.980	0.047	3.46	0.297
Malaysia	0.034	0.028	0.960	0.050	2.24	0.350
Mexico	0	0.032	0.962	0.050	2.24	0.350
Philippines	0	0.025	0.964	0.050	2.24	0.350
Sweden	0.020	0	0.950	0.050	2.24	0.350
Thailand	0.038	0.021	0.917	0.100	2.24	0.350
Turkey	0.012	0.024	0.900	0.050	2.24	0.350

Note. The benchmark model parameter values have been obtained from the business cycle literature: Argentina - Kydland and Zarazaga (2002), Brazil - Lama (2011), Chile - Bergoeing et al. (2002) and Simonovska and Soderling (2008), Korea - Otsu (2008), and Mexico - Meza (2008). For the remaining 8 countries, parameter values were obtained by calibration for the corresponding data.

Table 1.2. Pre-crisis Year and Change (%) in per capita real GDP

Country	Pre-crisis Year	Change (%) in per capita real GDP
Argentina	1980	-6.84
	1984	-6.81
	1988	-8.26
	1994	-4.07
	2001	-13.17
Brazil	1987	-2.37
	1991	-2.77
	1998	-1.91
Chile	1981	-15.45
	1998	-4.08
Finland	1990	-8.98
Indonesia	1997	-19.54
Israel	1983	-1.66
Korea	1997	-11.59
Malaysia	1997	-13.20
Mexico	1981	-4.17
	1994	-8.41
Philippines	1983	-8.66
	1997	-2.75
Sweden	1991	-3.48
Thailand	1997	-15.08
Turkey	1993	-10.63
	2000	-10.73
Average		-8.03

Note. A change (%) in per capita real GDP is calculated between the pre-crisis year and the following year for each episode.

Table 1.3. Data Availability

Country	Period
Argentina	1980 - 2005
Brazil	1980 - 2006
Chile	1980 - 2007
Finland	1980 - 2006
Indonesia	1980 - 2006
Israel	1980 - 2007
Korea	1980 - 2006
Malaysia	1980 - 2006
Mexico	1980 - 2005
Philippines	1980 - 2005
Sweden	1980 - 2007
Thailand	1980 - 2006
Turkey	1988 - 2005

Note. For Turkey, the data set runs from 1988 instead of 1980.

Table 1.4. Change in Output, Labor, Investment

		Change (%)		
Country	Pre-crisis Year	Output	Labor	Investment
Argentina	1980	-6.84	-2.38	-16.32
	1984	-6.81	-0.41	-17.90
	1988	-8.26	-0.24	-23.64
	1994	-4.07	-5.75	-13.70
	2001	-13.17	-7.20	-26.75
Brazil	1987	-2.37	-0.32	-0.28
	1991	-2.77	-4.02	-8.21
	1998	-1.91	-1.20	-5.65
Chile	1981	-15.45	-12.32	-33.41
	1998	-4.08	-3.24	-23.50
Finland	1990	-8.98	-5.81	-22.46
Indonesia	1997	-19.54	-4.27	-57.49
Israel	1983	-1.66	-0.54	-13.51
Korea	1997	-11.59	-8.28	-39.45
Malaysia	1997	-13.20	-3.37	-46.12
Mexico	1981	-4.17	0.62	-19.61
	1994	-8.41	-0.04	-18.63
Philippines	1983	-8.66	-2.94	-37.21
	1997	-2.75	-6.02	-20.18
Sweden	1991	-3.48	-4.87	-15.44
Thailand	1997	-15.08	-0.50	-48.42
Turkey	1993	-10.63	-0.01	-30.49
	2000	-10.73	-0.46	-39.50
Average		-8.03	-3.20	-25.12

Note. Output and investment are real values per person aged 15-64.

Table 1.5. Contributions of wedges to output drops

		Contribution (%) of each wedge		
Country	Pre-crisis Year	Efficiency	Labor	Investment
Argentina	1980	74.93	16.17	5.19
	1984	77.34	12.12	11.28
	1988	76.03	5.70	16.99
	1994	20.98	112.78	-6.12
	2001	48.88	58.48	-2.54
Brazil	1987	155.39	43.00	-74.67
	1991	40.12	54.99	-7.53
	1998	59.06	15.24	7.96
Chile	1981	31.11	56.65	-3.77
	1998	51.52	16.75	55.69
Finland	1990	50.27	18.08	15.29
Indonesia	1997	72.36	-15.98	37.88
Israel	1983	84.68	-27.21	77.00
Korea	1997	41.61	22.43	33.46
Malaysia	1997	75.02	-15.26	43.01
Mexico	1981	78.48	-18.21	29.91
	1994	64.10	2.82	-34.42
Philippines	1983	74.29	8.92	29.52
	1997	-26.33	121.09	15.67
Sweden	1991	11.98	50.98	20.46
Thailand	1997	72.43	-33.93	51.87
Turkey	1993	105.36	-1.66	-7.46
	2000	91.02	-5.61	8.31
Average		62.20	21.67	14.04

Table 1.6. Contributions of wedges during post-crisis years

		Contribution (%) of each wedge			
Country	Pre-crisis Year	Efficiency	Labor	Investment	Size of recovery
Argentina	1980	-1.50	-1.75	-0.19	-1.63
	1984	1.72	2.23	-0.27	2.72
	1988	10.94	4.79	-2.12	9.89
	1994	6.82	3.97	0.35	11.82
	2001	19.12	-2.74	5.19	21.24
Brazil	1987	-5.16	0.41	0.87	-1.43
	1991	5.56	-0.97	0.05	7.51
	1998	-3.04	3.81	-0.29	2.30
Chile	1981	-8.70	5.67	-1.69	-6.95
	1998	0.19	-0.65	0.81	0.45
Finland	1990	2.99	-2.81	-5.43	-8.49
Indonesia	1997	3.96	-2.51	2.07	-1.75
Israel	1983	8.01	1.59	-2.13	8.52
Korea	1997	-1.85	3.76	0.30	1.61
Malaysia	1997	1.25	0.96	-2.71	-3.11
Mexico	1981	-3.78	2.33	-5.29	-7.31
	1994	4.63	-0.29	1.16	7.50
Philippines	1983	-6.26	3.75	-2.89	-6.60
	1997	1.33	5.05	-0.66	6.33
Sweden	1991	7.07	-4.49	-1.63	0.70
Thailand	1997	12.08	-9.19	-0.11	-3.92
Turkey	1993	10.60	-4.94	1.15	9.23
	2000	11.72	-6.30	3.35	9.14
Average		3.38	0.07	-0.44	2.51

Note. Size of recovery is measured as $(y_{i,t+4} - y_{i,t+1})$.

Table 1.7. Correlations

(a) Correlations between output drop (%) and the contribution of the wedge: Overall

Contribution of the	Correlation with the output drop (%)
Efficiency wedge	0.087
Labor wedge	-0.338
Investment wedge	0.157

(b) Correlations between contributions of wedges and measures of banking crisis severity

	Correlation with measures of banking crisis severity					
	Share of		Credit drop from t to			
Contribution of the	bank closed	NPLs	$t+1$	$t+2$	$t+3$	$t+4$
Efficiency wedge	-0.046	0.033				
Labor wedge	-0.117	-0.190				
Investment wedge	0.149	0.198	0.049	0.182	0.266	0.200

(c) Correlations between output drop (%) and the contribution of the wedge: Asian crises versus European and Latin crises

	Correlation with the output drop (%)	
Contribution of the	Asia	Europe and Latin America
Efficiency wedge	0.778	-0.102
Labor wedge	-0.864	0.048
Investment wedge	0.794	-0.176

Table 1.8. Summary of Banking crises

Country	Crisis Year	Share of NPLs at peak (%)	Banks closed (%)	Brief summary
Argentina	1980	9	9.8	The failure of a large private bank (Banco de Intercambio Regional) led to runs on three other banks. Eventually, more than 70 institutions - 16% of commercial bank assets and 35% of finance company assets - were liquidated or subjected to central bank intervention.
	1985	30	N/A	In early May, the government closed a large bank, leading to large runs, which led the government to freeze dollar deposits on May 19.
	1989	27	15.8	Nonperforming assets accounted for 27% of aggregate portfolios and 37% of state banks' portfolios. Failed banks held 40% of financial system assets.
	1995	17	2.4	The Mexican devaluation led to a run on the banks, which resulted in an 18% decline in deposits between December and March. 8 banks suspended operations, and 3 banks collapsed. Through the end of 1997, 63 of 205 banking institutions were closed or merged.
	2001	20.1	0	In March 2001, a bank run started due to a lack of public confidence in government policy actions. In late November 2001, many banks were on the verge of collapsing, and partial withdrawal restrictions were imposed (*corralito*) and fixed term deposits (CDs) were reprogrammed to stop to outflows from banks (*corralon*). In December 2002, the corralito was lifted. In January 2003, one bank was closed, 3 banks were nationalized, and many others were reduced in size.

Table 1.8. Summary of Banking crises (continued)

Country	Crisis Year	Share of NPLs at peak (%)	Banks closed (%)	Brief summary
Brazil	1985	N/A	0	3 large banks (Comind, Maison Nave, and Auxiliar) were taken over by the government.
	1990	16	0	Deposits were converted to bonds. Liquidity assistance to public financial institutions.
	1994-1996	15	N/A	In 1994, 17 small banks were liquidated, 3 private banks were intervened, and 8 state banks were placed under administration. The Central Bank intervened in or put under temporary administration 43 financial institutions, and banking system nonperforming loans reached 15% by the end of 1997. Private banks returned to profitability in 1998, but public banks did not begin to recover until 1999.
Chile	1980	35.6	13.1	3 banks began to lose deposits; interventions began 2 month later. Interventions occurred in 4 banks and 4 nonbank financial institutions, accounting for 33% of outstanding loans. In 1983, there were 7 more bank Interventions and one *financiera*, accounting for 45% of financial system assets. By the end of 1983, 19% of loans were nonperforming.
	1998	1.44	0	N/A
Finland	1991-1994	13	0	A large bank (Skopbank) collapsed on September 19 and was intervened. Savings banks were badly affected; The government took control of 3 banks that together accounted for 31% of system deposits.
Indonesia	1997-2002	35.5	27.7	Through May 2002, Bank Indonesia closed 70 banks and nationalized 13 out of 237. Nonperforming loans were 65-

Table 1.8. Summary of Banking crises (continued)

Country	Crisis Year	Share of NPLs at peak (%)	Banks closed (%)	Brief summary
				75% of total loans at the peak of the crisis and fell to about 12% in February 2002.
Israel	1983	N/A	0	Stocks of the 4 largest banks collapsed and were nationalized by the state.
Korea	1997	35	37.3	Through May 2002, 5 banks were forced to exit the market through a "purchase and assumption formula," 303 financial institutions (215 of them credit unions) shut down, and 4 banks were nationalized. Banking system nonperforming loans peaked between 30 and 40% and fell to about 3% by March 2002.
Malaysia	1997	30	0	The finance company sector was restructured, and the number of finance institutions was reduced from 39 to 10 through mergers. 2 finance companies were taken over by the Central Bank, including the largest independent finance company. 2 banks - accounting for 14% of finance system assets were deemed insolvent and were to be merged with other banks. Nonperforming loans peaked between 25 and 35% of banking system assets but fell to 10.8% by March 2002.
Mexico	1981-1982	N/A	0	There was capital flight. The government responded by nationalizing the private banking system.
	1994-1997	18.9	0	In 1994, 9 banks were intervened and 11 participated in the loan/purchase programs of 34 commercial banks. The 9 banks

Table 1.8. Summary of Banking crises (continued)

Country	Crisis Year	Share of NPLs at peak (%)	Banks closed (%)	Brief summary
				accounted for 19% of financial system assets and were deemed insolvent. 1% of bank assets were owned by foreigners, and by 1998, 18% of bank assets were held by foreign banks.
Philippines	1981-1987	19	0	The commercial paper market collapsed, triggering bank runs and the failure of nonbank financial institutions and thrift banks. There were problems in two public banks accounting for 50% of banking system assets, 6 private banks accounting for 12% of banking system assets, 32 thrifts accounting for 53% of thrifts banking assets, and 128 rural banks.
	1997-1998	20	2.6	1 commercial bank, 7 of 88 thrifts, and 40 of 750 rural banks were placed under receivership. Banking system nonperforming loans reached 12% by November 1998 and were expected to reach 20% in 1999.
Sweden	1991-1994	13	0	The Swedish government rescued Nordbanken, the second largest bank. Nordbanken and Gota bank, with 22% of banking system assets, were insolvent. Sparbanken Foresta, accounting for 24% of banking system assets, intervened. 5 of the 6 largest banks, accounting for over 70% banking system assets, experienced difficulties.
Thailand	1996	33	2.4	As of May 2002, the Bank of Thailand shut down 59 of 91 financial companies (13% of financial system assets and 72% of finance company assets) and 1 of 15 domestic banks, and nationalized 4 banks. A publicly owned assets management

Table 1.8. Summary of Banking crises (continued)

Country	Crisis Year	Share of NPLs at peak (%)	Banks closed (%)	Brief summary
				company held 29.7% of financial system assets as of March 2002. Nonperforming loans peaked at 33% of total loans and were reduced to 10.3% of total loans in February 2002.
Turkey	1994	4.1	0	3 banks failed in April.
	2000	27.6	15	2 banks closed, 19 banks have been taken over by the Savings Deposit Insurance Fund.

Sources: Laeven and Valencia (2008) and Reinhart and Rogoff (2009)

Table 1.9. Contributions of wedges to output drops with alternative specification

		Contribution (%) of each wedge		
Country	Pre-crisis Year	Efficiency	Labor	Investment
Argentina	1980	55.90	22.54	3.65
	1984	67.74	11.38	16.54
	1988	68.75	3.00	23.84
	1994	-25.03	153.26	-4.98
	2001	30.00	74.94	-2.21
Brazil	1987	148.71	66.37	-124.39
	1991	-3.34	88.71	-23.73
	1998	38.24	28.21	6.50
Chile	1981	12.58	78.02	-9.33
	1998	31.04	29.44	68.42
Finland	1990	29.93	30.51	16.64
Indonesia	1997	59.47	-29.02	76.20
Israel	1983	19.47	117.47	134.49
Korea	1997	23.89	34.16	41.80
Malaysia	1997	64.46	-16.34	57.79
Mexico	1981	69.21	-37.49	179.16
	1994	57.13	-1.97	-39.83
Philippines	1983	59.40	10.06	41.37
	1997	-90.88	170.99	25.35
Sweden	1991	-29.76	82.86	22.39
Thailand	1997	66.39	-34.98	75.59
Turkey	1993	101.73	-2.06	-8.52
	2000	86.64	-6.56	13.24
Average		40.94	37.98	25.65

Table 1.10. Contributions of wedges during post-crisis years with alternative specification

Country	Pre-crisis Year	Contribution (%) of each wedge			Size of recovery
		Efficiency	Labor	Investment	
Argentina	1980	-0.16	-2.02	-1.11	-1.63
	1984	1.66	2.81	-0.97	2.72
	1988	10.89	5.15	-3.81	9.89
	1994	5.59	5.18	-0.15	11.82
	2001	18.50	-4.83	6.11	21.24
Brazil	1987	-5.05	0.42	2.02	-1.43
	1991	5.53	-1.62	0.82	7.51
	1998	-5.94	5.78	-0.66	2.30
Chile	1981	-11.49	8.17	-3.31	-6.95
	1998	0.21	-0.82	1.15	0.45
Finland	1990	6.19	-5.22	-6.82	-8.49
Indonesia	1997	3.80	-3.80	4.68	-1.75
Israel	1983	8.43	5.52	-4.54	8.52
Korea	1997	-3.55	5.28	0.04	1.61
Malaysia	1997	1.26	1.15	-3.77	-3.11
Mexico	1981	-3.19	2.85	-16.44	-7.31
	1994	2.97	-0.22	1.58	7.50
Philippines	1983	-7.35	5.47	-4.39	-6.60
	1997	-1.07	7.64	-1.80	6.33
Sweden	1991	9.29	-7.09	-1.96	0.70
Thailand	1997	14.74	-12.55	2.61	-3.92
Turkey	1993	13.20	-7.66	1.93	9.23
	2000	13.18	-8.92	4.72	9.14
Average		3.38	0.03	-1.05	2.51

Note. Size of recovery is measured as $(y_{i,t+4} - y_{i,t+1})$.

Table 1.11. Correlations with alternative specification: Variable capital utilization

(a) Correlations between output drop (%) and the contribution of the wedge: Overall

Contribution of the	Correlation with the output drop (%)
Efficiency wedge	0.262
Labor wedge	-0.509
Investment wedge	0.084

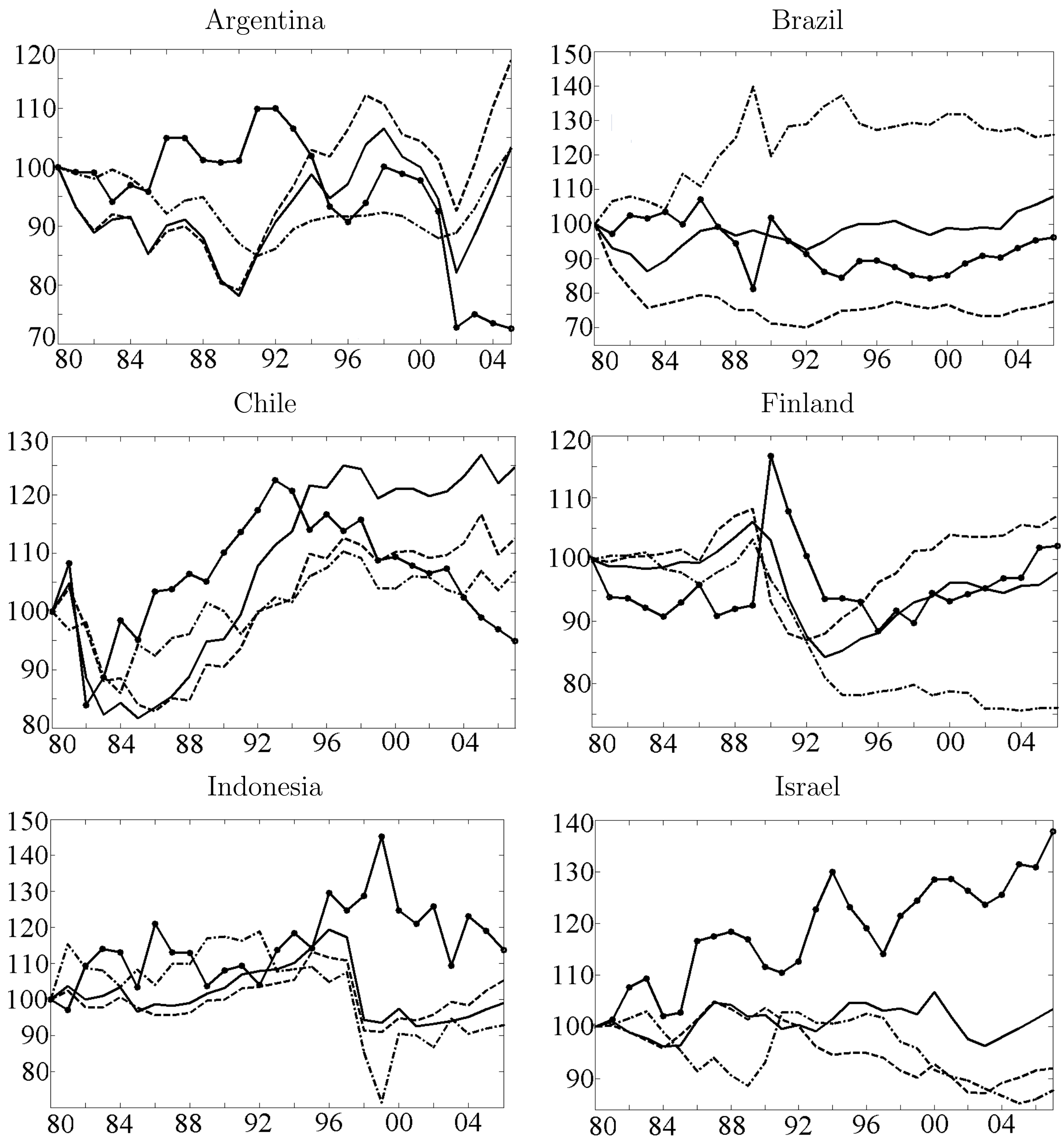
(b) Correlations between contributions of wedges and measures of banking crisis severity

	Correlation with measures of banking crisis severity					
	Share of		Credit drop from t to			
Contribution of the	bank closed	NPLs	$t+1$	$t+2$	$t+3$	$t+4$
Efficiency wedge	0.046	0.113				
Labor wedge	-0.210	-0.214				
Investment wedge	0.076	0.275	0.173	0.298	0.356	0.300

(c) Correlations between output drop (%) and the contribution of the wedge: Asian crises versus European and Latin crises

	Correlation with the output drop (%)	
Contribution of the	Asia	Europe and Latin America
Efficiency wedge	0.793	0.113
Labor wedge	-0.880	-0.240
Investment wedge	0.936	-0.190

Figure 1.1. Output paths and three measured wedges



Note. All values are normalized to equal 100 in 1980. For Turkey, in 1988. The solid line denotes the output path. The dashed, circle marker, and dash-dotted lines denote the measured efficiency, labor, and investment wedges, respectively.

Figure 1.1. Output paths and three measured wedges (continued)

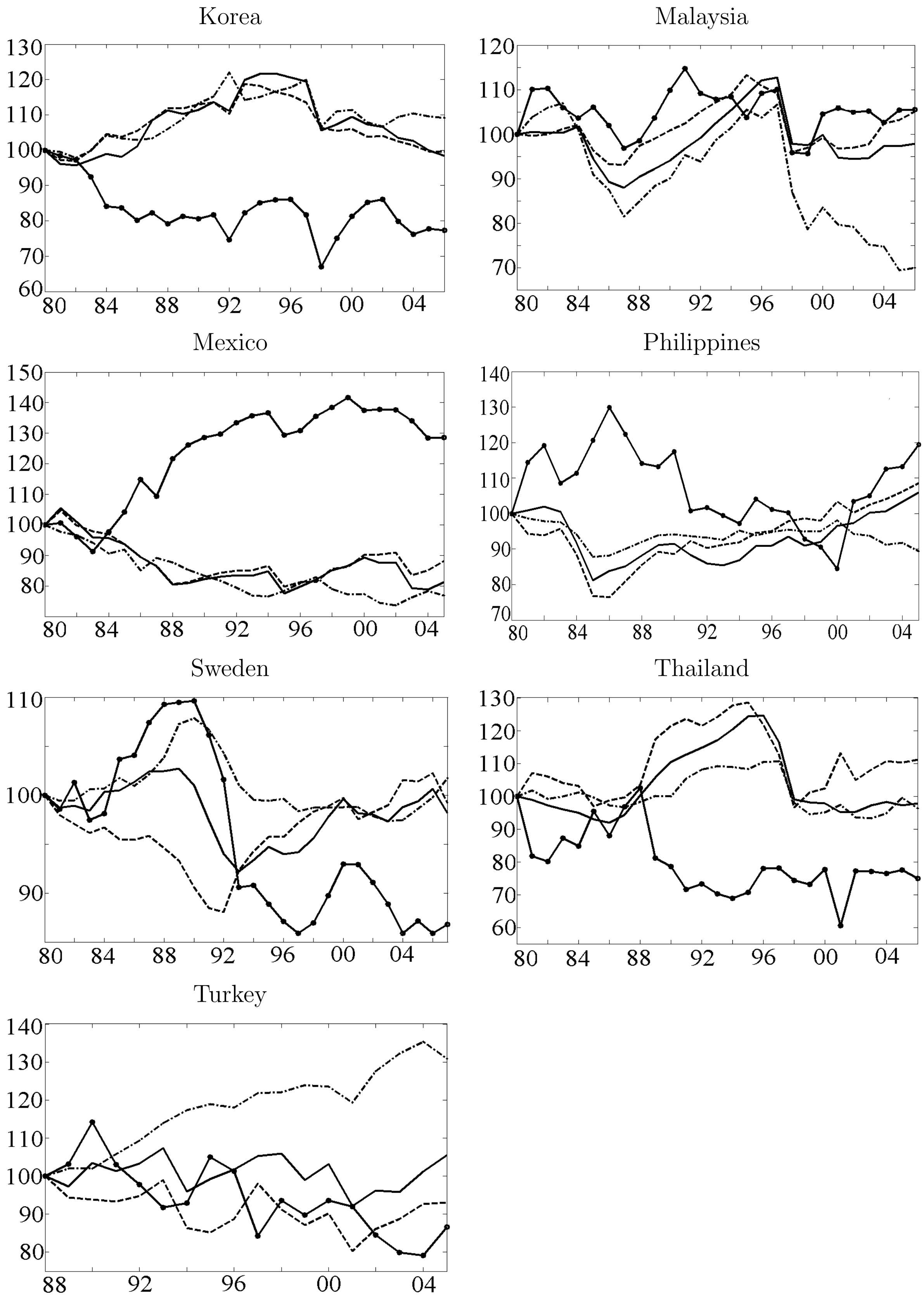
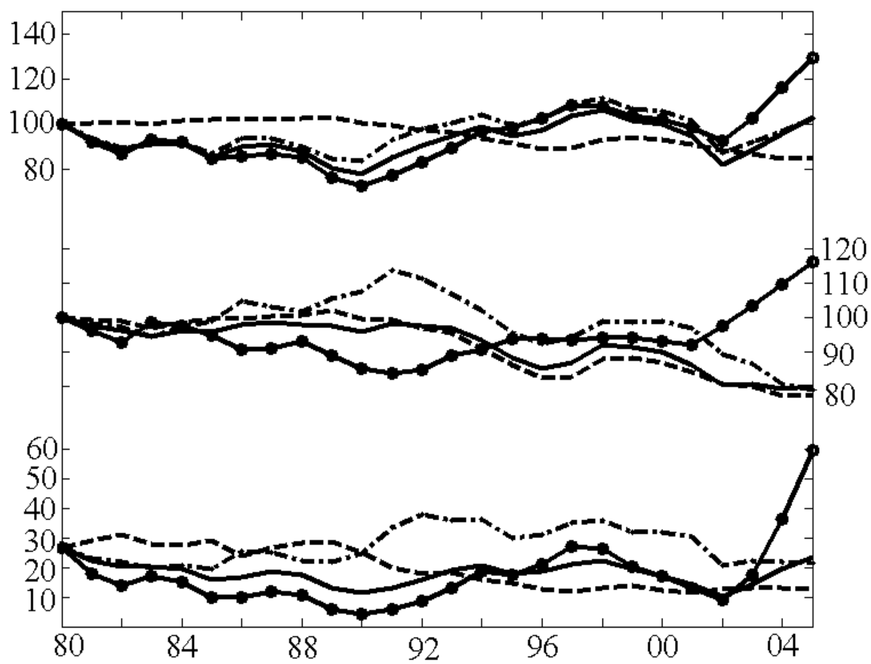


Figure 1.2. Data and predictions of the models with all wedges but one

Argentina



Note. The top, middle, and bottom panels are output, labor, and investment, respectively. The solid line denotes the data. The dashed, circle marker, and dash-dotted lines denote the predictions of the model with no efficiency wedge, of the model with no labor wedge, and of the model with no investment wedge, respectively.

Figure 1.2. Data and predictions of the models with all wedges but one (continued)

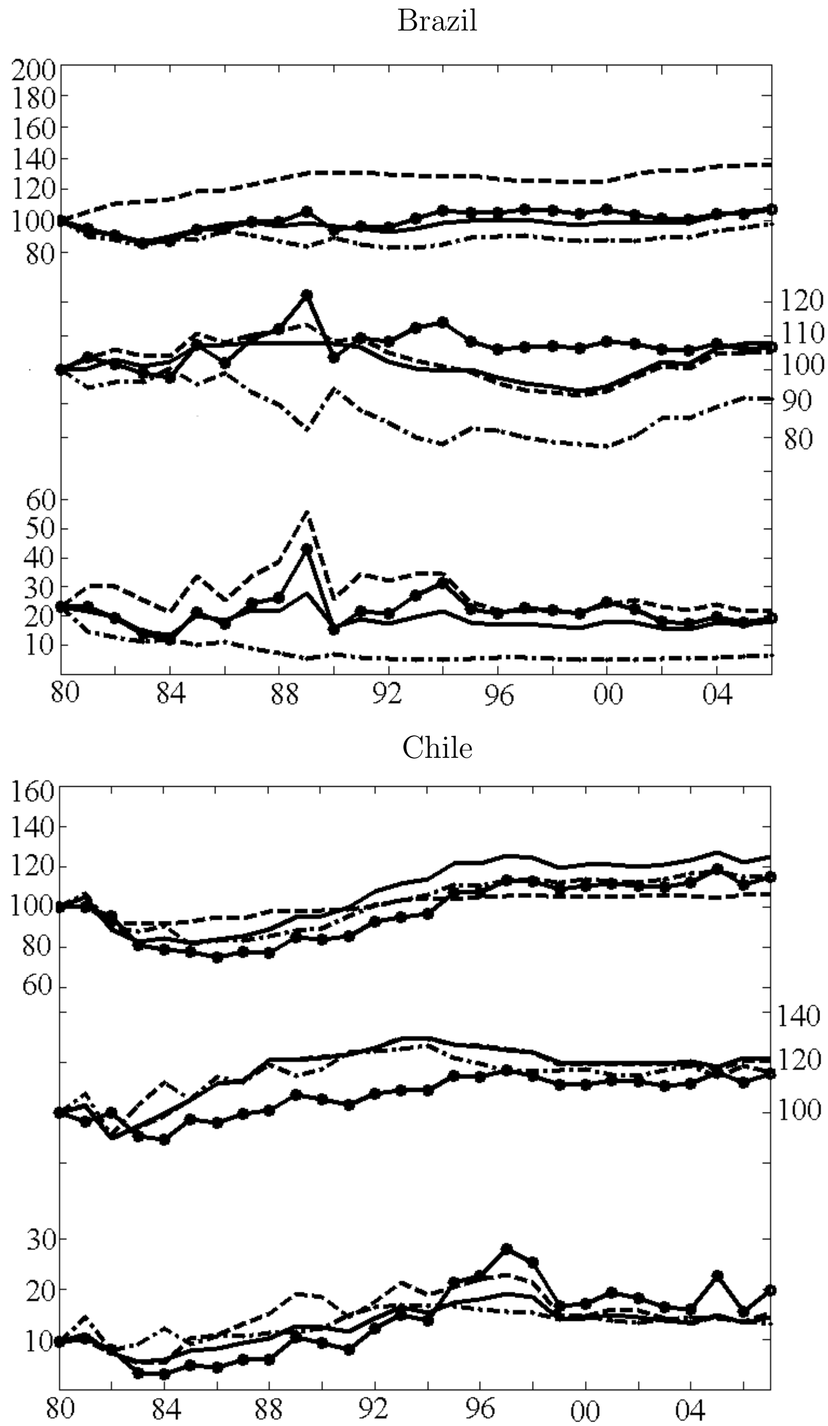
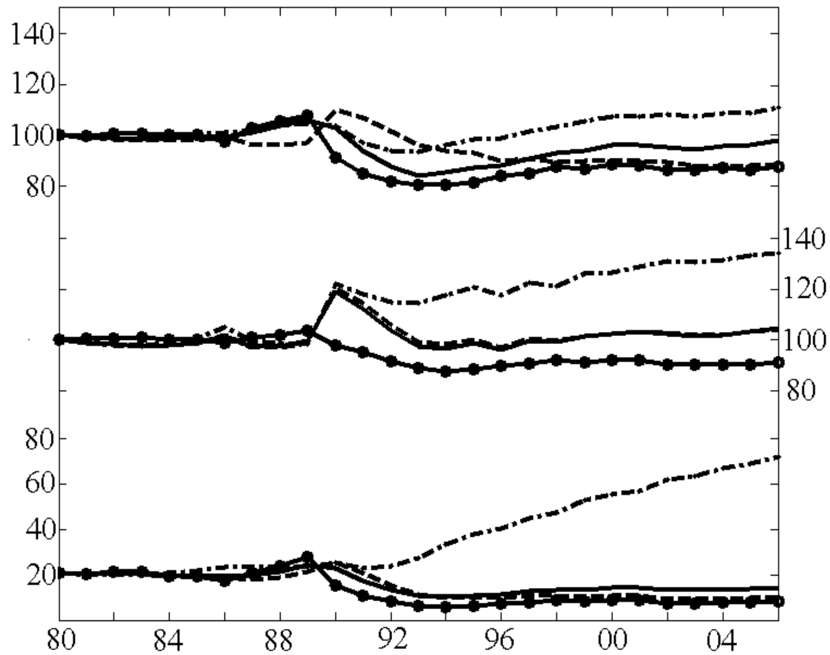


Figure 1.2. Data and predictions of the models with all wedges but one (continued)

Finland



Indonesia

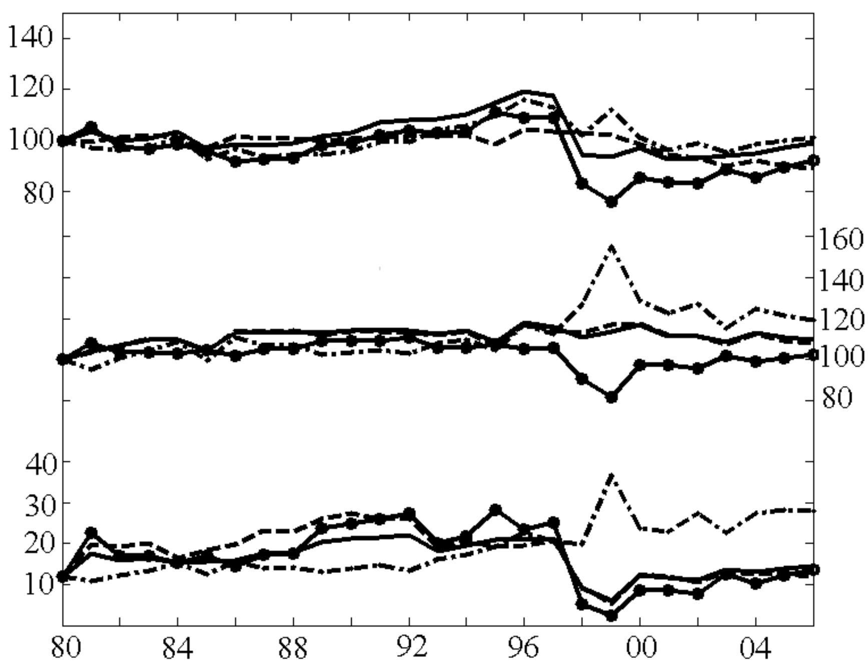
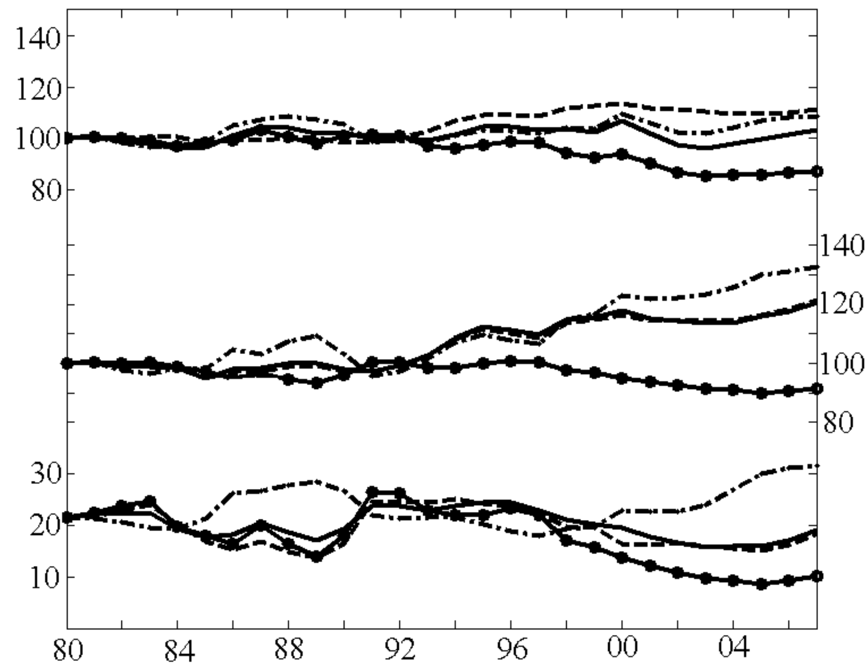


Figure 1.2. Data and predictions of the models with all wedges but one (continued)

Israel



Korea

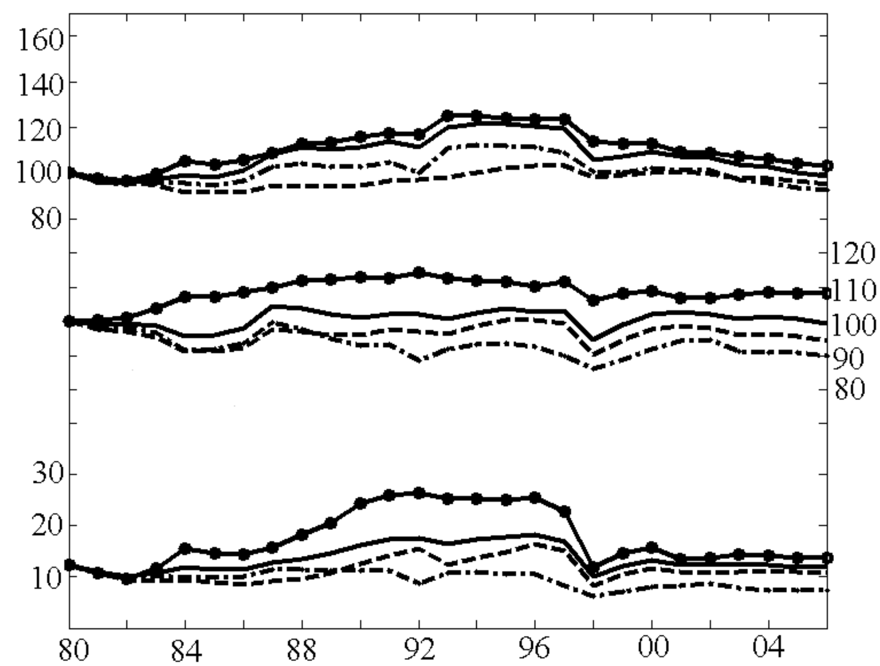


Figure 1.2. Data and predictions of the models with all wedges but one (continued)

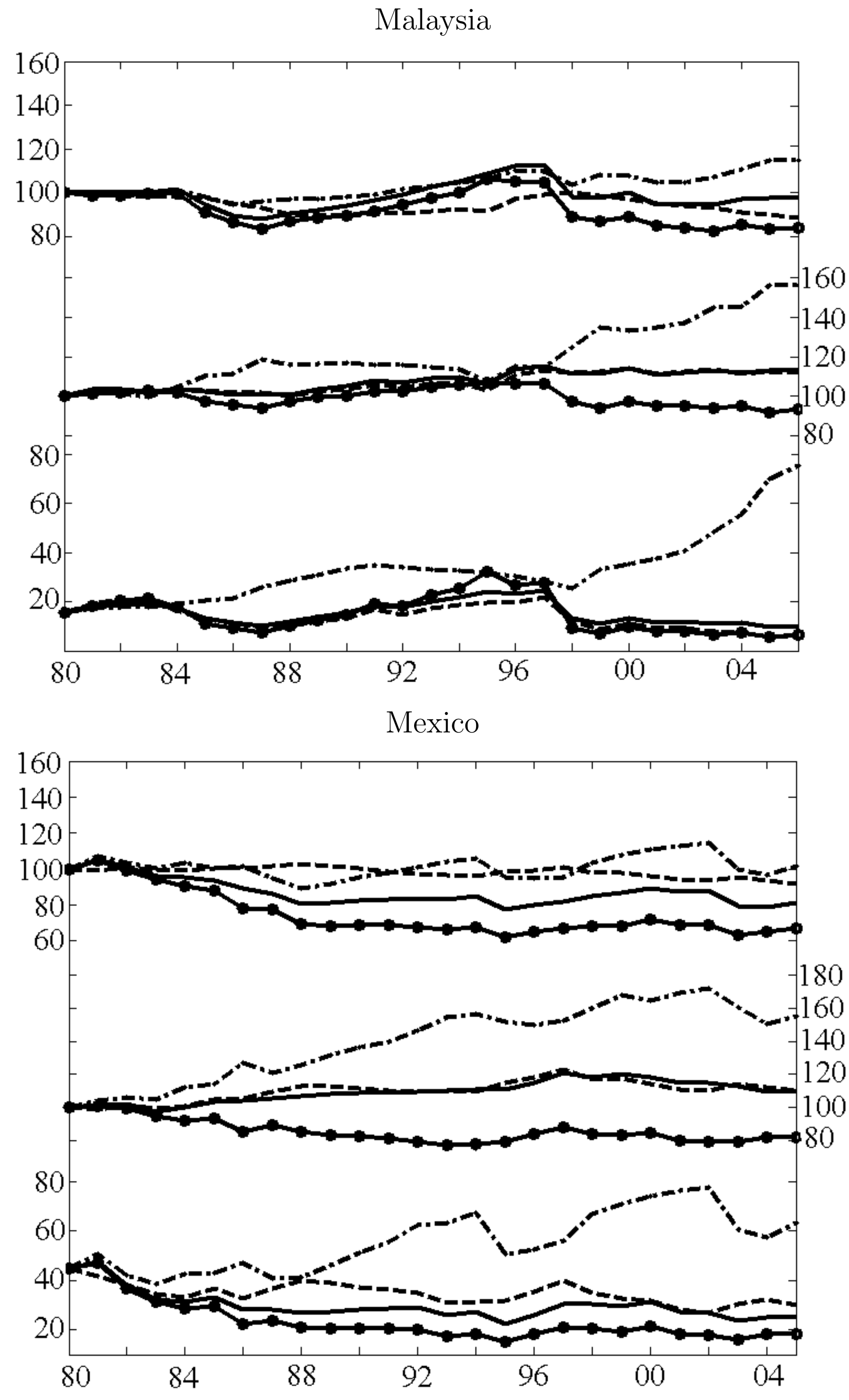
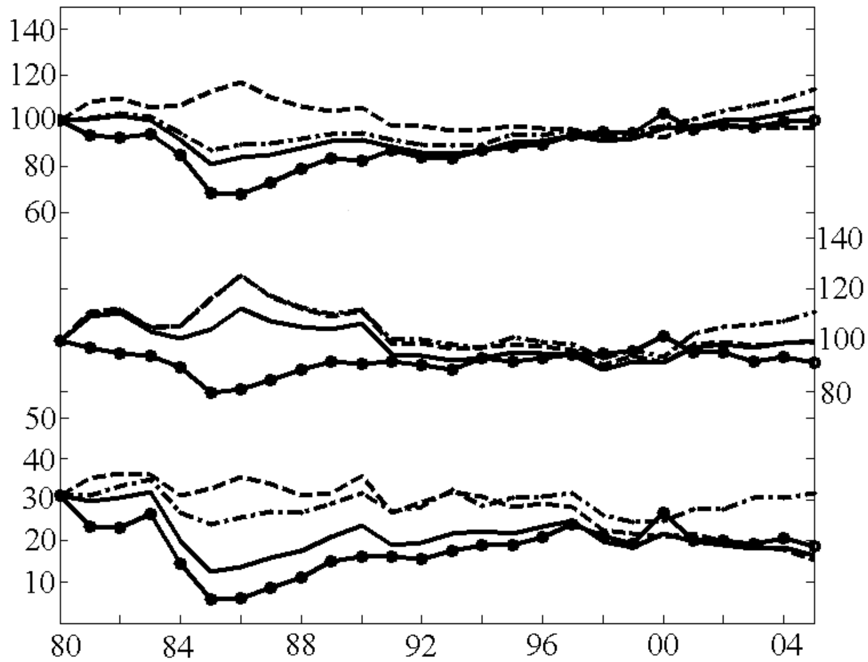


Figure 1.2. Data and predictions of the models with all wedges but one (continued)

Philippines



Sweden

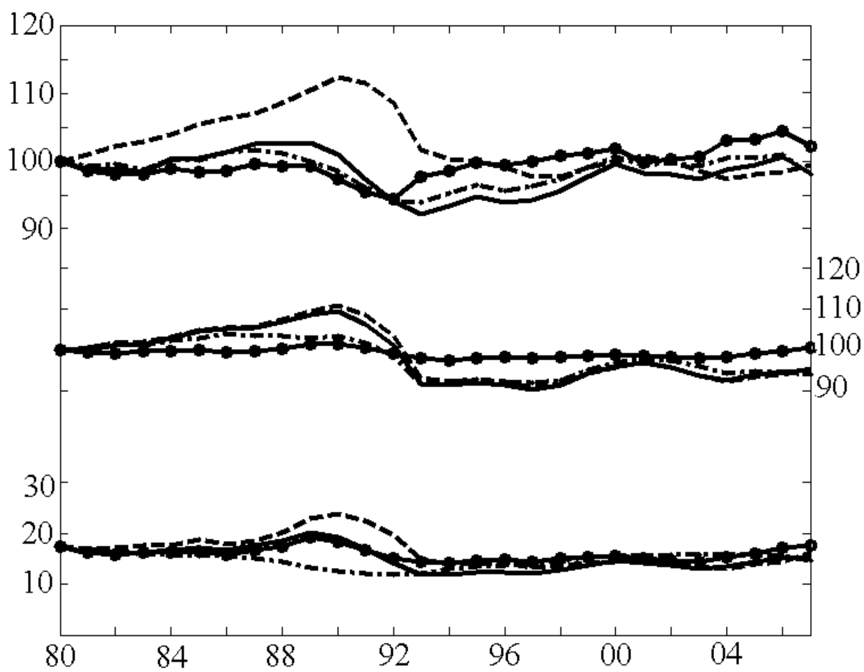


Figure 1.2. Data and predictions of the models with all wedges but one (continued)

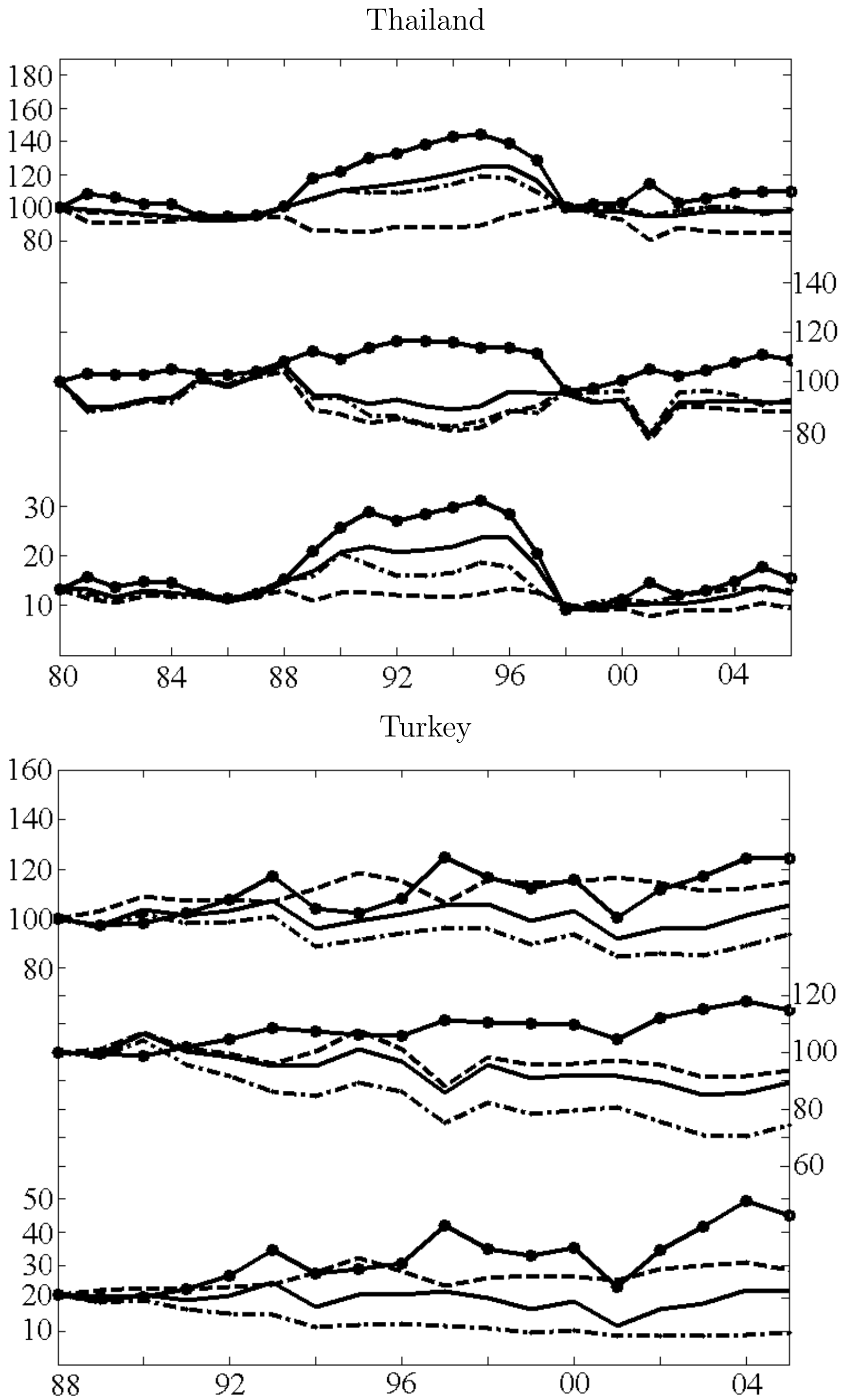
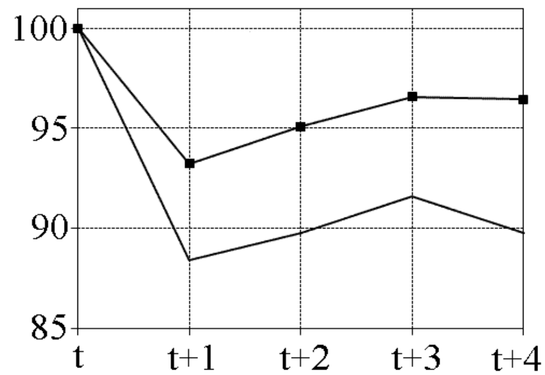
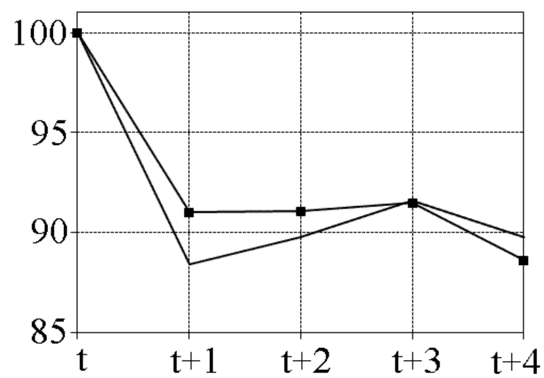


Figure 1.3. Predicted paths of output using two different models: A case of Korea

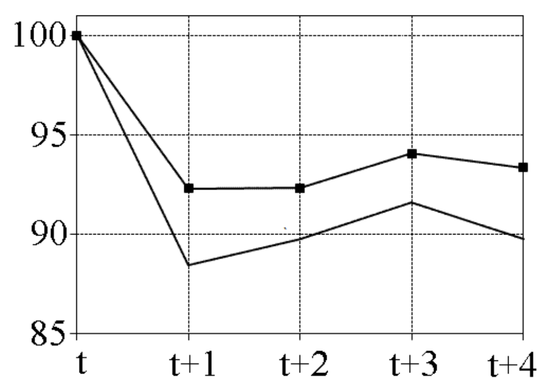
(a) Efficiency wedge



(b) Labor wedge



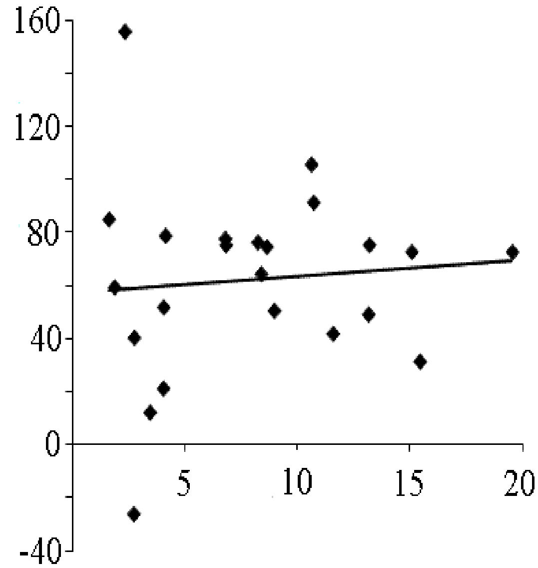
(c) Investment wedge



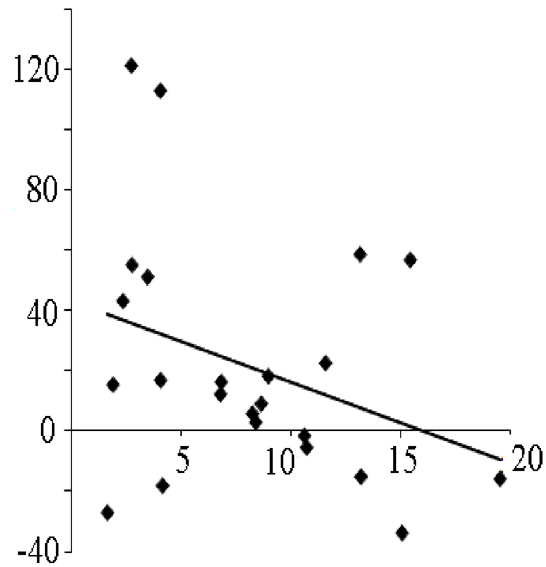
Note. Time t denotes the pre-crisis year for the Korean crisis episode. The solid line is the actual output path, and the line with square markers denotes the constructed output path.

Figure 1.4. Scatter plots: Association between contribution of wedge and output drop (%)

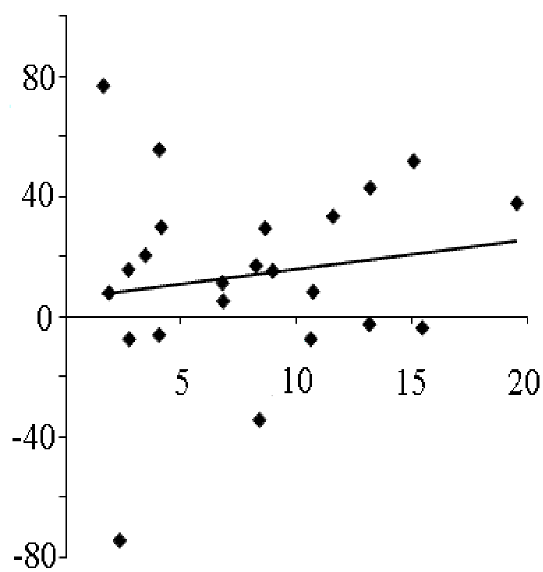
(a) Efficiency wedge



(b) Labor wedge



(c) Investment wedge

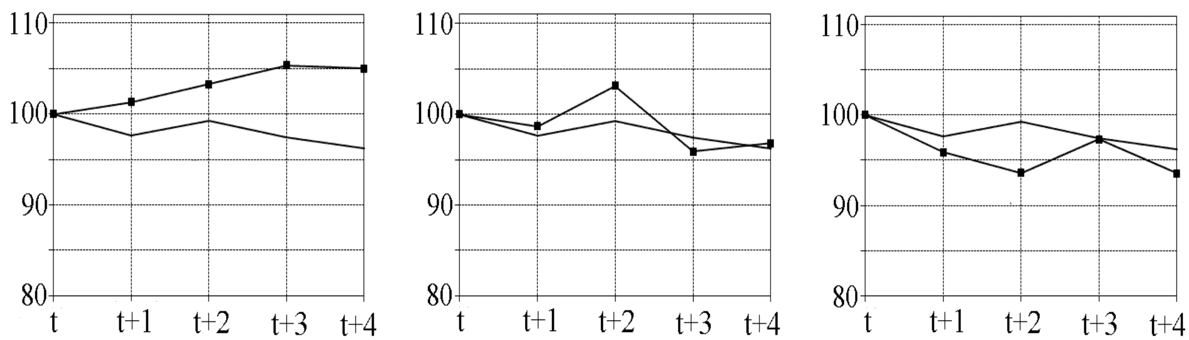


Note. The x-axis is the output drop (%), and the y-axis is the contribution of each wedge (%). The depicted straight line is the OLS regression line.

Figure 1.5. Predicted paths of output using two different models

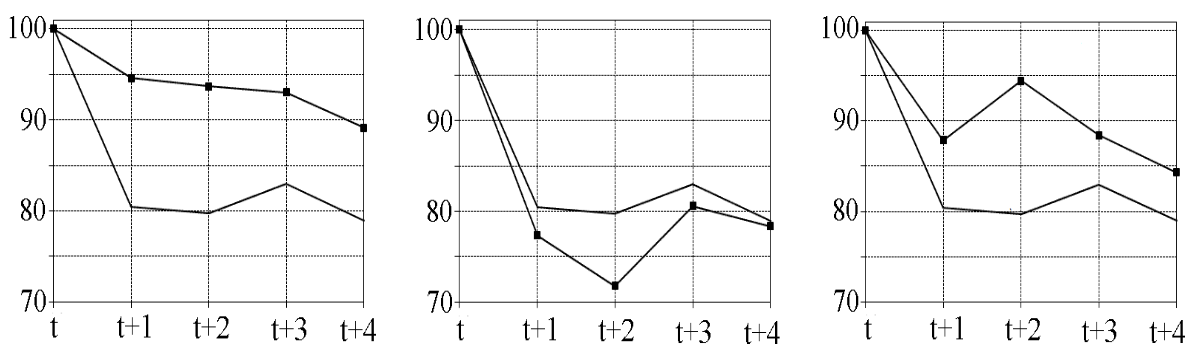
(1) Less severe banking crisis: Brazil 1987

(1a) Efficiency wedge (1b) Labor wedge (1c) Investment wedge



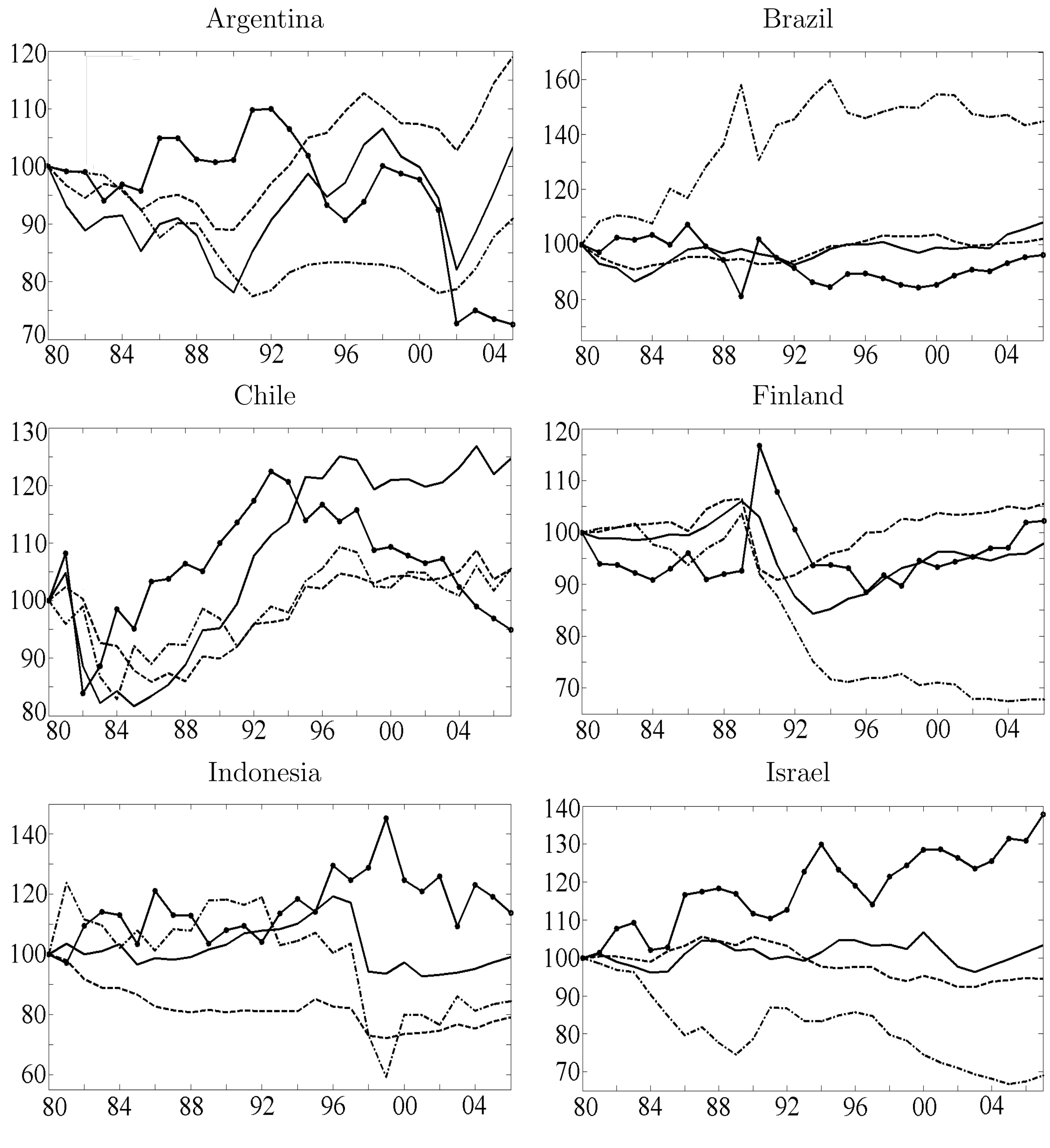
(2) More severe banking crisis: Indonesia 1997

(1a) Efficiency wedge (1b) Labor wedge (1c) Investment wedge



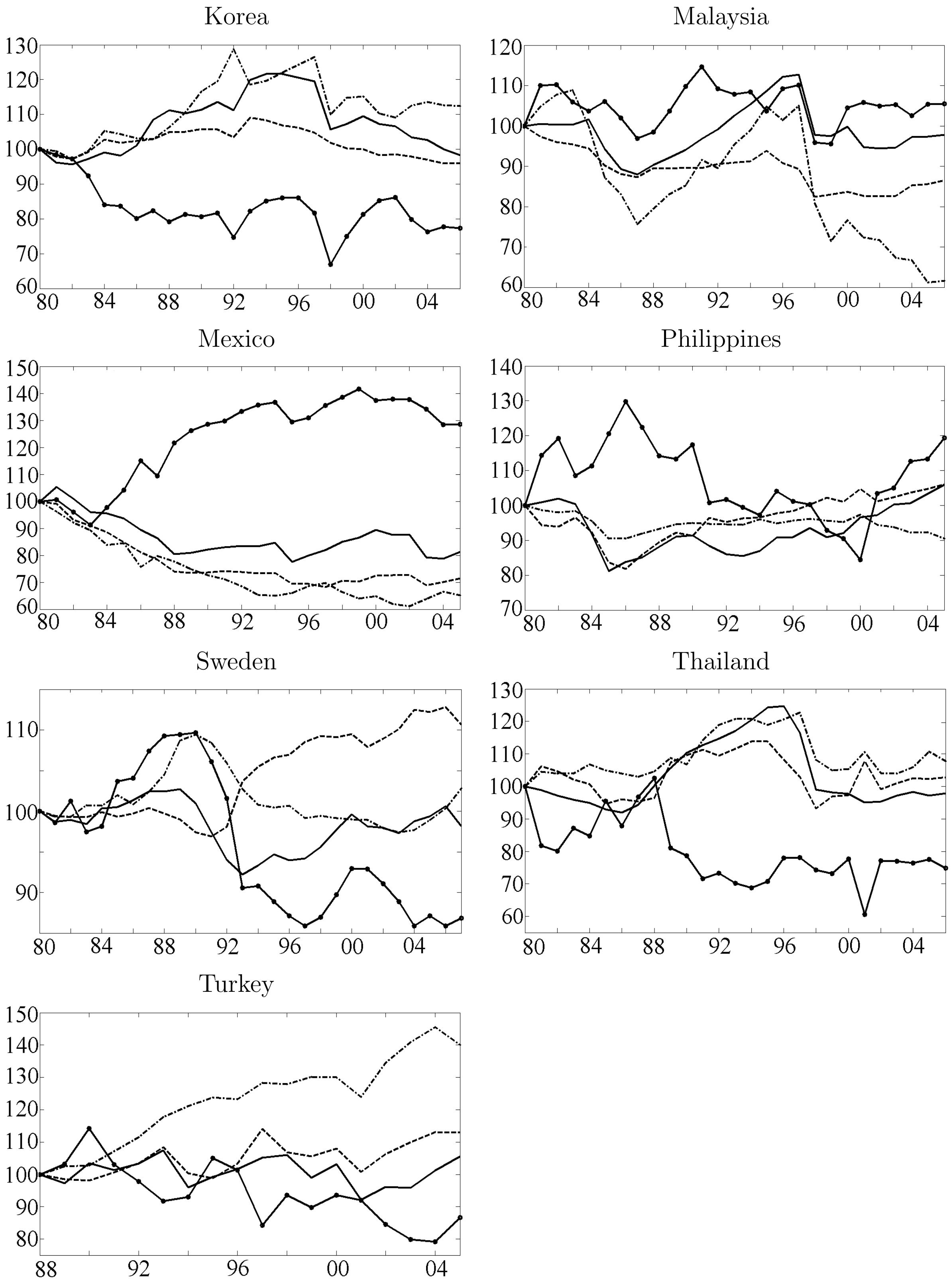
Note. Time t denotes the pre-crisis year for each crisis episode. The solid line is the actual output path, and the line with square markers denotes the constructed output path.

Figure 1.6. Output paths and three measured wedges using the models with VCU



Note. As for Figure 1.1.

Figure 1.6. Output paths and three measured wedges using the models with variable capital utilization (continued)



Chapter 2

Trade Intensity, Carry Trades and Exchange Rate Volatility

2.1 Introduction

For international economists, exchange rate determination is both a topic of perennial interest and a formidable challenge. While some models—e.g., Taylor et al. (2001), Molodtsova and Papell (2009), Mark (1995), and others—have been shown to outperform the random walk famously proposed by Meese and Rogoff (1983), the fraction of exchange rate movement that can be accounted for, let alone predicted, remains very low.[1] Moreover, some of the empirical regularities that have been found are at odds with theory. Most strikingly, a large literature (e.g., Hansen and Hodrick (1980), Fama (1984), Hodrick (1987, 1989), Froot and Thaler (1990), Engel (1996), Mark and Wu (1997), among others) has established the

[1] In a recent interview with *The Region*—a magazine published by the Minneapolis Fed—Kenneth Rogoff summarizes his view on the state of the literature by stating that, when it comes to understanding exchange rates, "the glass is 95 percent empty".

empirical failure of uncovered interest parity (UIP), a building block of many well-known international finance models (e.g., Dornbusch (1976), Flood and Garber (1984), and many others). In fact, the carry trade—an investment strategy that exploits the failure of UIP by borrowing low-interest currencies to invest in high-interest rate currencies—has attracted growing attention from investors and economists alike (see Brunnermeier et al. (2008), and Bhansali (2007), among others). Another empirical finding that is at odds with theory is the profitability of *momentum* strategies. As documented, for example, by Asness et al. (2009), trading strategies that exploit the persistence of exchange rate trends are popular among market participants and are on average profitable. Given that momentum and carry trading strategies are essentially blind to fundamentals, some authors, notably Brunnermeier et al. (2008) have remarked that these strategies are likely to give rise to *exchange rate bubbles*, temporarily driving exchange rates to unsustainable levels. Fortunately, however, other well-known models of exchange rate determination fare better than UIP when confronted with data. In particular, there is ample evidence that relative purchasing power parity (PPP) does have some traction in the medium/long run. While real exchange rates are notoriously volatile, they consistently tend to revert back to long-run equilibrium levels. Moreover, although linear models yield puzzlingly long half-lives of deviations from PPP (see, e.g., Rogoff (1996)), estimates from nonlinear models—where the speed at which deviations vanish is an increasing function of the size of the deviations—are more supportive of relative PPP (see, e.g., Taylor et al. (2001)). Combining the failure of UIP with the predictive power of fundamentals, Jordà and Taylor (2009) show that the crash risk, or negative skewness, of the carry trade can be greatly reduced using fundamentals-augmented carry trade strategies that take into account not only interest rate differentials, but also measures of fair value implied by fundamentals, such as relative PPP.

In this paper, we seek to further examine the mechanism by which exchange rates revert to PPP by considering the role of trade intensity. The theory behind this link is simply that PPP is based on the Law of One Price, which in turn hinges on goods arbitrage. As real exchange rate deviations from PPP widen, the number of tradable goods for which price differences exceed transaction costs also rises. After the usual J-curve lag, agents begin to take advantage of these opportunities for goods arbitrage, buying cheap currencies and selling expensive ones in the process. Our main hypothesis is that this reequilibration process should be stronger and faster the higher the trade intensity between countries.[2] In other words, our hypothesis is that trade intensity can help us understand and predict the dynamics of bilateral real exchange rate.

We consider a sample of 91 currency pairs involving 14 countries over the period 1980-2005. Following Betts and Kehoe (2008), we define trade intensity (maximum) between countries A and B as the greater of two fractions. The first is the fraction of country A's exports plus imports to country B divided by country A's total exports plus imports. The second is the fraction of country B's exports plus imports bound for country A divided by country B's total exports plus imports. We also define trade intensity (average), which is the average of the two aforementioned fractions, as an alternative measure to trade intensity (maximum). Not surprisingly, trade intensity and exchange rate volatility are negatively correlated in our

[2] Although turnover in foreign exchange markets far exceeds the value of world exports and imports, a commonly held view among foreign exchange practitioners is that goods trade nevertheless influences exchange rates in a non-negligible way. The reason for this is that, while day traders account for the bulk of speculative trades, they open and close their positions very frequently. By contrast, a goods-trade related foreign exchange transaction opens a position that is, so to speak, never closed. Therefore, export/import driven foreign exchange transactions typically exert pressure on a currency in a much more consistent direction than speculative trades.

sample. This correlation is likely a product of causality in both directions. As mentioned above, trade intensity may reduce volatility through goods arbitrage, which exerts pressure to reduce deviations from PPP. In the other direction, there is the argument—often brought up in defense of fixed exchange rates—that lower exchange rate volatility may increase trade intensity between countries by reducing uncertainty and hedging costs associated with trade between the two countries. Since we are primarily interested in the first direction of causality, we begin the analysis by implementing panel regressions with exchange rate volatility as a dependent variable and trade intensity as one of our independent variables, using the distance between two countries as an instrument. This approach is similar to that of Broda and Romalis (2009). Coefficient estimates from these regressions across various specifications repeatedly show a negative effect of trade intensity between two countries on their bilateral real exchange rate. We also find that, consistent with the literature on carry trades (see, for instance, Bhansali (2007)) exchange rate volatility increases with the absolute value of interest rate differentials. These results are robust to the use of different measures of exchange rate volatility and trade intensity, and to considering only major currency pairs, versus minor/exotic pairs. Finally, the results are qualitatively preserved when we restrict attention to just the first, or second half, of the 1980-2005 period.

In order to quantify how the size and persistence of deviations from PPP differ between high and low trade intensity currency pairs, we estimate a nonlinear model of exchange rate reversion. Specifically, we estimate a Smooth Transition Autoregressive ($STAR$) model, which allows the speed at which exchange rates converge to their long-run equilibrium values to depend on the size of the deviations. This is consistent with Taylor et al. (2001), who provide evidence of nonlinear mean reversion in a number of major real exchange rates.

The model thus allows for the possibility that real exchange rates may behave like unit root processes when close to their long-run equilibrium levels, while becoming increasingly mean-reverting the further they move away from equilibrium. Nonlinear models help explain so-called PPP puzzle—see Rogoff (1996)—which is the fact that estimates from linear models of half-lives of deviations from PPP seem implausibly long. For our comparison, we restrict attention to 35 highest and 35 lowest currency pairs, as ordered by trade intensity. We make this choice to ensure that the difference in trade intensities between the two sets of currency pairs is so large and stable that variations of trade intensity over time are negligible in comparison to the differences in trade intensities between the two sets of pairs. After estimating the $ESTAR$ models, we investigate the dynamic adjustment in response to the shock to real exchange rates of the estimated $ESTAR$ model by computing the generalized impulse response functions (GIs) using the Monte Carlo integration method introduced by Gallant et al. (1993). We find that, as hypothesized, the estimates of the half-lives of deviations from PPP for a given currency pair are higher the less intense the trade relationship between two countries. For currency pairs in the high trade intensity group, the average half-life of deviations from PPP is given by 21.57 months, whereas for low trade intensity pairs, it is 28.34 months. Moreover, this finding is statistically significant. We also verify that our result is not driven by Central Bank intervention. That is, a possible concern when interpreting our results is that, if Central Banks exhibit more *fear of floating* in response to exchange rate fluctuations against important trading partners, the observed differences in volatility may primarily be due to official reserve transactions, rather than trade. To address this concern, we consider various proxies for intervention—specifically the volatility of reserves and interest rates, following Calvo and Reinhart (2002). To judge by these measures, government intervention is unlikely to be the cause of the faster convergence of exchange rates in high trade intensity cases, since the degree of currency intervention is typically lower for currency pairs in the high trade intensity group.

Our findings on trade intensity and exchange rate dynamics may be used to improve the performance of trading strategies, such as the carry trade. To illustrate how to apply our findings, we carry out a simple exercise, similar in spirit to Jordà and Taylor (2009). In our exercise, we simulate a PPP-augmented carry trade strategy, which gives a buy signal only if there is a positive interest rate differential and the high interest currency is undervalued according to relative PPP. The criterion to decide whether a currency is over- or undervalued according to relative PPP is simply whether the (9 month lagged) real exchange rate is above or below its historical average by a percentage τ. Our findings resemble those of Jordà and Taylor (2009), since we find that the PPP-augmented strategy yields a higher Sharpe ratio and lower negative skew than the naive carry trade strategy, which simply buys high interest rate currencies regardless of any fundamental valuation measures. Trade intensity is useful to fine-tune this strategy by letting the threshold τ depend on trade intensity. For high trade intensity currency pairs, the best performing strategies become active starting at relatively small deviations from the long run real exchange rate. Specifically, the best performing strategies have τ equal to 30 or 70 percent, depending on whether the strategy includes momentum or not. On the other hand, we find that, for low trade intensity currency pairs, it is best to bet on mean reversion only once the deviations have become quite large. Specifically, the best performing strategy leans against a deviation from PPP only once this deviation is $\tau = 130\%$ or greater (both with and without momentum).

The rest of the paper is organized as follows. In Section 2.2, we describe our data. In

Section 2.3, we provide preliminary evidence of a linkage between trade intensity and exchange rate volatility. In Section 2.4, we introduce the *ESTAR* model, and describe how to estimate half-lives of deviations from PPP. In Section 2.5, we present and discuss empirical results from *ESTAR* models along with robustness checks conducted for results from panel regressions. Further, we investigate whether our half-life estimates are mainly driven by government intervention. In Section 2.6, we define carry trade returns, and the performance statistics for carry trade strategies is presented. In Section 2.7, we conclude.

2.2 Data

We collect monthly nominal exchange rates vis-à-vis the US Dollar (USD) from January 1980 through December 2008 for the following 13 currencies: Australian Dollar (AUD), Canadian Dollar (CAD), Danish Krone (DKK), Great Britain Pound (GBP), Japanese Yen (JPY), Korean Won (KRW), Mexican Peso (MXN), New Zealand Dollar (NZD), Norwegian Krone (NOK), Singapore Dollar (SGD), Swedish Krona (SEK), Swiss Franc (CHF), and Turkish Lira (TRY). We also collect monthly interest rates for 14 countries. The consumer price index (CPI) is used to measure the price level, and then the real exchange rate is constructed using Equation (2.1). The foreign exchange reserves are also collected to investigate whether half-life estimates are driven by government intervention, instead of trade. The data are mainly drawn from the *International Financial Statistics* (*IFS*), and the data for annual exports used to measure trade intensity are taken from Betts and Kehoe (2008).[3] When we conduct

[3] The data along with a data appendix for annual exports to measure trade intensity in this paper are publicly available at Timothy Kehoe's webpage, http://www.econ.umn.edu/˜tkehoe/research.html.

a preliminary analysis, we use the data ending in December 2005 due to data limitation for trade intensity. There are a number of combinations that can be made from currencies listed above, which result in 91 currency pairs. In what follows, we consider these 91 currency pairs, involving 14 countries to analyze a linkage between trade intensity and exchange rate volatility. When two currencies are paired, they are listed based on the alphabetical order of the base currency.

2.3 Evidence on the exchange rate volatility - trade intensity linkage

We study the link between trade intensity and exchange rate volatility. We conjecture that the more intense the trade relationship between two countries, the less volatile their bilateral real exchange rate. To investigate the link between them, we first document how to measure exchange rate volatility, and define trade intensity in the following two subsections.

2.3.1 Measuring exchange rate volatility

The real exchange rate, q_t, is defined in logarithmic form as

$$q_t \equiv s_t - p_t + p_t^* \tag{2.1}$$

where s_t is the logarithm of the nominal exchange rate which is measured as the price of the domestic currency in terms of the foreign currency, and p_t and p_t^* denote the logarithm of the domestic and foreign price levels, respectively. As noted in particular by Taylor et al. (2001), the real exchange rate may be interpreted as a measure of the deviation from PPP.

To measure exchange rate volatility between countries i and j, we calculate the standard deviation of the monthly logarithm of the bilateral real exchange rates over the one-year period for each currency pair. To consider a longer term than the one-year window, we implement panel regressions using different time windows such as the three-year window and six-year window for robustness checks, and results for different time windows are reported in Table 2.3 (c). Some other papers use the first-difference of the monthly logarithm of the bilateral real exchange rates (denoted by Δq_t) as a measure of exchange rate volatility.[4] (See, e.g. Brodsky (1984), Kenen and Rodrik (1986), Frankel and Wei (1993), Dell'Ariccia (1999), Rose (2000), and Clark et al. (2004)) As noted by Clark et al. (2004), this volatility measure has the property that it will be equal to zero if the exchange rate follows a constant trend, which could be expected and therefore would not be a source of uncertainty any more. More specifically, for monthly real exchange rates between countries i and j, we define exchange rate volatility as the standard deviation of the bilateral real exchange rate as

$$Volatility_{ij} = \left[\frac{1}{T-1} \sum_{t=1}^{T} \left(q_{ij,t} - \overline{q}_{ij} \right)^2 \right]^{\frac{1}{2}} \tag{2.2}$$

where $q_{ij,t}$ is the monthly logarithm of the bilateral real exchange rate between countries i and j, and $\overline{q}_{ij}$ is the mean value of $q_{ij,t}$ over time period T.

2.3.2 Trade intensity

We consider trade intensity which is defined as relative importance of the trade relationship between two countries. Following Betts and Kehoe (2008), we define trade intensity between

[4] When we use the first-difference of the monthly logarithm of the real exchange rates as a measure of exchange rate volatility rather than the level of the monthly logarithm of the real exchange rates, we obtain similar results with much higher statistical power to reject a null hypothesis.

any two countries, X and Y as the greater of two fractions which are given as follows

$$tradeint^{\max}_{X,Y,t} = \max \left[\begin{array}{c} \left(\dfrac{export_{X,Y,t} + export_{Y,X,t}}{\sum\limits_{all} export_{X,i,t} + \sum\limits_{all} export_{i,X,t}} \right), \\ \\ \left(\dfrac{export_{X,Y,t} + export_{Y,X,t}}{\sum\limits_{all} export_{Y,i,t} + \sum\limits_{all} export_{i,Y,t}} \right) \end{array} \right] \tag{2.3}$$

where $export_{X,Y,t}$ is measured as free on board (f.o.b.) merchandise exports from country X to country Y at year t , measured in year t US dollars. We denote this by $tradeint^{\max}_{X,Y,t}$ to distinguish $tradeint^{\text{avg}}_{X,Y,t}$ which is an alternative measure to (2.3), and is defined as (2.4) below. In this definition of trade intensity, Betts and Kehoe (2008) implicitly assume that trade intensity need only be high for one of the two countries in any bilateral trade relationship for the same strong relation between the relative price of goods and the real exchange rate to be observed. For example, the Chile-US relationship is a high trade intensity relationship, even though Chile accounts for only 0.4 percent of US trade, because the United States accounts for 20.5 percent of Chilean trade. In Betts and Kehoe (2008), a bilateral trade relationship with country X or country Y is defined as "high intensity" if $tradeint^{\max}_{X,Y}$ is greater than or equal to 15 percent and "low intensity" otherwise. Chile, for example, has a high intensity trade relationship with the United States, because trade with the United States accounts for 20.5 percent of Chile's total trade over 1980–2005, on average. In this paper, as a comparison, we define the alternative measure of trade intensity between any two countries, X and Y as

$$
tradeint^{\text{avg}}_{X,Y,t} = \text{avg}\left[\begin{array}{c} \left(\dfrac{export_{X,Y,t}+export_{Y,X,t}}{\sum\limits_{all} export_{X,i,t}+\sum\limits_{all} export_{i,X,t}}\right), \\ \\ \left(\dfrac{export_{X,Y,t}+export_{Y,X,t}}{\sum\limits_{all} export_{Y,i,t}+\sum\limits_{all} export_{i,Y,t}}\right) \end{array}\right] \tag{2.4}
$$

This definition uses the average of two fractions in any bilateral trade relationship. If we apply the definition in (2.4) to the Chile-US example given above, we obtain 10.5 percent instead of 20.5 percent between Chile and the United States. In what follows, we employ both measures, the maximum and the average of two aforementioned fractions. Tables 2.1 (a) and (b) illustrate trade intensity matrices based on the average over the entire sample period, 1980-2005 for both measures, respectively.

We first illustrate Figures 2.1 (a) and (b) showing scatter plots of exchange rate volatility against trade intensity (maximum) and trade intensity (average), respectively, for 91 currency pairs involving 14 countries over the period 1980-2005. It can be clearly seen that there is a negative relationship between exchange rate volatility and trade intensity. As a preliminary analysis, we implement panel regressions with a dependent variable being exchange rate volatility, and results from panel regressions are reported in Table 2.2. To investigate nonlinear mean reversion to PPP, we focus on 35 highest and 35 lowest trade intensity currency pairs based on trade intensity (average).[5] Using 70 currency pairs selected by a rank order of trade intensity (average), we estimate the *ESTAR* models, and then calculate half-lives of deviations from PPP by generating generalized impulse response functions (GIs). In

[5] When we use trade intensity (maximum) instead of trade intensity (average) in determining 35 highest and 35 lowest trade intensity currency pairs, there is little difference in rank orders, and this implies that results do not depend mainly on how we measure trade intensity.

the next two sections, we introduce the *ESTAR* model, and demonstrate how to measure half-lives of deviations from PPP.

2.4 Econometric Framework

2.4.1 The *ESTAR* model

In this section, we consider one of the regime-switching models which is known as the smooth transition autoregressive (*STAR*) model (Granger and Teräsvirta (1993) and Teräsvirta (1994)). In this model, adjustment takes place in every period but the speed of adjustment varies with the extent of the deviation from equilibrium. Specifically, we estimate the Exponential Smooth Transition Autoregressive (*ESTAR*) model which allows for regime-switching or state-dependent behavior to study a nonlinear mean reversion of real exchange rates (Taylor et al. (2001)). The *STAR* model allows for smooth rather than discrete adjustment in explaining nonlinear adjustment. The *STAR* model for the real exchange rate, q_t defined in (2.1) may be written as

$$(q_t - \mu) = \sum_{j=1}^{p} \theta_j \left(q_{t-j} - \mu\right) + \left[\sum_{j=1}^{p} \theta_j^* \left(q_{t-j} - \mu\right)\right] \Phi\left(q_{t-d} - \mu; \gamma, c\right) + \varepsilon_t \tag{2.5}$$

where $\{q_t\}$ is a stationary and ergodic process, $\varepsilon_t \sim iid\left(0, \sigma^2\right)$, and $\Phi(\cdot)$ is the transition function that determines the degree of mean reversion and itself governed by the parameter γ, which determines the speed of mean reversion to PPP. The parameter μ is the equilibrium level of $\{q_t\}$, and $d > 0$ is the delay parameter which is an integer.

The $STAR$ model (2.5) may also be written, reparameterized in a first difference form as

$$\Delta q_t = \alpha + \rho q_{t-1} + \sum_{j=1}^{p-1} \beta_j \Delta q_{t-j} + \left[\alpha^* + \rho^* q_{t-1} + \sum_{j=1}^{p-1} \beta_j^* \Delta q_{t-j} \right] \Phi\left(q_{t-d}; \gamma, c\right) + \varepsilon_t \quad (2.6)$$

where $\Delta q_{t-j} = q_{t-j} - q_{t-j-1}$. A transition function suggested by Granger and Teräsvirta (1993) is the exponential function

$$\Phi\left(q_{t-d}; \gamma, c\right) = 1 - \exp\left[-\gamma\left(q_{t-d} - c\right)^2 / \sigma_{q_{t-d}}\right] \quad \text{with } \gamma > 0 \qquad (2.7)$$

where q_{t-d} is a transition variable, $\sigma_{q_{t-d}}$ is the standard deviation of q_{t-d}, γ is a slope parameter, and c is a location parameter. The restriction on the parameter ($\gamma > 0$) is an identifying restriction. When the transition function is given by Equation (2.7), Equation (2.6) is called the exponential $STAR$ ($ESTAR$) model. The exponential function in Equation (2.7) is bounded between 0 and 1, and depends on the transition variable q_{t-d}. The exponential function also has the properties that $\Phi\left(q_{t-d}; \gamma, c\right) \to 1$ both as $q_{t-d} \to -\infty$ and $q_{t-d} \to \infty$ whereas $\Phi\left(q_{t-d}; \gamma, c\right) = 0$ for $q_{t-d} = c$, and is symmetrically inverse-bell shaped around zero. For either $\gamma \to 0$ or $\gamma \to \infty$, the exponential function given by Equation (2.7) approaches a constant which is equal to 0 and 1, respectively. Thus, the model reduces to a linear model in both cases, and the $ESTAR$ model does not nest a Self-Exciting Threshold Autoregressive ($SETAR$) model as a special case. The exponent in Equation (2.7) is normalized by dividing by $\sigma_{q_{t-d}}$ which is the standard deviation of q_{t-d}, and it allows the parameter γ to be approximately scale-free, and is useful for the initial estimates for the nonlinear least squares estimation algorithm. The values taken by the transition variable q_{t-d} and the transition parameter γ together will determine the speed of mean reversion to PPP. For any given value of q_{t-d}, the transition parameter γ determines the slope of the transition function, and thus the speed of transition between two extreme regimes, with low values of the transition parameter γ implying slower transitions.

In the *STAR* model given in the first difference form as in Equation (2.6), the pivotal parameters for the stability of q_t are ρ and ρ^* in the linear and nonlinear parts, respectively. Taylor et al. (2001) discuss that the influence of transactions costs suggests that the larger the deviation from PPP, the stronger the tendency to move back to long-run equilibrium. This implies that in Equation (2.6), while $\rho \geq 0$ is admissible, one must have $\rho^* < 0$ and $(\rho + \rho^*) < 0$ for q_t to be mean reverting. In other words, for small deviations, the real exchange rate, q_t may be characterized by unit root or explosive behavior, but for large deviations it is mean reverting.

The *ESTAR* model is reasonable to use for our study since it allows for symmetric and nonlinear adjustments between two extreme regimes, with the rate of which in turn depends on the state of specified transition variables. The *ESTAR* model has been applied to real (effective) exchange rates with a transition variable being q_{t-d}. (e.g. Michael et al. (1997), Sarantis (1999), and Taylor et al. (2001)). The *ESTAR* model has also been applied to various macroeconomic issues such as debt and inflation. Among others, Sarno (2001) provides strong empirical evidence of nonlinear mean reversion in the US debt-GDP ratio using the *ESTAR* model. Gregoriou and Kontonikas (2009) test nonlinearities in inflation deviations from the target by estimating the *ESTAR* model, and find that the model is capable of capturing the nonlinear behavior of inflation misalignments.

For empirical applications, Granger and Teräsvirta (1993) and Teräsvirta (1994) suggest choosing the order of the autoregression, p, through inspection of the partial autocorrelation function (PACF). The PACF is preferred to the use of an information criterion such as the Akaike information criterion (AIC), Bayesian information criterion (BIC) or Schwarz information criterion (SIC) because the information criterion may bias the chosen order of the autocorrelation toward low values and any remaining correlation may have an influence on the power of subsequent linearity tests. Therefore, a lag order of p for each currency pair is selected by the PACF of the real exchange rate, q_t. Following van Dijk et al. (2002b), we set the maximum value of the delay parameter, d equal to 6. We consider the lags of the real exchange rate as the transition variable, that is, q_{t-d} for $d = 1, 2, ..., 6$. Then, the delay parameter d is selected after we compare p-values of the Lagrange Multiplier (LM) test statistics for linearity applied to the time series for q_t. The p-values of the LM tests indicate that linearity can be rejected at a certain significance level when q_{t-d} ($d \in \{1, 2, ..., 6\}$) is used as the transition variable. Based on the p-values for the LM statistics, an appropriate d is selected as the delay parameter. In Table 2.4, the values selected for the lag order p and delay parameter d are reported in the second and third rows, respectively. Then, the $ESTAR$ model of the form (2.6) is estimated by nonlinear least squares (NLS) with the selected lag order p and delay parameter d which are suggested by the PACF and the linearity tests results, respectively, for 35 highest and 35 lowest trade intensity currency pairs.

2.4.2 Estimation of half-lives of deviations from PPP

Having estimated the $ESTAR$ model, we consider the nonlinear mean-reverting properties exhibited by real exchange rates. To be more specific, we investigate the dynamic adjustment in response to the shock of the estimated $ESTAR$ model by computing generalized impulse response functions (GIs). The Generalized Impulse Response Function (GI), proposed by

Koop et al. (1996) is designed to solve the problem of the treatment of the future that is dealt with by using the expectation operator conditioned only on the history and on the shock. In other words, the problem of dealing with shocks that occur in intermediate time periods is solved by averaging them out. Therefore, the response to be constructed is an average of what might occur given the present and past. The GI generalizes the concept of impulse response, and is known to be applicable to nonlinear models. The GI for a specific current shock $\varepsilon_t = \delta$ and history ω_{t-1} is defined as

$$GI_q\left(h, \delta, \omega_{t-1}\right) = E\left[q_{t+h} \mid \varepsilon_t = \delta, \omega_{t-1}\right] - E\left[q_{t+h} \mid \omega_{t-1}\right] \tag{2.8}$$

for $h = 0, 1, 2, ...$ In Equation (2.8), the expectation of q_{t+h} given that the specific current shock δ occurs at time t is conditioned only on the history and on this shock. Given the construction of the GI above, the natural baseline for the impulse response function is then defined as the expectations of q_{t+h} conditional only on the history of the process ω_{t-1}, and the current shock is also averaged out.

As pointed out by Koop et al. (1996), the GI is a function of both the shock δ and history ω_{t-1}, and we may treat them as realizations from the same stochastic process that generates the realizations of $\{q_t\}$. Thus, the GI defined above may be considered as the realization of a random variable defined as

$$GI_q\left(h, \varepsilon_t, \Omega_{t-1}\right) = E\left[q_{t+h} \mid \varepsilon_t, \Omega_{t-1}\right] - E\left[q_{t+h} \mid \Omega_{t-1}\right] \tag{2.9}$$

Equation (2.9) is the difference between two conditional expectations being themselves random variables. Thus, $GI_q\left(h, \varepsilon_t, \omega_{t-1}\right)$ represents a realization of this random variable. With nonlinear models, the shape of the GI is not independent of on the history of the time the shock occurs, the size of the shock, or the distribution of future exogenous innovations. We generate the GIs, both conditional on the history and conditional on the shock using the Monte Carlo integration method introduced by Gallant et al. (1993).[6] More specifically, we compute history- and shock-specific GIs as defined in (2.8) for all observations in the estimation sample and value of the initial shock. For the history and the initial shock, we compute $GI_{\Delta q}(h, \delta, \omega_{t-1})$ for horizons $h = 0, 1, 2, ..., 100$. The conditional expectations in Equation (2.8) are estimated as the means over 2000 realizations of Δq_{t+h}, accomplished by iterating on the *ESTAR* model, with and without using the selected initial shock to obtain Δq_t and using randomly sampled residuals of the estimated *ESTAR* model elsewhere. Impulse responses for the level of the real exchange rate, q_t are obtained by accumulating the impulse responses for the first differences as

$$GI_q(h, \delta, \omega_{t-1}) = \sum_{i=1}^{h} GI_{\Delta q}(i, \delta, \omega_{t-1}) \tag{2.10}$$

The estimated GIs for both high and low trade intensity currency pairs are depicted in Figures 2.2 (a) and (b), respectively. The initial shock is normalized to 1, and the generated GIs clearly show the nonlinear adjustment dynamics of real exchange rates to the shock. The half-lives of real exchange rates to the shock are calculated by measuring the discrete number of months taken until the shock to the level of the real exchange rate has fallen below a half. That is, we estimate half-lives considering how much the shock is persistent until the GI falls below 50 percent.

[6] Kiliç (2009b) suggests half-life measures conditional on various regimes to examine persistence in the PPP relations using nonlinear *ESTAR*(1) models. He computes regime-dependent half-lives for the point estimates by standard asymptotic normal methods and simulations. However, as noted by Baillie and Kapetanios (2010), the usual closed form solution for half-life, h, given by $h = \frac{\ln(0.5)}{\ln(\hat{\rho})}$, where $\hat{\rho}$ denotes the estimated AR coefficient of an $AR(1)$ model, is only valid for $AR(1)$ models, and there is no closed form solution for general $AR(p)$ models.

2.5 Empirical Results

2.5.1 Preliminary Analysis

Results from instrumental variable (IV) estimation using panel data

We consider how trade intensity between two countries affects exchange rate volatility. Before analyzing results from instrumental variable (IV) estimation using panel data, we first look at scatter plots for a quick overview of the data. Figure 2.1 depicts scatter plots for real exchange rate volatility against trade intensity (maximum) and trade intensity (average), respectively for 91 currency pairs involving 14 countries over the periods 1980-2005. The straight line is depicted by the Ordinary Least Squares (OLS) regression. As evidenced by the OLS estimates reported, which are significant at the 1 percent level for both measures, a negative relationship between real exchange rate volatility and trade intensity begins to emerge.

In case there is the issue of endogeneity, the ordinary least squares (OLS) regression generally produces biased and inconsistent estimates. In order to control for the potential endogeneity, we use the instrumental variable (IV) estimation approach. Specifically, we use the distance between two countries as an instrument for trade intensity. The distance between two countries is exogenous and not determined by exchange rate volatility, but it is also an appropriate proxy variable for trade intensity. Table 2.2 presents a preliminary instrumental variable (IV) estimation using panel data for the effects of trade intensity on real exchange rate volatility. Although preliminary, the negative association between trade intensity and exchange rate volatility continues to appear. Both measures of trade intensity, maximum and average, are negatively related with real exchange rate volatility. Besides this main finding, we also find that exchange rate volatility increases with the absolute value of interest rate differentials, which is consistent with the view that carry trades—known for their negative skewness or crash risk—lead to an increase in volatility of the exchange rates between investment and funding currencies.

Robustness checks

In Table 2.3, we conduct a number of robustness checks for results from instrumental variable (IV) estimation using panel data: (a) outliers truncated for the real exchange rate volatility variable, (b) by subperiods: 1980-1992 and 1993-2005, (c) by Major vs. Minor, or "Exotic", currency pairs, and (d) by different time windows: 3 year-window and 6 year-window. First, in Table 2.3 (a), we truncate outliers of the dependent variable, which is real exchange rate volatility by excluding all observations that are more than about two standard deviations from the mean in any period t. This has little impact on the results, suggesting that they are not primarily driven by outlier observations. Second, we divide the entire sample period into two subperiods: 1980-1992 (a first half of the entire sample period) and 1993-2005 (a second half of the entire sample period). This division of the period makes no difference to the main results, as reported in Table 2.3 (b). Third, we investigate whether our results are different for Major currency crosses, which add up to 42 out of our total of 91, and Exotic currency crosses, which include the remaining 49 out of 91.[7] This robustness test is

[7] The most traded currency pairs in the foreign exchange market are called the Major currency pairs. They involve the currencies such as Australian Dollar (AUD), Canadian Dollar (CAD), Euro (EUR), Great Britain Pound (GBP), Japanese Yen (JPY), Swiss Franc (CHF), and US Dollar (USD). On the other hand, the Exotic currency pairs are defined as those pairs that are emerging economies rather than developed countries.

driven by potential concerns about volatility differences being driven by market liquidity, which is greater for Major currency pairs. As can be seen from Table 2.3 (c), the results in both subsamples are almost exactly equal to each other and to the overall results reported in Table 2.2. Finally, we check to make sure our results are robust to a longer term than 1 year-window which is considered in the base case, 3 year-window and 6 year-window. As evidenced by Table 2.3 (d), these different time-windows do not at all affect the coefficients on any of the other variables of interest. Overall, the negative relationship between trade intensity and exchange rate volatility holds up well across the different robustness tests.

2.5.2 Estimation results from *ESTAR* models

While the preliminary analyses have the advantage of simplicity, they fail to capture the nonlinearity of exchange rates. In Table 2.4, we report estimation results from *ESTAR* models as given by (2.6). Following Teräsvirta (1994), the *ESTAR* models are estimated by nonlinear least squares (NLS), with the starting values obtained from a grid search over γ and c. The estimations are also implemented with the selected lag order p and delay parameter d which are suggested by the PACF and the linearity tests results, respectively, for both high and low trade intensity currency pairs. As explained above, regression results are consistent with discussion by Taylor et al. (2001) which states that in Equation (2.6), while $\rho \geq 0$ is admissible, meaning that random walk or explosive dynamics are possible when deviations from PPP are small, one must have $\rho^* < 0$ and $(\rho + \rho^*) < 0$ for q_t to be overall mean reverting. The theory behind nonlinear mean reversion is related to transactions costs. As deviations from PPP grow, an increasing number of trade ventures become profitable in spite of transaction costs. Trade-driven currency transactions intensify, and exert stronger pressure steering the exchange rate back to the PPP level.

Details of residual diagnostic tests applied to the model are also reported in the last panel of Table 2.4. LM test results show that the $ESTAR$ model appears to capture all of the residual autocorrelation for most currency pairs considered in this paper. The residual standard deviations, denoted by $\hat{\sigma}_{\varepsilon}$ and the sum of squared residuals (SSR) from the regression are also reported. The results for the test of no remaining nonlinearity in the residuals suggest that the model selected is adequate as there is no evidence for remaining nonlinearity in the residuals. Also, AIC, BIC and the sample size T are reported in the last three rows in Table 2.4.

Having estimated $ESTAR$ models,[8] we first generate generalized impulse response functions (GIs) as described above. Then, using the GIs, we calculate half-lives of deviations from PPP to investigate the persistence of the shock to real exchange rates. In Table 2.5, the estimated half-lives for real exchange rates (measured in months) are reported for high and low trade intensity currency pairs, respectively. Typically, our estimates of the half-lives of deviations from PPP for a given currency pair are higher the less intense the trade relationship between two countries. More specifically, the average of half-lives for high trade intensity currency pairs is greater than that for low trade intensity currency pairs by about 6.8 months, as can be seen in Table 2.5. The t -statistic for the difference in means test is 2.11, and this results in a rejection of the null hypothesis of no difference in means.[9] Thus, the half-lives

[8] The estimated transition functions, plotted against time for high and low trade intensity currency pairs are available from the authors.

[9] Although trade is endogenous to the real exchange rate, the differences in trade intensity between these two sets of country pairs very large and stable. In spite of dramatic movement in real exchange rates throughout the sample period, trade intensity for all low-intensity

of deviations from PPP based on the estimations of the $ESTAR$ models and the generated GIs suggest that deviations from PPP are corrected faster for country pairs with relatively more intense trade relationships.

2.5.3 Half-lives and government intervention

We also investigate whether these differences in volatility may be due to Central Bank intervention in currency markets, or *fear of floating*, instead of trade. To investigate this, we construct measures of official intervention using volatility of reserves and interest rates as proxies for intervention, as in Calvo and Reinhart (2002). We then examine whether there is an association between the half-lives of deviations from PPP and government intervention which is measured by two indicators. The bilateral exchange rates are reported with respect to the US Dollar (USD), and with respect to the Euro (EUR) for the US Dollar (USD).[10] We denote the absolute value of the percent change in the exchange rate and foreign exchange reserves by $\epsilon, \Delta F/F$, respectively. The absolute value of the change in interest rate is given by $\Delta i \ (= i_t - i_{t-1})$. We denote some critical threshold by x^c, and then estimate the probability that the variable x falls within some prespecified bounds. We set x^c at 2.5 percent, as in Calvo and Reinhart (2002). The probability that the monthly exchange rate change falls within the 2.5 percent band should be greater for currencies that are more intervened, or less floating. The opposite should apply to changes in foreign exchange reserves, as the most common form of intervention is precisely to buy or sell reserves. Similarly, volatile interest rates are taken as evidence that monetary authorities use interest rate policy as a means

country pairs remain far below any high-intensity pair at all times.

[10] The European currency unit (ECU) which was the precursor of the new single European currency, the Euro (EUR) is used before the introduction of the Euro on January 1, 1999.

of stabilizing the exchange rate. Thus, the probability that interest rates change by 400 basis points (4 percent) or more on any given month should be greater for more intervened currencies.

Table 2.6 presents evidence on the frequency distribution of monthly percent changes in the exchange rate, foreign exchange reserves, and nominal money market interest rates for different exchange regimes. For example, as can be seen in the second column of Table 2.6, for the United States, there is about 63.5 percent probability that the monthly USD/EUR exchange rate change would fall within a 2.5 percent band. For USD/JPY, the probability is slightly lower at 59.48 percent. To quantify a degree of government intervention, we use a rank order for reserves and interest rates which is assigned 1 for most floating exchange regimes, and 14 for least floating exchange regimes. We use an average value of two rank orders assigned for each country, and when currency pairs are considered, we average the ranks out.

When we compute intervention rankings for high versus low trade intensity currency pairs, we obtain an average of 5.66 for high trade intensity currency pairs, and 8.91 for low trade intensity pairs.[11] This suggests that our half-life estimates are not mainly driven by government intervention. In other words, Central Bank intervention is unlikely to be the cause of the faster convergence of exchange rates to their long run levels, since the degree of currency intervention is typically lower for currency pairs in our high trade intensity group.

[11] When we use percents instead of rank orders, there is little difference between high and low trade intensity currency pairs. The use of percents does not change our main results on government intervention.

2.6 Application to carry trades

2.6.1 Definition of carry trade returns

Following Brunnermeier et al. (2008), we denote the excess return to a carry trade strategy of an investment in the target currency financed by borrowing in the funding currency by

$$\mathrm{ER}_{t+h} = (i_t - i_t^*) - \Delta s_{t+h} \tag{2.11}$$

where the period h is the point where the investor shorts the investment currency, i_t is the interest rate at time t for the investment currency, i_t^* is the interest rate at time t for the funding currency, s_t is the logarithm of the nominal exchange rate which is measured as the price of the domestic currency in terms of the foreign currency, and the second term on the left hand side, Δs_{t+h} is a depreciation or an appreciation of the investment currency. Under the assumption that uncovered interest rate parity (UIP) condition holds, there should be no excess return to the carry trade strategy on average

$$E_t\left(\mathrm{ER}_{t+h}\right) = 0 \tag{2.12}$$

or

$$E_t\left(\Delta s_{t+h}\right) = (i_t - i_t^*) \tag{2.13}$$

where E_t is the conditional expectations operator on a sigma field of all relevant information up to and including time t.

It implies that the interest rate differential should, on average, be equal to the future expected exchange rate change. To offset the positive interest rate differential, the nominal exchange rate at time $t+h$, s_{t+h} should increase so that the investment currency depreciates, or equivalently the funding currency appreciates. However, empirically UIP does not hold in the sense that the investment currency appreciates, or the investment currency depreciates less than the interest rate differential. In either case, it makes the carry trade strategy profitable, on average.

2.6.2 Portfolio Analysis

Conditioning carry trade strategies on trade intensity

In recent years, the strategy known as the carry trade has received growing attention, both from investors and academic researchers. In its simplest, or naïve form, the carry trade consists of borrowing low interest rate currencies to invest in high interest rate currencies. This carry trade is called naïve because it is blind to fundamentals other than the interest rate. It has been well documented that the carry trade is profitable on average, given the empirical failure of uncovered interest parity (UIP). However, the carry trade has also been known to be subject to large crash risk, or negative skewness of returns. To mitigate this risk, some authors have proposed diversification (Burnside et al. (2007)), the use of options (Burnside et al. (2011)), and conditioning on fundamentals. The latter strategy has been proposed by Jordà and Taylor (2009), who show that the crash risk of the carry trade can be substantially reduced by taking macroeconomic fundamentals into account, i.e., by following a fundamentals-augmented carry trade strategy.

In the spirit of Jordà and Taylor (2009), we examine the usefulness of our findings on trade intensity for carry trades. For the currencies in our sample over the period, January 1980 - December 2008, we implement a PPP-augmented carry trade strategy as follows. For each currency cross, we compare a 15-year moving average of the real exchange rate to the current real exchange rate, lagged by 9 months.[12] The PPP-augmented carry trade strategy purchases currency A against currency B only if the interest rate differential between currency A and currency B exceeds the difference between a median and minimum of all the interest rates in our data set (also with currency A's interest rate being greater than currency B's interest rate), and currency A is undervalued vis-à-vis currency B, according to PPP (with the aforementioned 9 month lag). If one of these two conditions fails, currency A is not purchased against currency B. We use trade intensity to decide at what point we consider a currency to be sufficiently over- or undervalued. We take the ratio of the 9-month-lagged real exchange rate to the 15-year moving average of the real exchange rate, and consider a currency overvalued if this ratio is greater than $1 + \tau$, where τ ranges from 0 to 2, in increments of 0.1. We also experiment with the inclusion/exclusion of a third condition, momentum, which specifies that currency A is to be purchased only if it appreciated against currency B in the previous month. Although momentum strategies have little or no theoretical underpinnings, they are quite popular among traders.

In Table 2.7 (a) and (b), we report performance statistics for carry trade portfolios without and with a momentum trading strategy, respectively over the entire sample period. In Table 2.7 (a) which has been implemented without a momentum trading strategy, for high trade intensity currency pairs, the naïve carry trade strategy yields an annualized return of -1.6 percent, with a standard deviation of 0.011, resulting in a Sharpe ratio equal to -0.121, on a monthly basis. When we implement the PPP-augmented carry trade strategy with a

[12] When we use a 10-year moving average of the real exchange rate instead of a 15-year moving average, the main results do not change substantially.

threshold τ of 0 percent, the Sharpe ratio increases up to 0.018 with the annualized return and standard deviation being 0.4 percent and 0.020, respectively. This annualized return refers only to months in which the strategy is active. For any given currency pair, there are months in which the PPP-augmented strategy is inactive, because the high-interest rate currency is not undervalued. A similar improvement is also observed for low trade intensity currency pairs, as the Sharpe ratio increases from 0.031 for the naïve strategy to 0.061 for the PPP-augmented strategy. Likewise, in Table 2.7 (b) which has been implemented with the addition of a momentum requirement, for high trade intensity currency pairs, the naïve carry trade strategy yields an annualized return of 0.9 percent, with a standard deviation of 0.020, resulting in a Sharpe ratio equal to 0.039, on a monthly basis. When we implement the PPP-augmented carry trade strategy with a threshold τ of 0 percent, the Sharpe ratio increases up to 0.055 with the annualized return and standard deviation being 1.9 percent and 0.029, respectively. A similar improvement is also observed for low trade intensity currency pairs, as the Sharpe ratio increases from 0.110 for the naïve strategy to 0.141 for the PPP-augmented strategy. These gains in performance achieved when taking PPP into account are consistent with Jordà and Taylor (2009).

Trade intensity begins to play a role as we raise the threshold τ. Figure 2.3, panels (a) and (b), show how Sharpe ratios change as we increase the thresholds without and with a momentum trading strategy, respectively. When we implement the strategy without a momentum condition, for both high and low trade intensity currency pairs, the Sharpe ratio is hump-shaped, peaking when τ equals 0.7 and 1.3, respectively and falling for higher levels of τ. Similarly, when we implement the strategy with a momentum trading, the Sharpe ratio peaks when τ equals 0.3 and 1.3, respectively and falling for higher levels of τ. For high trade intensity currency pairs, as τ rises above 0.7 or 0.3 for each case, the number of active months falls drastically, and the standard deviation rises, as the strategies are almost never active. On the other hand, for low trade intensity currency pairs, deviations from PPP above 70 or 30 percent are not rare, and Sharpe ratios continue to rise as τ rises above 0.7 or 0.3, and are highest when τ equals 130 percent. Figure 2.4, panels (a) and (b), show the cumulative performance of fundamentals-augmented carry trade portfolios without and with a momentum trading strategy, respectively over time, for various thresholds. Each line shows the evolution of one dollar for a different 'overvaluation' threshold over the entire sample period. As the graphs show, returns accrue in a relatively smooth fashion. Although there are some periods in which the strategies yield losses, the crashes that are typical of the naïve carry trade are notoriously absent. That is, as in Jordà and Taylor (2009), the inclusion of PPP fundamentals is effective in reducing the negative skewness, or 'Peso problem' of the simple carry trade.

Overall, these results suggest that conditioning on trade intensity may be a useful way to fine-tune fundamentals-augmented carry trade strategies. In particular, for high trade intensity currency pairs, it is best to set the threshold for over/undervaluation at a lower level than for low trade intensity pairs. These results fit squarely with our main finding that deviations from PPP have shorter half-lives for high trade intensity currency pairs.

2.7 Conclusion

In recent years, researchers interested in exchange rate volatility have devoted growing amounts of attention to trading strategies that are unrelated to fundamentals, such as the carry trades and momentum trades. This represents an important addition to the literature on exchange rates, which previously focused mostly on macroeconomic fundamentals. The view that emerges from combining old with new insights is that, while fundamentals drive exchange rates in the long run, short run speculative trading strategies may give rise to substantial but temporary deviations of exchange rates from their long run fundamental values.

This paper explores further the interaction between volatility and fundamentals by examining the role of trade intensity in the reversion of exchange rates to long-run equilibrium values. Following recent literature on nonlinearity, we estimate an $ESTAR$ model, which allows the speed at which exchange rates converge to their long-run equilibrium to depend on the size of these deviations. We find estimates of the half-lives of deviations from PPP to be higher the less intense the trade relationship between two countries. These results continue to hold as we perform a series of robustness tests. Moreover, exchange rate volatility increases with the absolute value of interest rate differentials, which is consistent with the notion that carry trades tend to increase volatility. We also verify that the faster convergence to equilibrium values observed for high trade intensity pairs does not appear to be driven by Central Bank intervention. Finally, we show that taking trade intensity into account may be useful to fine tune carry trade strategies that are sophisticated in the sense that they take fundamentals into account, purchasing currencies only if they are undervalued according to PPP. Specifically, the performance of these strategies improves if the threshold used to define overvaluation or undervaluation is allowed to depend on trade intensity.

Several avenues for future work are worth pursuing. One is to provide further support for the findings of this paper by providing more detailed evidence on the exchange rate impact of trade-related currency transactions. Another avenue, on the theoretical front, would be to build a model of exchange rate determination that combines speculative and trade-related currency transactions.

Table 2.1. Trade intensity matrices

(a) Trade intensity (maximum) matrix

	Aus.	Can.	Den.	G.B.	Jap.	Kor.	Mex.	N.Z.	Nor.	Sin.	Swe.	Swi.	Tur.	U.S.
Aus.		0.028	0.011	0.091	0.346	0.077	0.003	0.339	0.004	0.072	0.019	0.022	0.016	0.254
Can.	0.028		0.015	0.051	0.052	0.033	0.020	0.024	0.044	0.012	0.023	0.032	0.025	0.877
Den.	0.011	0.015		0.268	0.084	0.018	0.004	0.005	0.155	0.011	0.232	0.051	0.021	0.140
G.B.	0.091	0.051	0.268		0.113	0.041	0.014	0.107	0.361	0.070	0.257	0.241	0.242	0.401
Jap.	0.346	0.052	0.084	0.113		0.353	0.051	0.214	0.049	0.315	0.067	0.134	0.099	0.560
Kor.	0.077	0.033	0.018	0.041	0.353		0.011	0.039	0.017	0.077	0.016	0.027	0.045	0.421
Mex.	0.003	0.020	0.004	0.014	0.051	0.011		0.008	0.002	0.005	0.008	0.016	0.003	0.889
N.Z.	0.339	0.024	0.005	0.107	0.214	0.039	0.008		0.002	0.037	0.009	0.008	0.003	0.206
Nor.	0.004	0.044	0.155	0.361	0.049	0.017	0.002	0.002		0.010	0.265	0.017	0.014	0.109
Sin.	0.072	0.012	0.011	0.070	0.315	0.077	0.005	0.037	0.010		0.011	0.027	0.015	0.402
Swe.	0.019	0.023	0.232	0.257	0.067	0.016	0.008	0.009	0.265	0.011		0.061	0.045	0.199
Swi.	0.022	0.032	0.051	0.241	0.134	0.027	0.016	0.008	0.017	0.027	0.061		0.099	0.355
Tur.	0.016	0.025	0.021	0.242	0.099	0.045	0.003	0.003	0.014	0.015	0.045	0.099		0.373
U.S	0.254	0.877	0.140	0.401	0.560	0.421	0.889	0.206	0.109	0.402	0.199	0.355	0.373	

Note. Trade intensity (maximum) is calculated as an average value over the sample period, 1980-2005, using Equation (2.3). Betts and Kehoe (2008) use this measure of trade intensity in the paper.

Table 2.1. Trade intensity matrices (continued)

(b) Trade intensity (average) matrix

	Aus.	Can.	Den.	G.B.	Jap.	Kor.	Mex.	N.Z.	Nor.	Sin.	Swe.	Swi.	Tur.	U.S.
Aus.		0.017	0.008	0.064	0.209	0.062	0.002	0.214	0.004	0.071	0.017	0.018	0.010	0.138
Can.	0.017		0.008	0.039	0.051	0.022	0.014	0.013	0.025	0.007	0.013	0.018	0.013	0.620
Den.	0.008	0.008		0.160	0.046	0.012	0.002	0.004	0.136	0.008	0.184	0.045	0.015	0.073
G.B.	0.064	0.039	0.160		0.085	0.034	0.012	0.059	0.228	0.050	0.172	0.152	0.131	0.243
Jap.	0.209	0.051	0.046	0.085		0.236	0.034	0.113	0.028	0.191	0.039	0.076	0.051	0.398
Kor.	0.061	0.022	0.012	0.034	0.236		0.010	0.022	0.012	0.064	0.012	0.019	0.025	0.239
Mex.	0.002	0.014	0.002	0.012	0.034	0.010		0.005	0.001	0.004	0.006	0.011	0.002	0.518
N.Z.	0.214	0.013	0.004	0.059	0.113	0.022	0.005		0.001	0.024	0.006	0.006	0.003	0.105
Nor.	0.004	0.025	0.136	0.228	0.028	0.012	0.001	0.001		0.008	0.235	0.017	0.009	0.058
Sin.	0.071	0.007	0.008	0.050	0.191	0.064	0.004	0.024	0.008		0.010	0.021	0.009	0.219
Swe.	0.017	0.013	0.184	0.172	0.039	0.012	0.006	0.006	0.235	0.010		0.054	0.028	0.107
Swi.	0.018	0.018	0.045	0.152	0.076	0.019	0.011	0.006	0.017	0.021	0.054		0.063	0.187
Tur.	0.010	0.013	0.015	0.131	0.051	0.025	0.002	0.003	0.009	0.009	0.028	0.063		0.190
U.S	0.138	0.620	0.073	0.243	0.398	0.239	0.518	0.105	0.058	0.219	0.107	0.187	0.190	

Note. Trade intensity (average) is calculated as an average value over the sample period, 1980-2005, using Equation (2.4). This is an alternative measure to Trade intensity (maximum) in Betts and Kehoe (2008).

Table 2.2. Effects of trade intensity on real exchange rate volatility - IV estimation

	[1]	[2]	[3]	[4]
Real exchange rate volatility at time t-1			0.123	0.123
			(0.021)	(0.021)
Trade intensity (maximum)	-0.054		-0.049	
	(0.007)		(0.007)	
Trade intensity (average)		-0.077		-0.070
		(0.010)		(0.006)
Interest rate differential in an absolute value	0.033	0.033	0.034	0.033
	(0.004)	(0.004)	(0.005)	(0.005)
Intercept	0.045	0.045	0.039	0.039
	(0.003)	(0.003)	(0.003)	(0.003)
No. of observations	2366	2366	2275	2275

Note. Results from instrumental variable estimation using panel data with country fixed effects are reported. The distance between two countries (in logs) is used as an instrument to estimate the relationship between trade intensity and real exchange rate volatility. The sample period is from January 1980 to December 2005, and all of 91 currency pairs involving 14 countries are included. The dependent variable is real exchange rate volatility. Standard errors are reported in parentheses below the corresponding coefficients.

Table 2.3. Effects of trade intensity on real exchange rate volatility - Robustness checks

(a) By truncating outliers

	[1]	[2]	[3]	[4]
Real exchange rate volatility at time t-1			0.140	0.141
			(0.022)	(0.022)
Trade intensity (maximum)	-0.058		-0.052	
	(0.005)		(0.005)	
Trade intensity (average)		-0.084		-0.075
		(0.007)		(0.007)
Interest rate differential in an absolute value	0.014	0.014	0.019	0.019
	(0.003)	(0.003)	(0.003)	(0.003)
Intercept	0.038	0.039	0.052	0.052
	(0.002)	(0.002)	(0.003)	(0.003)
No. of observations	2156	2156	2065	2065

Note. Results from instrumental variable estimation using panel data with country fixed effects are reported. The distance between two countries (in logs) is used as an instrument to estimate the relationship between trade intensity and real exchange rate volatility. The sample period is from January 1980 to December 2005, and all of 91 currency pairs involving 14 countries are included. We truncate outliers of the real exchange rate volatility variable. The dependent variable is real exchange rate volatility. Standard errors are reported in parentheses below the corresponding coefficients.

Table 2.3. Effects of trade intensity on real exchange rate volatility - Robustness checks (continued)

(b) By subperiods

	Robustness checks							
	Subperiod for 1980-1992				Subperiod for 1993-2005			
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
Real exchange rate volatility at time t-1			0.113	0.114			0.103	0.103
			(0.032)	(0.032)			(0.030)	(0.030)
Trade intensity (maximum)	-0.062		-0.059		-0.045		-0.038	
	(0.010)		(0.011)		(0.009)		(0.009)	
Trade intensity (average)		-0.092		-0.088		-0.063		-0.054
		(0.015)		(0.017)		(0.012)		(0.013)
Interest rate differential in an abs. value	0.017	0.016	0.011	0.010	0.044	0.044	0.044	0.043
	(0.007)	(0.007)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
Intercept	0.041	0.042	0.054	0.054	0.037	0.037	0.033	0.033
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
No. of observations	1183	1183	1092	1092	1183	1183	1092	1092

Note. Results from instrumental variable estimation using panel data with country fixed effects are reported. The distance between two countries (in logs) is used as an instrument to estimate the relationship between trade intensity and real exchange rate volatility. The sample period is from January 1980 to December 2005, and all of 91 currency pairs involving 14 countries are included. The entire sample period is divided into two subperiods: 1980-1992 (a first half) and 1993-2005 (a second half). The dependent variable is real exchange rate volatility. Standard errors are reported in parentheses below the corresponding coefficients.

Table 2.3. Effects of trade intensity on real exchange rate volatility - Robustness checks (continued)

(c) By Major vs. Exotic currency pairs

	Robustness checks							
	42 Major currency pairs				49 Exotic currency pairs			
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
Real exchange rate volatility at time t-1			0.120	0.117			0.093	0.093
			(0.031)	(0.032)			(0.029)	(0.028)
Trade intensity (maximum)	-0.049		-0.043		-0.048		-0.047	
	(0.006)		(0.007)		(0.013)		(0.013)	
Trade intensity (average)		-0.068		-0.060		-0.075		-0.073
		(0.009)		(0.009)		(0.020)		(0.020)
Interest rate differential in an abs. value	0.190	0.190	0.176	0.175	0.030	0.030	0.032	0.031
	(0.022)	(0.022)	(0.024)	(0.024)	(0.005)	(0.005)	(0.005)	(0.005)
Intercept	0.046	0.045	0.041	0.040	0.051	0.052	0.065	0.065
	(0.003)	(0.003)	(0.004)	(0.004)	(0.007)	(0.007)	(0.009)	(0.009)
No. of observations	1092	1092	1050	1050	1274	1274	1225	1225

Note. Results from instrumental variable estimation using panel data with country fixed effects are reported. The distance between two countries (in logs) is used as an instrument to estimate the relationship between trade intensity and real exchange rate volatility. The sample period is from January 1980 to December 2005, and 91 currency pairs are divided into 42 Majors and 49 Exotics. The dependent variable is real exchange rate volatility. Standard errors are reported in parentheses below the corresponding coefficients.

Table 2.3. Effects of trade intensity on real exchange rate volatility - Robustness checks (continued)

(d) By different time windows

	Robustness checks							
	3-year window				6-year window			
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
Real exchange rate volatility at time t-1			0.017	0.017			0.072	0.069
			(0.039)	(0.039)			(0.060)	(0.060)
Trade intensity (maximum)	-0.107		-0.098		-0.098		-0.070	
	(0.014)		(0.016)		(0.020)		(0.022)	
Trade intensity (average)		-0.154		-0.141		-0.140		-0.101
		(0.021)		(0.023)		(0.029)		(0.032)
Interest rate differential in an abs. value	0.062	0.061	0.073	0.072	0.108	0.106	0.113	0.112
	(0.010)	(0.010)	(0.011)	(0.011)	(0.017)	(0.016)	(0.016)	(0.016)
Intercept	0.072	0.072	0.076	0.078	0.070	0.071	0.052	0.053
	(0.007)	(0.007)	(0.009)	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)
No. of observations	819	819	728	728	455	455	364	364

Note. Results from instrumental variable estimation using panel data with country fixed effects are reported. The distance between two countries (in logs) is used as an instrument to estimate the relationship between trade intensity and real exchange rate volatility. The sample period is from January 1980 to December 2005, and different time windows are considered to investigate a longer term: 3-year window and 6-year window. The dependent variable is real exchange rate volatility. Standard errors are reported in parentheses below the corresponding coefficients.

Table 2.4. Estimation results from *ESTAR* models

(a) 35 highest TI currency pairs

	USD/CAD	USD/MXN	USD/JPY	USD/GBP	USD/KRW	KRW/JPY
p	8	11	2	1	10	4
d	1	3	5	5	2	3
Linear part						
ρ	0.002	0.080	0.139	-0.027	0.062	0.096
	(0.129)	(0.547)	(0.132)	(0.047)	(0.048)	(0.086)
β_1	0.368	-1.196	-0.222		1.353	0.435
	(0.173)	(0.674)	(0.250)		(0.250)	(0.203)
β_2	0.367	-0.548			-0.094	0.181
	(0.186)	(0.612)			(0.175)	(0.186)
β_3	-0.132	-0.237			0.488	0.137
	(0.096)	(0.274)			(0.196)	(0.155)
β_4	0.670	-0.332			-0.510	
	(0.198)	(0.228)			(0.205)	
β_5	0.005	-0.147			0.495	
	(0.154)	(0.185)			(0.235)	
β_6	-0.288	-0.296			-0.577	
	(0.189)	(0.240)			(0.246)	
β_7	0.846	-0.190			0.015	
	(0.216)	(0.293)			(0.175)	
β_8		-0.010			0.201	
		(0.253)			(0.258)	
β_9		0.447			0.574	
		(0.247)			(0.232)	
β_{10}		0.918				
		(0.069)				
Nonlinear part						
ρ	-0.018	-0.125	-0.166	-0.011	-0.113	-0.131
	(0.128)	(0.550)	(0.132)	(0.054)	(0.065)	(0.089)
β_1^*	-0.362	1.201	0.355		-1.830	-0.525
	(0.186)	(0.671)	(0.263)		(0.293)	(0.254)
β_2^*	-0.384	0.554			0.110	-0.139
	(0.199)	(0.612)			(0.206)	(0.225)
β_3^*	0.133	0.309			-0.591	-0.347
	(0.125)	(0.288)			(0.220)	(0.202)
β_4^*	-0.708	0.252			0.320	
	(0.215)	(0.256)			(0.264)	

Table 2.4. Estimation results from *ESTAR* models (continued)

(a) 35 highest TI currency pairs

	USD/CAD	USD/MXN	USD/JPY	USD/GBP	USD/KRW	KRW/JPY
β_5^*	-0.029	0.180			-0.539	
	(0.175)	(0.189)			(0.253)	
β_6^*	0.242	0.255			0.755	
	(0.216)	(0.250)			(0.267)	
β_7^*	-0.845	0.188			-0.161	
	(0.243)	(0.297)			(0.227)	
β_8^*		0.017			-0.224	
		(0.257)			(0.329)	
β_9^*		-0.393			-0.484	
		(0.256)			(0.272)	
β_{10}^*		-0.845				
		(0.089)				
γ	41.509	500.000	20.795	10.444	8.534	10.753
	(1.073)	(3.058)	(1.379)	(1.256)	(0.177)	(0.634)
c	-0.735	-3.075	-5.545	-0.166	-7.449	2.038
	(0.002)	(0.0001)	(0.009)	(0.016)	(0.005)	(0.015)
$\hat{\sigma}_\varepsilon$	0.017	0.045	0.032	0.030	0.022	0.040
LM(4)	1.043	0.852	1.043	2.332	8.674	4.493
	(0.385)	(0.493)	(0.385)	(0.056)	(0.001)	(0.002)
LM(8)	3.424	0.680	0.937	1.665	5.985	2.757
	(0.001)	(0.709)	(0.486)	(0.106)	(0.001)	(0.006)
pRNL	0.632	0.152	0.767	0.183	0.194	0.427
SSR	0.098	0.686	0.358	0.313	0.163	0.546
AIC	-8.032	-6.039	-6.813	-6.959	-7.490	-6.367
BIC	-7.807	-5.743	-6.723	-6.892	-7.218	-6.232
T	348	348	348	348	348	348

Note. Currency pairs are listed based on trade intensity. Heteroscedasticity-consistent standard errors are reported in parentheses below the corresponding coefficient. $\hat{\sigma}_\varepsilon$ denotes the residual standard deviation. LM(4) and LM(8) denote the F variant of the LM test of no remaining autocorrelation in the residuals up to and including lag 4 and lag 8, respectively. The p-values are reported in parentheses below the corresponding values of the test statistics. pRNL is the p-value for the test of no remaining nonlinearity in the residuals. SSR is the sum of squared residuals of the regression from the estimated *ESTAR* models. AIC and BIC are the Akaike and Bayesian information criteria, respectively. T refers to the sample size.

Table 2.4. Estimation results from *ESTAR* models (continued)

(a) 35 highest TI currency pairs

	SEK/NOK	GBP/NOK	USD/SGD	NZD/AUD	JPY/AUD	SGD/JPY
p	1	12	1	4	12	1
d	2	3	6	6	2	6
Linear part						
ρ	0.239	-0.028	0.360	-0.062	-0.042	0.119
	(0.141)	(0.043)	(0.083)	(0.093)	(0.027)	(0.096)
β_1		0.052		-0.010	0.211	
		(0.100)		(0.200)	(0.091)	
β_2		0.127		-0.040	-0.055	
		(0.105)		(0.165)	(0.078)	
β_3		-0.057		0.223	0.117	
		(0.104)		(0.187)	(0.073)	
β_4		-0.029			-0.194	
		(0.080)			(0.093)	
β_5		-0.151			0.226	
		(0.100)			(0.097)	
β_6		-0.066			-0.128	
		(0.091)			(0.090)	
β_7		0.025			-0.015	
		(0.092)			(0.076)	
β_8		0.073			0.022	
		(0.078)			(0.082)	
β_9		-0.031			-0.050	
		(0.086)			(0.080)	
β_{10}		0.072			-0.015	
		(0.096)			(0.081)	
β_{11}		0.112			0.206	
		(0.089)			(0.092)	
Nonlinear part						
ρ	-0.267	-0.048	-0.372	-0.057	-0.003	-0.149
	(0.141)	(0.086)	(0.084)	(0.111)	(0.043)	(0.097)
β_1^*		-0.275		0.004	-0.194	
		(0.245)		(0.243)	(0.236)	
β_2^*		-0.527		0.182	0.073	
		(0.257)		(0.204)	(0.210)	

Table 2.4. Estimation results from *ESTAR* models (continued)

(a) 35 highest TI currency pairs

	SEK/NOK	GBP/NOK	USD/SGD	NZD/AUD	JPY/AUD	SGD/JPY
β_3^*		-0.036		-0.133	0.086	
		(0.252)		(0.214)	(0.158)	
β_4^*		-0.011			0.272	
		(0.241)			(0.200)	
β_5^*		0.484			-0.654	
		(0.276)			(0.240)	
β_6^*		0.255			0.283	
		(0.252)			(0.218)	
β_7^*		0.280			0.002	
		(0.225)			(0.193)	
β_8^*		-0.085			0.339	
		(0.194)			(0.197)	
β_9^*		-0.092			0.275	
		(0.212)			(0.212)	
β_{10}^*		-0.263			0.025	
		(0.230)			(0.204)	
β_{11}^*		-0.018			-0.273	
		(0.220)			(0.239)	
γ	50.519	4.166	371.426	6.369	1.195	13.220
	(1.302)	(0.221)	(25.787)	(1.046)	(0.363)	(1.149)
c	0.057	-2.369	-0.898	-1.484	5.102	-4.488
	(0.002)	(0.021)	(0.001)	(0.036)	(0.116)	(0.013)
$\hat{\sigma}_\varepsilon$	0.019	0.023	0.015	0.027	0.045	0.029
LM(4)	0.503	0.322	5.320	2.080	0.345	1.063
	(0.733)	(0.863)	(0.001)	(0.083)	(0.847)	(0.375)
LM(8)	0.657	0.452	2.694	1.110	0.540	1.211
	(0.729)	(0.889)	(0.007)	(0.356)	(0.826)	(0.292)
pRNL	0.701	0.854	0.519	0.771	0.840	0.995
SSR	0.123	0.179	0.079	0.241	0.682	0.281
AIC	-7.895	-7.367	-8.337	-7.183	-6.030	-7.068
BIC	-7.827	-7.049	-8.270	-7.048	-5.711	-7.000
T	348	348	348	348	348	348

Table 2.4. Estimation results from *ESTAR* models (continued)

(a) 35 highest TI currency pairs

	USD/TRY	SEK/DKK	USD/CHF	GBP/SEK	GBP/DKK	GBP/CHF
p	4	12	12	1	4	1
d	4	1	2	5	6	4
Linear part						
ρ	0.208	0.004	0.109	-0.053	0.050	0.162
	(0.199)	(0.015)	(0.088)	(0.049)	(0.119)	(0.246)
β_1	0.355	0.001	-0.112		-0.875	
	(0.296)	(0.080)	(0.130)		(0.301)	
β_2	-0.095	0.120	0.069		-0.278	
	(0.274)	(0.070)	(0.096)		(0.250)	
β_3	-0.069	0.016	-0.141		-0.590	
	(0.204)	(0.111)	(0.119)		(0.441)	
β_4		-0.031	-0.043			
		(0.083)	(0.093)			
β_5		-0.105	0.098			
		(0.097)	(0.099)			
β_6		-0.050	-0.105			
		(0.064)	(0.097)			
β_7		0.003	0.196			
		(0.063)	(0.094)			
β_8		0.090	-0.047			
		(0.093)	(0.099)			
β_9		0.074	0.051			
		(0.117)	(0.094)			
β_{10}		-0.011	0.028			
		(0.068)	(0.083)			
β_{11}		-0.005	0.248			
		(0.079)	(0.091)			
Nonlinear part						
ρ	-0.229	-0.282	-0.150	-0.075	-0.068	-0.185
	(0.200)	(4.097)	(0.091)	(0.081)	(0.120)	(0.248)
β_1^*	-0.348	5.365	0.299		1.093	
	(0.324)	(77.248)	(0.158)		(0.307)	
β_2^*	0.057	-5.339	-0.155		0.310	
	(0.302)	(80.042)	(0.143)		(0.263)	

Table 2.4. Estimation results from *ESTAR* models (continued)

(a) 35 highest TI currency pairs

	USD/TRY	SEK/DKK	USD/CHF	GBP/SEK	GBP/DKK	GBP/CHF
β_3^*	0.012	2.995	0.336		0.721	
	(0.212)	(43.880)	(0.153)		(0.446)	
β_4^*		-3.506	0.031			
		(48.676)	(0.164)			
β_5^*		3.513	-0.127			
		(52.839)	(0.148)			
β_6^*		2.994	0.128			
		(43.558)	(0.162)			
β_7^*		-1.375	-0.174			
		(20.813)	(0.157)			
β_8^*		-5.227	0.044			
		(75.456)	(0.153)			
β_9^*		-6.763	0.091			
		(97.367)	(0.151)			
β_{10}^*		3.328	-0.138			
		(48.932)	(0.146)			
β_{11}^*		-2.714	-0.184			
		(41.236)	(0.145)			
γ	39.991	0.135	13.537	3.507	500.000	500.000
	(0.939)	(0.185)	(0.635)	(0.438)	(4.587)	(9.712)
c	-1.212	0.104	-0.971	-2.285	-2.414	-0.782
	(0.004)	(18.662)	(0.007)	(0.034)	(0.0001)	(0.0004)
$\hat{\sigma}_\varepsilon$	0.040	0.020	0.032	0.026	0.024	0.028
LM(4)	1.945	8.488	0.892	0.620	2.992	1.725
	(0.103)	(0.001)	(0.469)	(0.649)	(0.019)	(0.144)
LM(8)	1.626	6.634	0.749	0.594	1.787	1.852
	(0.117)	(0.001)	(0.648)	(0.783)	(0.079)	(0.067)
pRNL	0.751	0.874	0.962	0.975	0.401	0.096
SSR	0.558	0.128	0.342	0.224	0.189	0.269
AIC	-6.345	-7.704	-6.719	-7.294	-7.430	-7.111
BIC	-6.210	-7.385	-6.401	-7.227	-7.295	-7.043
T	348	348	348	348	348	348

Table 2.4. Estimation results from *ESTAR* models (continued)

(a) 35 highest TI currency pairs

	USD/AUD	NOK/DKK	GBP/TRY	NZD/JPY	USD/SEK	USD/NZD
p	1	1	1	1	8	8
d	2	4	2	5	5	5
Linear part						
ρ	0.144	0.073	0.856	0.173	-0.033	-0.033
	(0.101)	(0.041)	(0.477)	(0.123)	(0.028)	(0.060)
β_1					-0.026	0.047
					(0.114)	(0.113)
β_2					0.010	0.102
					(0.082)	(0.110)
β_3					0.040	0.073
					(0.100)	(0.104)
β_4					0.157	-0.167
					(0.112)	(0.110)
β_5					0.144	-0.181
					(0.083)	(0.152)
β_6					0.045	0.187
					(0.076)	(0.124)
β_7					0.082	0.187
					(0.071)	(0.111)
Nonlinear part						
ρ	-0.182	-0.138	-0.901	-0.207	-0.054	-0.058
	(0.100)	(0.041)	(0.477)	(0.122)	(0.093)	(0.077)
β_1^*					0.561	0.024
					(0.471)	(0.168)
β_2^*					-0.195	-0.131
					(0.187)	(0.167)
β_3^*					0.329	0.219
					(0.280)	(0.172)
β_4^*					-0.442	0.273
					(0.381)	(0.156)
β_5^*					-0.185	0.396
					(0.306)	(0.189)
β_6^*					-0.332	-0.179
					(0.344)	(0.177)

Table 2.4. Estimation results from *ESTAR* models (continued)

(a) 35 highest TI currency pairs

	USD/AUD	NOK/DKK	GBP/TRY	NZD/JPY	USD/SEK	USD/NZD
β_7^*					0.047	-0.077
					(0.202)	(0.158)
γ	23.338	5.658	500.000	277.480	0.997	4.140
	(1.692)	(0.730)	(5.087)	(3.862)	(0.823)	(0.330)
c	-0.624	0.038	-1.089	-6.581	-2.808	0.828
	(0.006)	(0.016)	(0.0003)	(0.001)	(0.262)	(0.026)
$\hat{\sigma}_\varepsilon$	0.032	0.017	0.046	0.040	0.031	0.033
LM(4)	0.998	1.227	2.027	1.329	1.573	0.444
	(0.409)	(0.299)	(0.090)	(0.259)	(0.181)	(0.777)
LM(8)	1.060	1.388	1.345	1.606	1.507	2.214
	(0.391)	(0.201)	(0.220)	(0.122)	(0.154)	(0.026)
pRNL	0.758	0.957	0.638	0.674	0.717	0.815
SSR	0.339	0.098	0.732	0.553	0.319	0.365
AIC	-6.880	-8.116	-6.109	-6.388	-6.852	-6.717
BIC	-6.812	-8.049	-6.042	-6.321	-6.626	-6.491
T	348	348	348	348	348	348

Table 2.4. Estimation results from *ESTAR* models (continued)

(a) 35 highest TI currency pairs

	GBP/JPY	CHF/JPY	USD/DKK	SGD/AUD	SGD/KRW	GBP/AUD
p	2	1	4	1	10	1
d	3	2	6	2	2	2
Linear part						
ρ	0.461	0.335	0.038	0.078	0.029	0.537
	(0.155)	(0.141)	(0.054)	(0.075)	(0.038)	(0.302)
β_1	-0.236		-0.212		0.710	
	(0.363)		(0.167)		(0.307)	
β_2			0.214		0.015	
			(0.184)		(0.148)	
β_3			0.010		-0.130	
			(0.142)		(0.118)	
β_4					-0.190	
					(0.111)	
β_5					0.187	
					(0.091)	
β_6					-0.124	
					(0.117)	
β_7					0.133	
					(0.096)	
β_8					-0.079	
					(0.110)	
β_9					0.247	
					(0.101)	
Nonlinear part						
ρ	-0.489	-0.378	-0.080	-0.171	-0.273	-0.570
	(0.155)	(0.142)	(0.052)	(0.068)	(0.089)	(0.301)
β_1^*	0.369		0.385		-1.690	
	(0.369)		(0.181)		(0.432)	
β_2^*			-0.191		0.088	
			(0.203)		(0.324)	
β_3^*			0.056		0.450	
			(0.170)		(0.181)	
β_4^*					0.200	
					(0.171)	

Table 2.4. Estimation results from *ESTAR* models (continued)

(a) 35 highest TI currency pairs

	GBP/JPY	CHF/JPY	USD/DKK	SGD/AUD	SGD/KRW	GBP/AUD
β_5^*					-0.278	
					(0.172)	
β_6^*					0.544	
					(0.138)	
β_7^*					-0.323	
					(0.158)	
β_8^*					0.290	
					(0.150)	
β_9^*					-0.490	
					(0.177)	
γ	120.424	62.657	8.003	4.715	2.066	121.028
	(3.370)	(1.524)	(0.795)	(1.068)	(0.084)	(2.097)
c	-5.347	-4.265	-2.788	0.473	-6.434	-0.499
	(0.001)	(0.001)	(0.020)	(0.032)	(0.036)	(0.001)
$\hat{\sigma}_\varepsilon$	0.034	0.031	0.031	0.029	0.024	0.036
LM(4)	1.239	1.238	0.869	1.230	8.436	0.594
	(0.294)	(0.295)	(0.483)	(0.298)	(0.001)	(0.667)
LM(8)	0.880	0.951	0.813	0.776	6.443	0.814
	(0.534)	(0.474)	(0.591)	(0.625)	(0.001)	(0.591)
pRNL	0.423	0.574	0.818	0.975	0.375	0.999
SSR	0.397	0.320	0.318	0.295	0.195	0.443
AIC	-6.709	-6.936	-6.908	-7.018	-7.314	-6.612
BIC	-6.619	-6.869	-6.773	-6.950	-7.042	-6.544
T	348	348	348	348	348	348

Table 2.4. Estimation results from *ESTAR* models (continued)

(a) 35 highest TI currency pairs

	TRY/CHF	KRW/AUD	GBP/NZD	USD/NOK	CHF/SEK
p	1	10	1	1	1
d	3	2	1	1	4
Linear part					
ρ	0.297	0.073	0.133	0.253	0.093
	(0.162)	(0.105)	(0.257)	(0.344)	(0.051)
β_1		0.559			
		(0.378)			
β_2		-0.095			
		(0.120)			
β_3		-0.169			
		(0.119)			
β_4		0.085			
		(0.135)			
β_5		-0.161			
		(0.126)			
β_6		-0.030			
		(0.114)			
β_7		0.010			
		(0.105)			
β_8		0.006			
		(0.105)			
β_9		0.161			
		(0.134)			
Nonlinear part					
ρ	-0.328	-0.196	-0.198	-0.285	-0.140
	(0.161)	(0.121)	(0.254)	(0.343)	(0.051)
β_1^*		-0.737			
		(0.402)			
β_2^*		0.263			
		(0.165)			
β_3^*		0.184			
		(0.202)			
β_4^*		-0.254			
		(0.193)			

Table 2.4. Estimation results from *ESTAR* models (continued)

(a) 35 highest TI currency pairs

	TRY/CHF	KRW/AUD	GBP/NZD	USD/NOK	CHF/SEK
β_5^*		0.222			
		(0.156)			
β_6^*		0.149			
		(0.161)			
β_7^*		-0.142			
		(0.205)			
β_8^*		-0.015			
		(0.180)			
β_9^*		-0.051			
		(0.184)			
γ	58.695	13.780	21.151	33.520	8.679
	(2.022)	(0.372)	(2.140)	(1.540)	(0.721)
c	0.287	6.776	1.137	-2.730	-1.650
	(0.003)	(0.005)	(0.010)	(0.005)	(0.011)
$\hat{\sigma}_\varepsilon$	0.048	0.034	0.036	0.030	0.025
LM(4)	1.310	4.248	0.641	1.825	1.422
	(0.266)	(0.002)	(0.634)	(0.124)	(0.226)
LM(8)	1.349	2.187	0.598	1.393	1.405
	(0.218)	(0.028)	(0.780)	(0.198)	(0.193)
pRNL	0.412	0.121	0.912	0.629	0.132
SSR	0.793	0.401	0.436	0.308	0.208
AIC	-6.028	-6.592	-6.627	-6.974	-7.368
BIC	-5.961	-6.320	-6.560	-6.906	-7.300
T	348	348	348	348	348

Table 2.4. Estimation results from *ESTAR* models (continued)

(b) 35 lowest TI currency pairs

	CHF/NOK	CAD/AUD	TRY/DKK	MXN/CAD	SEK/CAD	TRY/CAD
p	12	1	1	11	1	1
d	5	3	4	2	5	4
Linear part						
ρ	0.362	0.383	0.517	0.129	-0.031	0.522
	(0.850)	(0.255)	(0.149)	(0.912)	(0.068)	(0.292)
β_1	-0.257			-0.390		
	(0.875)			(1.032)		
β_2	0.153			0.940		
	(0.925)			(0.317)		
β_3	-0.146			-0.681		
	(0.820)			(0.340)		
β_4	-0.450			-0.293		
	(0.806)			(0.317)		
β_5	-1.367			-0.396		
	(0.406)			(0.268)		
β_6	0.149			0.696		
	(0.367)			(0.312)		
β_7	0.284			-0.164		
	(0.457)			(0.346)		
β_8	-0.173			0.389		
	(0.247)			(0.239)		
β_9	0.392			-0.633		
	(0.282)			(0.346)		
β_{10}	-0.585			1.217		
	(0.401)			(0.093)		
β_{11}	0.681					
	(0.207)					
Nonlinear part						
ρ	-0.398	-0.456	-0.553	-0.158	-0.020	-0.542
	(0.851)	(0.255)	(0.150)	(0.913)	(0.071)	(0.292)
β_1^*	0.261			0.364		
	(0.878)			(1.034)		
β_2^*	-0.147			-0.942		
	(0.859)			(0.317)		

Table 2.4. Estimation results from *ESTAR* models (continued)

(b) 35 lowest TI currency pairs

	CHF/NOK	CAD/AUD	TRY/DKK	MXN/CAD	SEK/CAD	TRY/CAD
β_3^*	0.160			0.775		
	(0.795)			(0.351)		
β_4^*	0.449			0.235		
	(0.812)			(0.338)		
β_5^*	1.301			0.428		
	(0.409)			(0.269)		
β_6^*	-0.199			-0.731		
	(0.372)			(0.318)		
β_7^*	-0.283			0.160		
	(0.468)			(0.349)		
β_8^*	0.145			-0.348		
	(0.258)			(0.243)		
β_9^*	-0.376			0.700		
	(0.292)			(0.347)		
β_{10}^*	0.647			-1.187		
	(0.400)			(0.103)		
β_{11}^*	-0.656					
	(0.219)					
γ	500.000	500.000	238.526	500.000	26.375	348.676
	(1.462)	(3.892)	(3.674)	(3.204)	(2.196)	(3.892)
c	-1.563	0.237	-1.191	2.203	1.606	0.364
	(0.0001)	(0.0002)	(0.001)	(0.0002)	(0.008)	(0.0004)
$\hat{\sigma}_\varepsilon$	0.020	0.027	0.043	0.046	0.031	0.040
LM(4)	1.280	2.255	3.309	1.182	2.168	2.073
	(0.278)	(0.063)	(0.011)	(0.319)	(0.072)	(0.084)
LM(8)	1.256	1.897	2.575	0.861	2.362	1.549
	(0.266)	(0.060)	(0.010)	(0.550)	(0.018)	(0.140)
pRNL	0.650	0.080	0.654	0.403	0.484	0.836
SSR	0.132	0.248	0.620	0.696	0.336	0.553
AIC	-7.674	-7.193	-6.275	-6.024	-6.886	-6.388
BIC	-7.355	-7.125	-6.207	-5.729	-6.819	-6.321
T	348	348	348	348	348	348

Note. As for Table 2.4 (a).

Table 2.4. Estimation results from *ESTAR* models (continued)

(b) 35 lowest TI currency pairs

	NZD/CAD	SEK/KRW	NOK/KRW	GBP/MXN	KRW/DKK	CHF/MXN
p	4	10	10	11	1	11
d	6	2	6	3	2	4
Linear part						
ρ	0.012	0.050	0.057	0.045	0.520	0.214
	(0.156)	(0.152)	(0.729)	(0.567)	(0.292)	(1.147)
β_1	0.577	-0.422	0.914	-0.618		-0.909
	(0.408)	(0.230)	(0.789)	(0.806)		(1.165)
β_2	-0.048	-0.097	0.209	-0.193		-1.365
	(0.203)	(0.152)	(0.762)	(0.566)		(1.681)
β_3	-0.332	0.264	0.728	1.437		-0.384
	(0.370)	(0.187)	(0.804)	(0.456)		(1.108)
β_4		-0.293	-0.056	0.690		0.354
		(0.137)	(0.658)	(0.361)		(0.340)
β_5		0.220	-0.550	-0.183		0.874
		(0.165)	(0.742)	(0.240)		(0.477)
β_6		0.059	-0.640	0.144		0.496
		(0.176)	(0.316)	(0.251)		(0.456)
β_7		0.129	-0.891	-0.386		-0.642
		(0.146)	(0.228)	(0.427)		(0.600)
β_8		-0.160	-0.997	0.210		1.193
		(0.205)	(0.413)	(0.378)		(1.001)
β_9		0.189	0.303	0.154		2.427
		(0.136)	(0.268)	(0.412)		(0.630)
β_{10}				1.307		1.752
				(0.143)		(0.342)
Nonlinear part						
ρ	-0.034	-0.740	-0.144	-0.091	0.535	-0.264
	(0.157)	(0.766)	(0.732)	(0.570)	(0.290)	(1.152)
β_1^*	-0.637	-0.152	-0.981	0.726		0.984
	(0.408)	(0.153)	(0.797)	(0.819)		(1.157)
β_2^*	0.076	0.707	-0.086	0.214		1.392
	(0.240)	(0.278)	(0.775)	(0.573)		(1.685)
β_3^*	0.479	0.311	-0.804	-1.380		0.494
	(0.376)	(0.197)	(0.803)	(0.462)		(1.118)

Table 2.4. Estimation results from *ESTAR* models (continued)

(b) 35 lowest TI currency pairs

	NZD/CAD	SEK/KRW	NOK/KRW	GBP/MXN	KRW/DKK	CHF/MXN
β_4^*		-0.247	-0.023	-0.697		-0.371
		(0.223)	(0.659)	(0.374)		(0.354)
β_5^*		0.362	0.633	0.220		-0.828
		(0.159)	(0.748)	(0.244)		(0.481)
β_6^*		-0.218	0.730	-0.251		-0.523
		(0.196)	(0.330)	(0.258)		(0.456)
β_7^*		-0.035	0.852	0.394		0.679
		(0.212)	(0.241)	(0.433)		(0.605)
β_8^*		-0.211	1.010	-0.190		-1.188
		(0.188)	(0.416)	(0.381)		(1.004)
β_9^*		0.342	-0.111	-0.100		-2.300
		(0.224)	(0.282)	(0.419)		(0.632)
β_{10}^*		-0.150		-1.320		-1.733
		(0.167)		(0.149)		(0.341)
γ	165.502	26.083	286.582	56.800	32.866	216.122
	(3.233)	(0.677)	(2.334)	(1.139)	(0.879)	(1.968)
c	-1.887	-5.006	-4.757	-2.772	4.768	-1.947
	(0.001)	(0.002)	(0.0002)	(0.001)	(0.003)	(0.001)
$\hat{\sigma}_\varepsilon$	0.032	0.039	0.035	0.052	0.043	0.059
LM(4)	0.857	0.823	3.911	0.881	1.216	0.542
	(0.490)	(0.511)	(0.004)	(0.475)	(0.304)	(0.705)
LM(8)	1.048	1.030	2.634	0.756	0.648	0.491
	(0.400)	(0.413)	(0.008)	(0.642)	(0.737)	(0.863)
pRNL	0.901	0.099	0.295	0.640	0.559	0.729
SSR	0.356	0.506	0.402	0.917	0.642	1.163
AIC	-6.794	-6.360	-6.590	-5.749	-6.240	-5.512
BIC	-6.659	-6.088	-6.317	-5.454	-6.173	-5.216
T	348	348	348	348	348	348

Table 2.4. Estimation results from *ESTAR* models (continued)

(b) 35 lowest TI currency pairs

	SEK/SGD	MXN/KRW	TRY/AUD	TRY/NOK	TRY/SGD	DKK/AUD
p	1	11	6	9	1	10
d	2	3	1	1	1	3
Linear part						
ρ	0.062	0.176	0.201	0.189	0.341	0.212
	(0.074)	(0.435)	(0.227)	(0.191)	(0.277)	(0.115)
β_1		-0.337	0.663	0.183		-0.440
		(0.695)	(0.306)	(0.116)		(0.187)
β_2		-0.157	-0.340	0.659		0.076
		(0.385)	(0.199)	(0.269)		(0.176)
β_3		0.271	0.264	-0.048		0.077
		(0.300)	(0.258)	(0.143)		(0.171)
β_4		0.588	0.193	-0.003		-0.069
		(0.357)	(0.225)	(0.188)		(0.128)
β_5		0.480	0.209	-0.304		0.037
		(0.401)	(0.171)	(0.189)		(0.179)
β_6		0.135		0.067		0.075
		(0.437)		(0.208)		(0.152)
β_7		0.010		0.159		0.389
		(0.384)		(0.204)		(0.200)
β_8		-0.472		0.026		0.229
		(0.742)		(0.151)		(0.162)
β_9		0.269				-0.035
		(0.254)				(0.163)
β_{10}		2.528				
		(1.913)				
Nonlinear part						
ρ	-0.118	-0.208	-0.212	-0.202	-0.365	-0.253
	(0.067)	(0.437)	(0.227)	(0.194)	(0.276)	(0.119)
β_1^*		0.249	-0.651	-0.121		0.538
		(0.699)	(0.316)	(0.187)		(0.204)
β_2^*		0.174	0.450	-0.755		-0.228
		(0.390)	(0.214)	(0.277)		(0.217)
β_3^*		-0.272	-0.327	0.022		-0.005
		(0.314)	(0.276)	(0.193)		(0.213)

Table 2.4. Estimation results from *ESTAR* models (continued)

(b) 35 lowest TI currency pairs

	SEK/SGD	MXN/KRW	TRY/AUD	TRY/NOK	TRY/SGD	DKK/AUD
β_4^*		-0.698	-0.360	-0.161		0.053
		(0.363)	(0.244)	(0.221)		(0.163)
β_5^*		-0.469	-0.390	0.289		-0.132
		(0.402)	(0.196)	(0.201)		(0.210)
β_6^*		-0.165		-0.039		-0.043
		(0.441)		(0.219)		(0.183)
β_7^*		-0.051		-0.122		-0.421
		(0.399)		(0.226)		(0.230)
β_8^*		0.493		-0.109		-0.317
		(0.749)		(0.171)		(0.196)
β_9^*		-0.214				0.209
		(0.254)				(0.184)
β_{10}^*		-2.496				
		(1.909)				
γ	15.383	51.056	51.563	53.757	13.029	6.832
	(2.314)	(0.886)	(0.880)	(1.664)	(0.652)	(0.290)
c	1.376	-4.274	0.891	-1.311	-0.024	2.044
	(0.015)	(0.004)	(0.002)	(0.002)	(0.011)	(0.011)
$\hat{\sigma}_\varepsilon$	0.028	0.052	0.043	0.043	0.041	0.035
LM(4)	2.721	1.298	0.998	1.852	2.206	0.877
	(0.030)	(0.271)	(0.409)	(0.119)	(0.068)	(0.478)
LM(8)	2.112	1.053	1.258	1.456	1.382	1.033
	(0.034)	(0.396)	(0.265)	(0.173)	(0.204)	(0.411)
pRNL	0.377	0.795	0.485	0.836	0.584	0.984
SSR	0.271	0.917	0.618	0.621	0.585	0.408
AIC	-7.101	-5.749	-6.220	-6.169	-6.334	-6.573
BIC	-7.033	-5.454	-6.040	-5.920	-6.266	-6.301
T	348	348	348	348	348	348

Table 2.4. Estimation results from *ESTAR* models (continued)

(b) 35 lowest TI currency pairs

	SGD/NOK	DKK/CAD	SGD/DKK	SGD/CAD	SEK/MXN	SEK/NZD
p	1	1	10	1	11	1
d	3	6	3	3	1	4
Linear part						
ρ	0.157	0.077	0.010	0.301	0.192	0.054
	(0.166)	(0.104)	(0.159)	(0.133)	(0.378)	(0.223)
β_1			-0.459		-0.480	
			(0.351)		(0.365)	
β_2			0.405		-1.926	
			(0.344)		(0.896)	
β_3			-0.110		0.284	
			(0.305)		(0.754)	
β_4			-0.372		0.682	
			(0.339)		(0.547)	
β_5			0.046		-0.793	
			(0.328)		(0.729)	
β_6			0.712		0.240	
			(0.291)		(0.458)	
β_7			0.525		0.459	
			(0.352)		(0.370)	
β_8			0.037		0.433	
			(0.264)		(0.647)	
β_9			0.053		-0.524	
			(0.275)		(0.205)	
β_{10}					1.113	
					(0.547)	
Nonlinear part						
ρ	-0.187	-0.104	-0.023	-0.313	-0.215	-0.091
	(0.164)	(0.101)	(0.161)	(0.133)	(0.377)	(0.224)
β_1^*			0.499		0.530	
			(0.357)		(0.372)	
β_2^*			-0.422		1.979	
			(0.349)		(0.898)	
β_3^*			0.193		-0.187	
			(0.327)		(0.765)	

Table 2.4. Estimation results from *ESTAR* models (continued)

(b) 35 lowest TI currency pairs

	SGD/NOK	DKK/CAD	SGD/DKK	SGD/CAD	SEK/MXN	SEK/NZD
β_4^*			0.410		-0.721	
			(0.360)		(0.558)	
β_5^*			-0.033		0.856	
			(0.343)		(0.730)	
β_6^*			-0.712		-0.291	
			(0.302)		(0.464)	
β_7^*			-0.456		-0.420	
			(0.365)		(0.374)	
β_8^*			-0.0001		-0.460	
			(0.278)		(0.655)	
β_9^*			0.101		0.682	
			(0.292)		(0.216)	
β_{10}^*					-1.032	
					(0.556)	
γ	30.028	13.847	26.892	297.821	45.770	500.000
	(1.072)	(1.644)	(0.642)	(3.632)	(0.737)	(6.104)
c	-1.491	1.913	-1.645	0.159	-0.248	3.649
	(0.005)	(0.020)	(0.003)	(0.0003)	(0.002)	(0.0003)
$\hat{\sigma}_\varepsilon$	0.026	0.032	0.026	0.021	0.055	0.036
LM(4)	0.682	1.474	1.333	0.253	2.736	1.347
	(0.605)	(0.210)	(0.258)	(0.908)	(0.029)	(0.252)
LM(8)	0.924	1.370	1.353	0.393	1.439	1.264
	(0.497)	(0.209)	(0.217)	(0.924)	(0.180)	(0.262)
pRNL	0.703	0.803	0.280	0.939	0.165	0.933
SSR	0.239	0.356	0.227	0.151	1.030	0.444
AIC	-7.227	-6.829	-7.162	-7.690	-5.633	-6.608
BIC	-7.159	-6.761	-6.890	-7.623	-5.338	-6.541
T	348	348	348	348	348	348

Table 2.4. Estimation results from *ESTAR* models (continued)

(b) 35 lowest TI currency pairs

	CHF/NZD	NZD/MXN	NZD/DKK	SGD/MXN	NOK/AUD	TRY/NZD
p	1	11	1	11	1	1
d	4	4	3	4	2	1
Linear part						
ρ	0.047	0.226	0.749	0.423	0.125	0.071
	(0.090)	(0.166)	(0.283)	(0.280)	(0.140)	(0.172)
β_1		-0.184		-0.356		
		(0.169)		(0.251)		
β_2		-0.258		0.060		
		(0.197)		(0.331)		
β_3		-0.689		-0.239		
		(0.413)		(0.305)		
β_4		-0.072		0.555		
		(0.350)		(0.427)		
β_5		0.797		-0.545		
		(0.389)		(0.424)		
β_6		-0.292		-0.394		
		(0.313)		(0.698)		
β_7		0.336		0.530		
		(0.355)		(0.387)		
β_8		0.102		-0.0002		
		(0.344)		(0.491)		
β_9		-0.199		-0.224		
		(0.260)		(0.421)		
β_{10}		1.186		1.475		
		(0.270)		(0.156)		
Nonlinear part						
ρ	-0.157	-0.266	-0.798	-0.459	-0.241	-0.145
	(0.087)	(0.166)	(0.284)	(0.282)	(0.134)	(0.149)
β_1^*		0.228		0.334		
		(0.184)		(0.270)		
β_2^*		0.245		-0.048		
		(0.214)		(0.333)		
β_3^*		0.837		0.275		
		(0.424)		(0.309)		

Table 2.4. Estimation results from *ESTAR* models (continued)

(b) 35 lowest TI currency pairs

	CHF/NZD	NZD/MXN	NZD/DKK	SGD/MXN	NOK/AUD	TRY/NZD
β_4^*		0.027		-0.629		
		(0.370)		(0.436)		
β_5^*		-0.806		0.585		
		(0.391)		(0.428)		
β_6^*		0.308		0.357		
		(0.320)		(0.700)		
β_7^*		-0.294		-0.551		
		(0.357)		(0.390)		
β_8^*		-0.047		0.027		
		(0.345)		(0.495)		
β_9^*		0.238		0.290		
		(0.262)		(0.417)		
β_{10}^*		-1.071		-1.437		
		(0.276)		(0.160)		
γ	14.142	34.497	500.000	68.666	13.971	10.587
	(1.374)	(1.386)	(3.892)	(1.133)	(0.686)	(3.254)
c	2.029	-4.063	-3.693	-2.082	2.134	2.589
	(0.012)	(0.006)	(0.0002)	(0.002)	(0.010)	(0.031)
$\hat{\sigma}_\varepsilon$	0.038	0.056	0.036	0.046	0.034	0.049
LM(4)	0.707	1.897	0.640	0.831	0.465	2.918
	(0.587)	(0.111)	(0.634)	(0.506)	(0.761)	(0.021)
LM(8)	0.731	1.179	0.831	0.503	0.824	2.664
	(0.664)	(0.311)	(0.576)	(0.854)	(0.582)	(0.008)
pRNL	0.519	0.462	0.970	0.855	0.656	0.439
SSR	0.495	1.037	0.431	0.717	0.406	0.748
AIC	-6.501	-5.626	-6.639	-5.995	-6.699	-6.086
BIC	-6.433	-5.331	-6.572	-5.699	-6.632	-6.019
T	348	348	348	348	348	348

Table 2.4. Estimation results from *ESTAR* models (continued)

(b) 35 lowest TI currency pairs

	MXN/DKK	MXN/AUD	TRY/MXN	NOK/NZD	NOK/MXN
p	11	12	11	1	11
d	6	5	2	3	4
Linear part					
ρ	0.365	0.623	0.053	-0.094	0.138
	(0.655)	(0.698)	(0.883)	(0.069)	(0.366)
β_1	-0.279	0.631	-0.236		-0.302
	(0.638)	(1.086)	(0.744)		(0.469)
β_2	-2.142	-0.567	0.312		-0.327
	(0.946)	(0.932)	(1.003)		(0.703)
β_3	0.088	-0.989	1.080		-0.155
	(0.845)	(0.810)	(0.458)		(0.512)
β_4	-1.299	-1.249	0.538		-1.532
	(0.683)	(1.151)	(0.847)		(1.175)
β_5	0.157	-0.617	-1.656		-0.028
	(0.549)	(0.490)	(0.958)		(0.493)
β_6	0.226	-1.332	-1.085		-0.032
	(0.242)	(1.262)	(0.801)		(0.280)
β_7	0.760	-0.636	1.616		0.177
	(0.234)	(0.453)	(0.916)		(0.275)
β_8	1.027	-0.590	-2.321		0.125
	(0.239)	(0.287)	(1.512)		(0.177)
β_9	0.033	-0.170	-1.640		-0.016
	(0.416)	(0.171)	(1.281)		(0.217)
β_{10}	1.074	1.113	1.608		
	(0.121)	(0.185)	(0.660)		
β_{11}		0.366			
		(0.156)			
Nonlinear part					
ρ	-0.403	-0.662	-0.089	-0.026	-0.172
	(0.658)	(0.699)	(0.880)	(0.085)	(0.368)
β_1^*	0.322	-0.635	0.334		0.389
	(0.641)	(1.092)	(0.763)		(0.476)
β_2^*	2.206	0.567	-0.292		0.366
	(0.948)	(0.934)	(1.007)		(0.737)

Table 2.4. Estimation results from *ESTAR* models (continued)

(b) 35 lowest TI currency pairs

	MXN/DKK	MXN/AUD	TRY/MXN	NOK/NZD	NOK/MXN
β_3^*	0.018	0.984	-1.030		0.251
	(0.848)	(0.821)	(0.460)		(0.523)
β_4^*	1.245	1.192	-0.592		1.571
	(0.694)	(1.176)	(0.861)		(1.178)
β_5^*	-0.112	0.636	1.686		0.067
	(0.553)	(0.498)	(0.958)		(0.499)
β_6^*	-0.258	1.330	1.088		-0.010
	(0.265)	(1.271)	(0.802)		(0.290)
β_7^*	-0.756	0.697	-1.564		-0.153
	(0.240)	(0.466)	(0.917)		(0.283)
β_8^*	-1.031	0.670	2.315		-0.140
	(0.242)	(0.298)	(1.513)		(0.185)
β_9^*	0.110	0.237	1.671		0.120
	(0.422)	(0.185)	(1.285)		(0.231)
β_{10}^*	-1.028	-1.029	-1.524		
	(0.134)	(0.199)	(0.660)		
β_{11}^*		-0.301			
		(0.188)			
γ	120.667	293.130	52.107	7.836	77.307
	(1.149)	(1.594)	(0.660)	(1.384)	(0.924)
c	0.442	2.701	-1.617	3.593	-0.597
	(0.001)	(0.0002)	(0.002)	(0.020)	(0.002)
$\hat{\sigma}_\varepsilon$	0.055	0.052	0.055	0.034	0.060
LM(4)	2.858	1.803	2.403	1.053	0.903
	(0.024)	(0.128)	(0.050)	(0.380)	(0.463)
LM(8)	1.565	1.225	1.946	0.715	0.646
	(0.135)	(0.284)	(0.053)	(0.679)	(0.738)
pRNL	0.864	0.807	0.612	0.736	0.667
SSR	1.009	0.907	1.003	0.404	1.208
AIC	-5.654	-5.744	-5.659	-6.702	-5.488
BIC	-5.358	-5.425	-5.364	-6.635	-5.216
T	348	348	348	348	348

Table 2.5. Half-life estimates for real exchange rates

High trade intensity currency pairs	Half-life	Low trade intensity currency pairs	Half-life
USD/CAD	32	CHF/NOK	23
USD/MXN	16	CAD/AUD	11
USD/JPY	31	TRY/DKK	19
USD/GBP	14	MXN/CAD	28
USD/KRW	7	SEK/CAD	21
KRW/JPY	13	TRY/CAD	33
SEK/NOK	36	NZD/CAD	35
GBP/NOK	3	SEK/KRW	12
USD/SGD	56	NOK/KRW	7
NZD/AUD	35	GBP/MXN	17
JPY/AUD	22	KRW/DKK	43
SGD/JPY	25	CHF/MXN	21
USD/TRY	39	SEK/SGD	19
SEK/DKK	8	MXN/KRW	22
USD/CHF	18	TRY/AUD	39
GBP/SEK	12	TRY/NOK	41
GBP/DKK	38	TRY/SGD	32
GBP/CHF	27	DKK/AUD	62
USD/AUD	17	SGD/NOK	28
NOK/DKK	18	DKK/CAD	64
GBP/TRY	17	SGD/DKK	45
NZD/JPY	24	SGD/CAD	53
USD/SEK	18	SEK/MXN	49
USD/NZD	19	SEK/NZD	23
GBP/JPY	31	CHF/NZD	6
CHF/JPY	19	NZD/MXN	24
USD/DKK	26	NZD/DKK	14
SGD/AUD	16	SGD/MXN	26
SGD/KRW	1	NOK/AUD	16
GBP/AUD	21	TRY/NZD	27
TRY/CHF	21	MXN/DKK	24
KRW/AUD	4	MXN/AUD	27
GBP/NZD	12	TRY/MXN	27
USD/NOK	23	NOK/NZD	6
CHF/SEK	36	NOK/MXN	48
Average	21.57		28.34

Note. The half-lives are measured as the discrete number of months taken until the shock to the level of the real exchange rate has fallen below a half.

Table 2.6. Volatility of selected indicators for different exchange regimes

	Probability that the monthly change is		
	Within a ± 2.5 percent band:		Greater than ± 4 percent (400 basis points):
Country	Exchange rate	Reserves	Nominal interest rate
Australia	68.10	39.37	0.00
Canada	87.36	43.97	1.72
Denmark	62.36	36.63	2.30
Great Britain	65.52	60.63	0.00
Japan	59.48	81.03	0.00
Korea	86.21	49.14	0.57
Mexico	70.40	41.38	14.66
New Zealand	66.38	23.85	2.01
Norway	66.09	38.22	0.29
Singapore	91.38	78.74	0.00
Sweden	61.49	38.79	1.44
Switzerland	54.02	45.40	0.29
Turkey	49.09	30.46	29.89
United States	63.51	68.39	0.29

Note. The frequency distribution of monthly percent changes in the exchange rate, foreign exchange reserves, and nominal money market interest rates is reported for different exchange rate regimes. The sample period is from January 1980 to December 2008.

Table 2.7. Performance statistics for carry trade portfolios

(a) *Without* momentum trading

	High TI currency pairs			Low TI currency pairs		
Strategy	Return	Std. Dev.	Sharpe	Return	Std. Dev.	Sharpe
Naïve carry	-0.016	0.011	-0.121	0.006	0.016	0.031
PPP - $\tau = 0$	0.004	0.020	0.018	0.015	0.021	0.061
PPP - $\tau = 0.1$	0.019	0.034	0.048	0.011	0.027	0.032
PPP - $\tau = 0.2$	0.043	0.046	0.079	0.035	0.035	0.084
PPP - $\tau = 0.3$	0.047	0.040	0.097	0.053	0.048	0.092
PPP - $\tau = 0.4$	0.059	0.041	0.118	0.067	0.039	0.141
PPP - $\tau = 0.5$	0.054	0.035	0.128	0.062	0.036	0.144
PPP - $\tau = 0.6$	0.039	0.031	0.105	0.072	0.032	0.184
PPP - $\tau = 0.7$	0.060	0.028	0.176	0.074	0.033	0.186
PPP - $\tau = 0.8$	0.038	0.020	0.160	0.067	0.028	0.200
PPP - $\tau = 0.9$	0.021	0.015	0.117	0.052	0.027	0.160
PPP - $\tau = 1.0$	0.014	0.012	0.100	0.053	0.024	0.181
PPP - $\tau = 1.1$	0.009	0.011	0.069	0.057	0.025	0.189
PPP - $\tau = 1.2$	0.006	0.011	0.048	0.060	0.022	0.231
PPP - $\tau = 1.3$	0.006	0.011	0.048	0.062	0.022	0.238
PPP - $\tau = 1.4$	0.004	0.010	0.032	0.058	0.021	0.230
PPP - $\tau = 1.5$	0.005	0.007	0.061	0.052	0.020	0.214
PPP - $\tau = 1.6$	0.005	0.007	0.061	0.054	0.020	0.228
PPP - $\tau = 1.7$	0.005	0.007	0.061	0.052	0.019	0.224
PPP - $\tau = 1.8$	0.005	0.007	0.061	0.041	0.018	0.189
PPP - $\tau = 1.9$	.	.	.	0.027	0.016	0.140
PPP - $\tau = 2.0$	.	.	.	0.022	0.016	0.120

Note. We report performance statistics for carry trade portfolios with strategies (15-year moving average, interest rate differential (greater than (med-min)), and no momentum trading) over the sample period, January 1980 - December 2008: annualized return, standard deviation, and Sharpe ratio on a monthly basis. "PPP - $\tau = 0$" means that we use PPP-augmented carry trade strategy with a threshold of $\tau = 0$ percent. Monthly returns are given only for months in which strategies are active. For naïve carry trades, all months are active, for PPP-augmented carry trades, the number of active months falls as the threshold increases.

Table 2.7. Performance statistics for carry trade portfolios (continued)

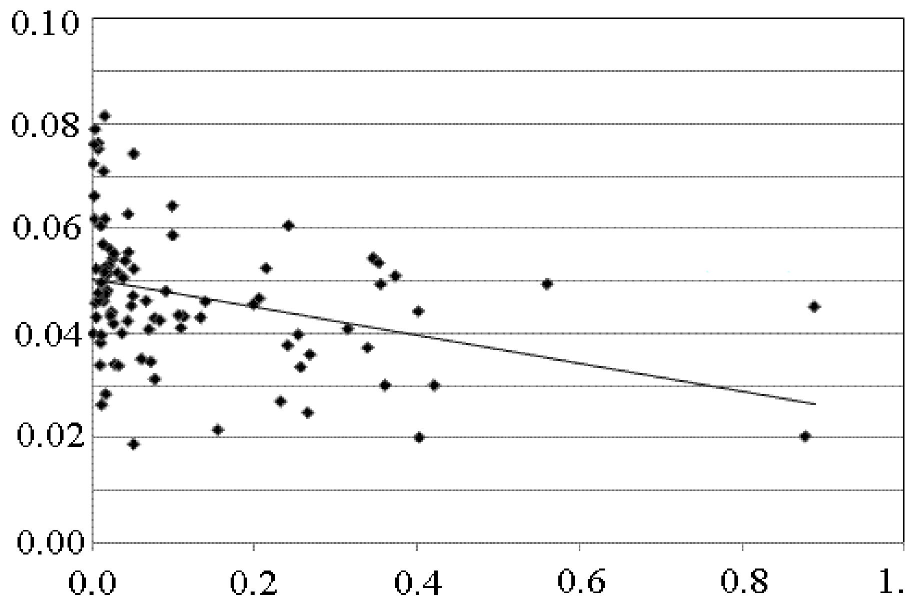
(b) *With* momentum trading

	High TI currency pairs			Low TI currency pairs		
Strategy	Return	Std. Dev.	Sharpe	Return	Std. Dev.	Sharpe
Naïve carry	0.009	0.020	0.039	0.029	0.022	0.110
PPP - $\tau = 0$	0.019	0.029	0.055	0.053	0.031	0.141
PPP - $\tau = 0.1$	0.039	0.042	0.076	0.076	0.045	0.141
PPP - $\tau = 0.2$	0.086	0.044	0.163	0.076	0.048	0.132
PPP - $\tau = 0.3$	0.082	0.039	0.172	0.073	0.039	0.158
PPP - $\tau = 0.4$	0.045	0.033	0.114	0.077	0.040	0.160
PPP - $\tau = 0.5$	0.048	0.032	0.125	0.069	0.036	0.159
PPP - $\tau = 0.6$	0.034	0.028	0.101	0.059	0.032	0.155
PPP - $\tau = 0.7$	0.040	0.025	0.134	0.069	0.032	0.180
PPP - $\tau = 0.8$	0.025	0.017	0.119	0.056	0.025	0.188
PPP - $\tau = 0.9$	0.012	0.013	0.081	0.042	0.023	0.152
PPP - $\tau = 1.0$	0.006	0.009	0.057	0.048	0.021	0.193
PPP - $\tau = 1.1$	0.001	0.008	0.008	0.052	0.021	0.208
PPP - $\tau = 1.2$	-0.002	0.007	-0.027	0.054	0.020	0.228
PPP - $\tau = 1.3$	-0.002	0.007	-0.027	0.054	0.018	0.243
PPP - $\tau = 1.4$	-0.005	0.006	-0.061	0.050	0.018	0.229
PPP - $\tau = 1.5$	.	.	.	0.042	0.017	0.204
PPP - $\tau = 1.6$	.	.	.	0.045	0.017	0.226
PPP - $\tau = 1.7$	.	.	.	0.042	0.016	0.214
PPP - $\tau = 1.8$	.	.	.	0.027	0.014	0.162
PPP - $\tau = 1.9$	.	.	.	0.014	0.011	0.103
PPP - $\tau = 2.0$	.	.	.	0.010	0.010	0.077

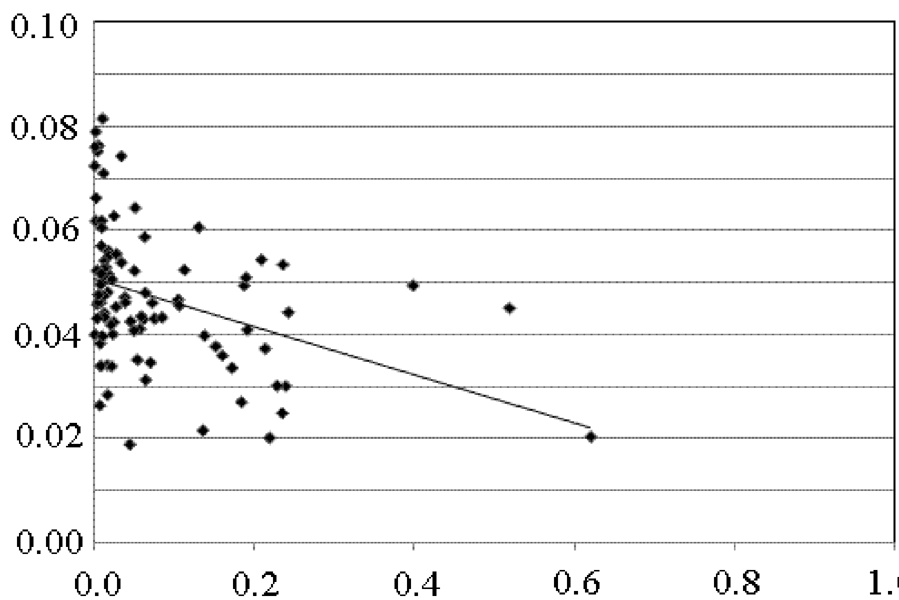
Note. We report performance statistics for carry trade portfolios with strategies (15-year moving average, interest rate differential (greater than (med-min)), and momentum trading) over the sample period, January 1980 - December 2008: annualized return, standard deviation, and Sharpe ratio on a monthly basis. "PPP - $\tau = 0$" means that we use PPP-augmented carry trade strategy with a threshold of $\tau = 0$ percent. Monthly returns are given only for months in which strategies are active. For naïve carry trades, all months are active, for PPP-augmented carry trades, the number of active months falls as the threshold increases.

Figure 2.1. Scatter plots

(a) Scatter plot of exchange rate volatility against trade intensity (maximum)



(b) Scatter plot of exchange rate volatility against trade intensity (average)

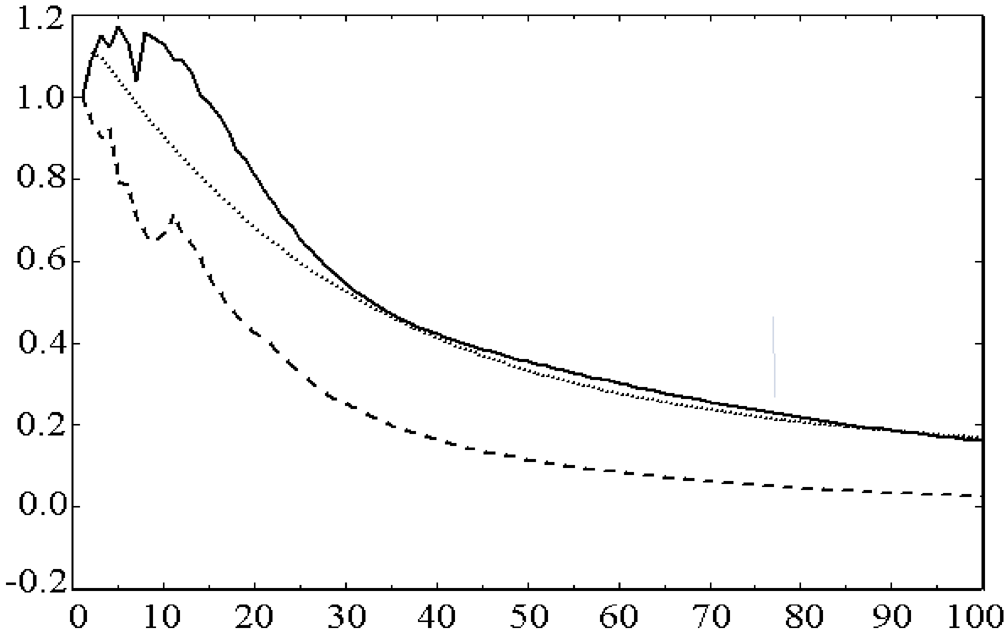


Note. The x-axis is trade intensity (maximum) and trade intensity (average) for (a) and (b), respectively. The y-axis is real exchange rate volatility. Scatter plots are for 91 currency pairs involving 14 countries over the period 1980-2005. The straight line is depicted by running the Ordinary Least Squares (OLS) regression.

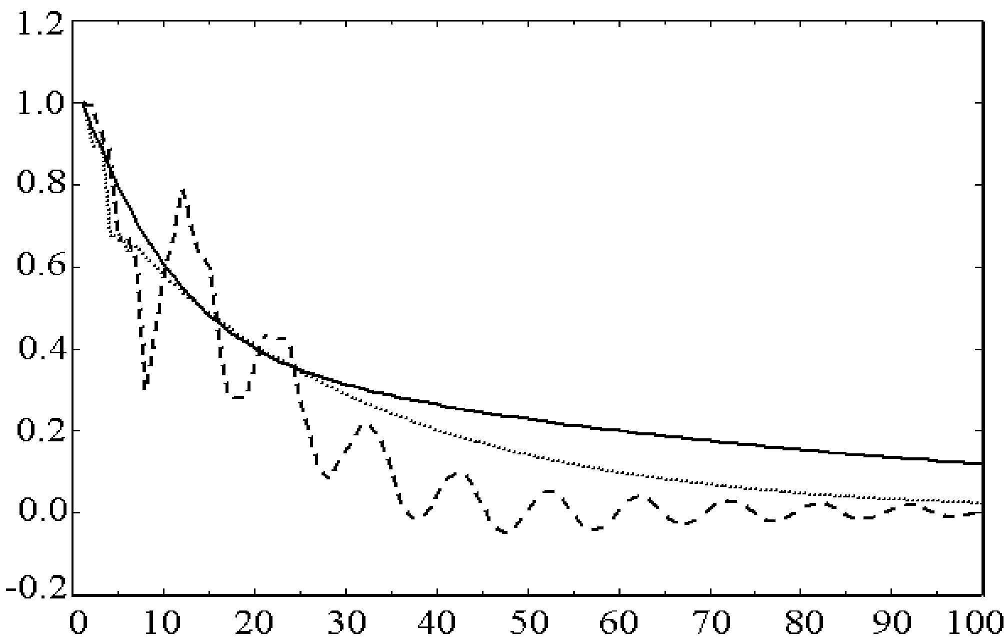
Figure 2.2. Generalized impulse response functions (GIs)

(a) 35 highest TI currency pairs

(i) USD/CAD, (ii) USD/MXN, (iii) USD/JPY



(i) USD/GBP, (ii) USD/KRW, (iii) KRW/JPY

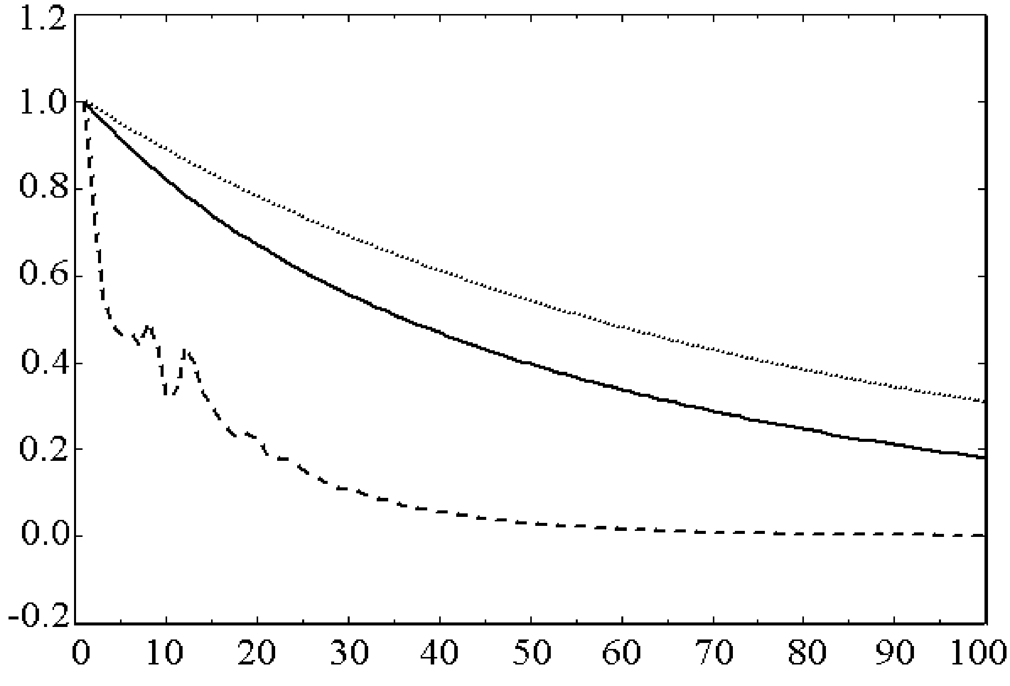


Note. The GIs for the currency pairs in order are plotted with the solid, dashed, and dotted lines, respectively.

Figure 2.2. Generalized impulse response functions (GIs) (continued)

(a) 35 highest TI currency pairs

(i) SEK/NOK, (ii) GBP/NOK, (iii) USD/SGD



(i) NZD/AUD, (ii) JPY/AUD, (iii) SGD/JPY

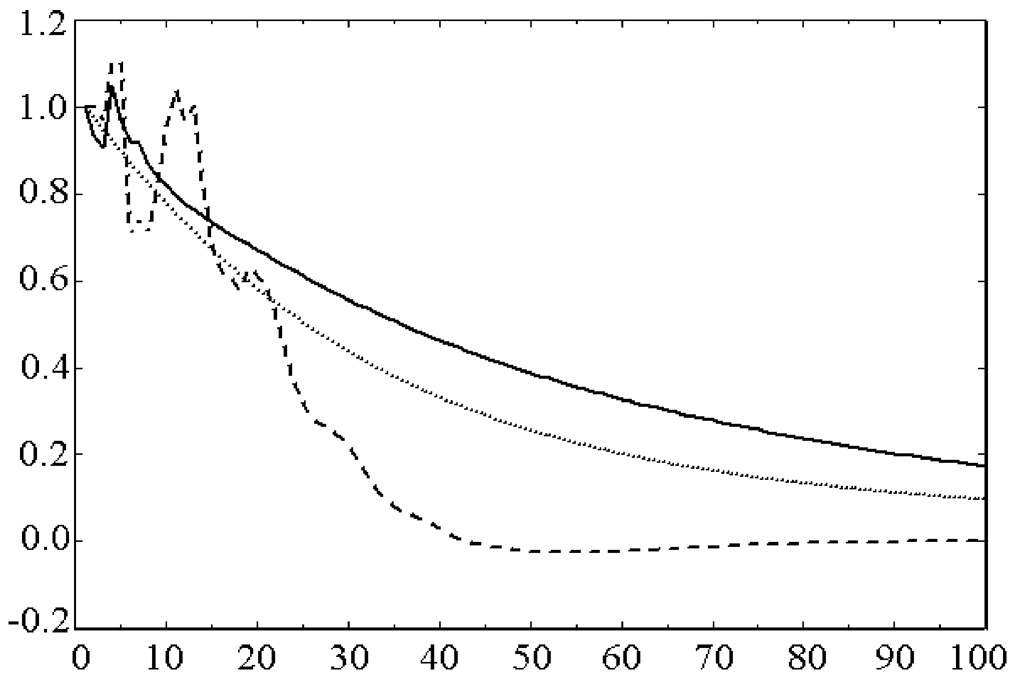
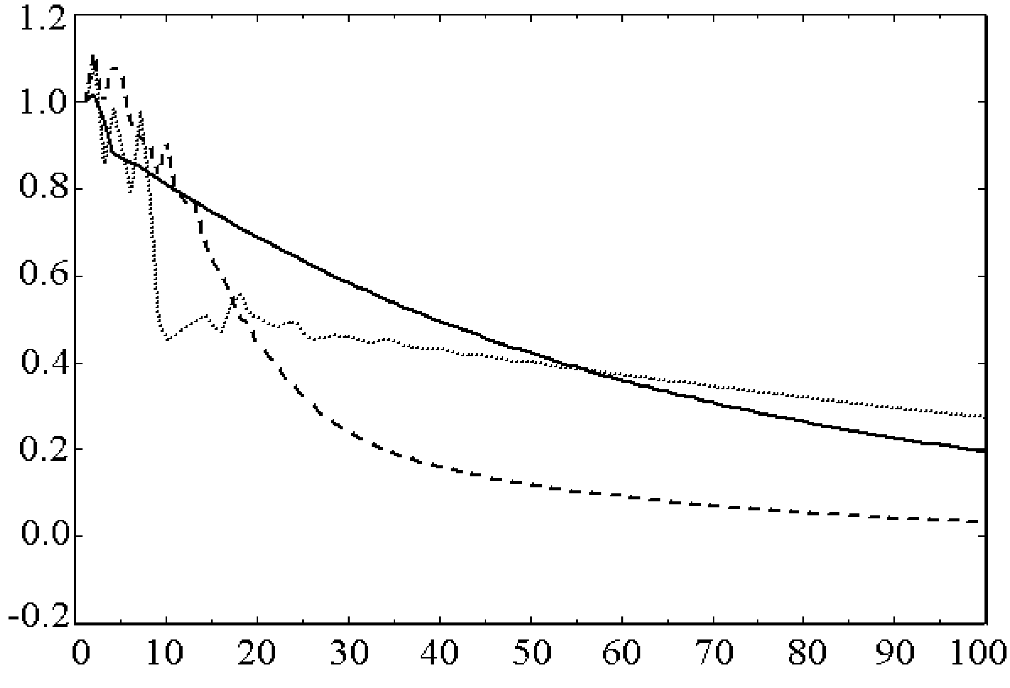


Figure 2.2. Generalized impulse response functions (GIs) (continued)

(a) 35 highest TI currency pairs

(i) USD/TRY, (ii) USD/CHF, (iii) SEK/DKK



(i) GBP/SEK, (ii) GBP/DKK, (iii) GBP/CHF

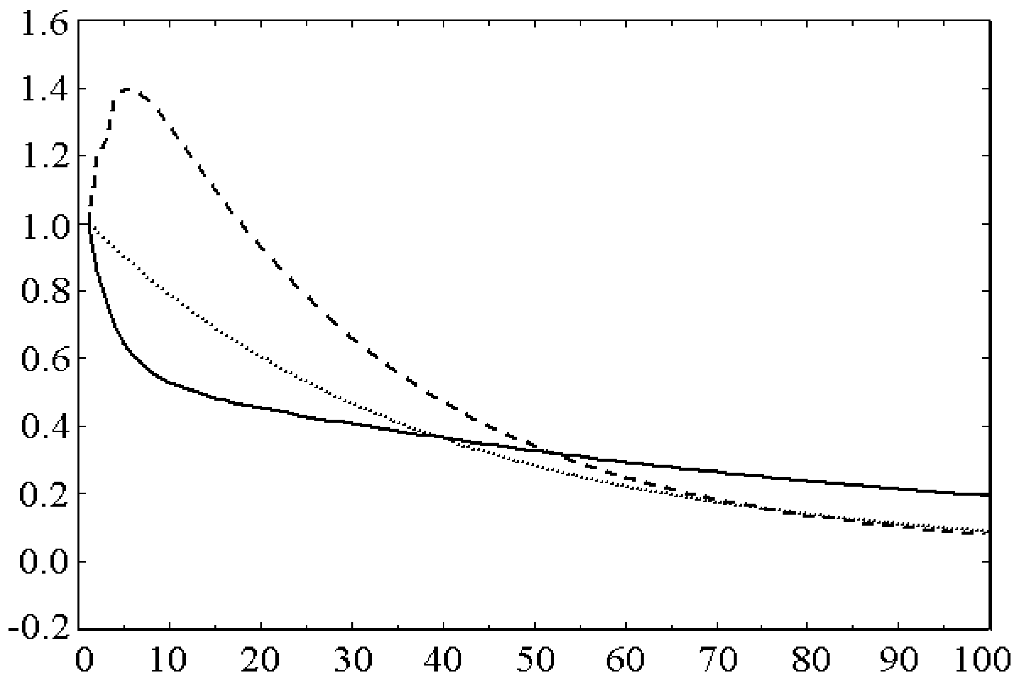
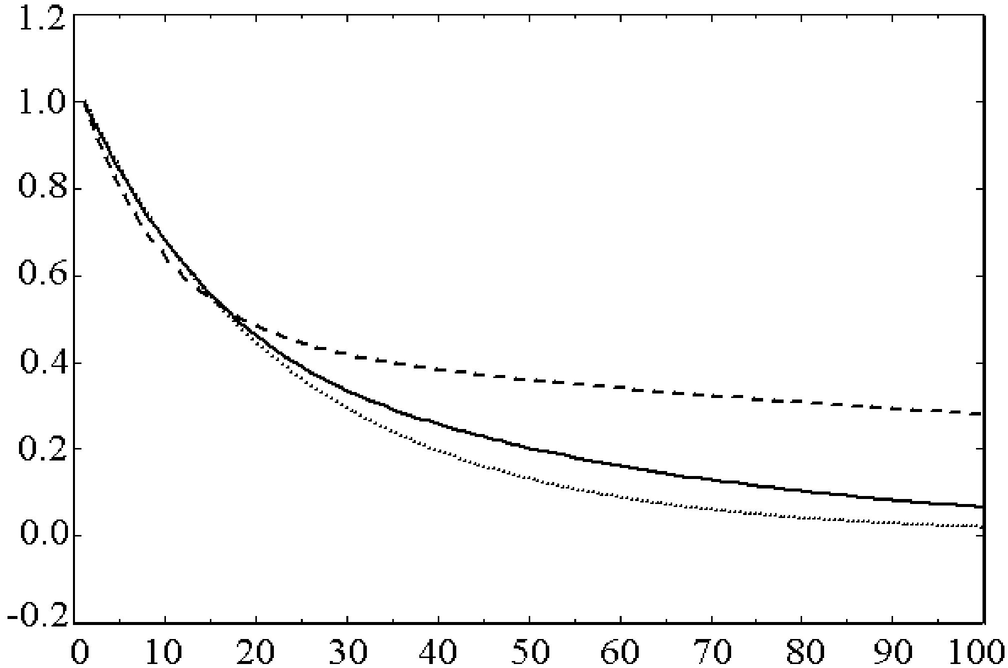


Figure 2.2. Generalized impulse response functions (GIs) (continued)

(a) 35 highest TI currency pairs

(i) USD/AUD, (ii) NOK/DKK, (iii) GBP/TRY



(i) NZD/JPY, (ii) USD/SEK, (iii) USD/NZD

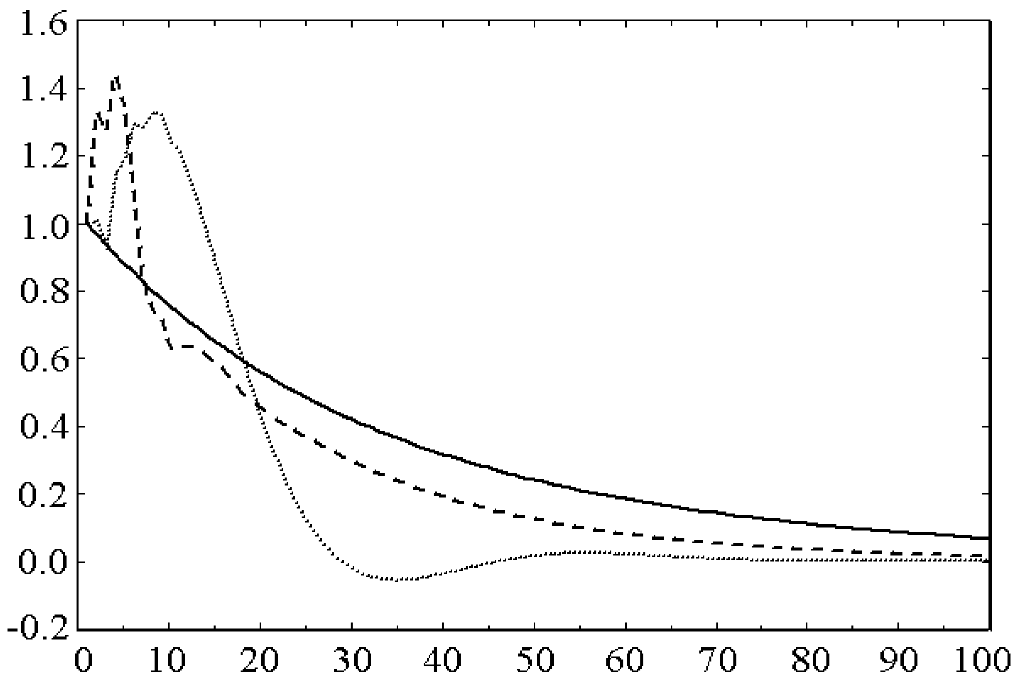
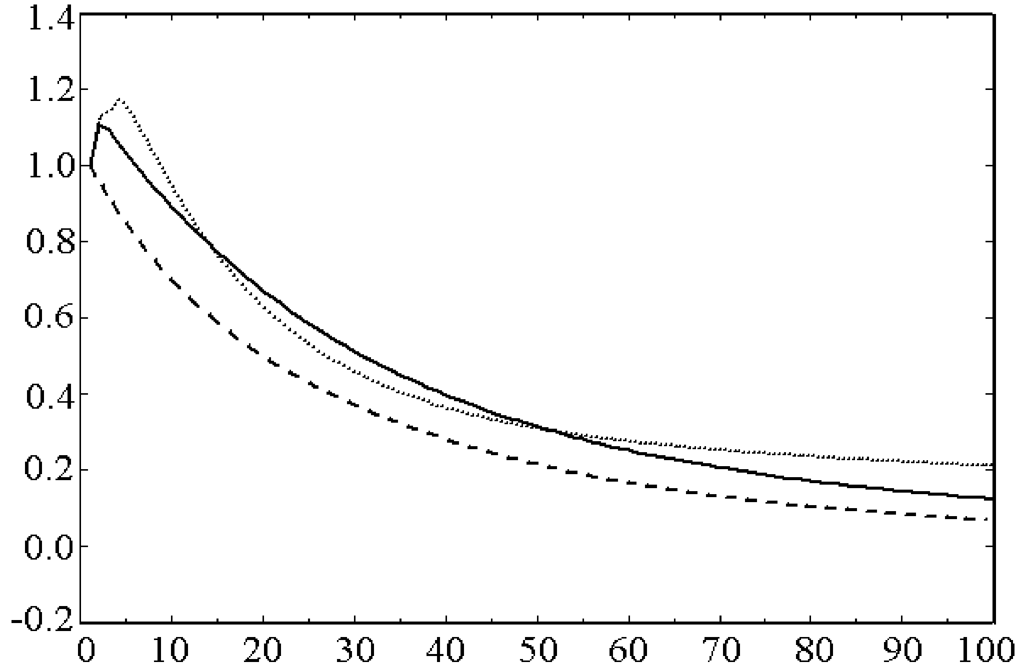


Figure 2.2. Generalized impulse response functions (GIs) (continued)

(a) 35 highest TI currency pairs

(i) GBP/JPY, (ii) CHF/JPY, (iii) USD/DKK



(i) SGD/AUD, (ii) SGD/KRW, (iii) GBP/AUD

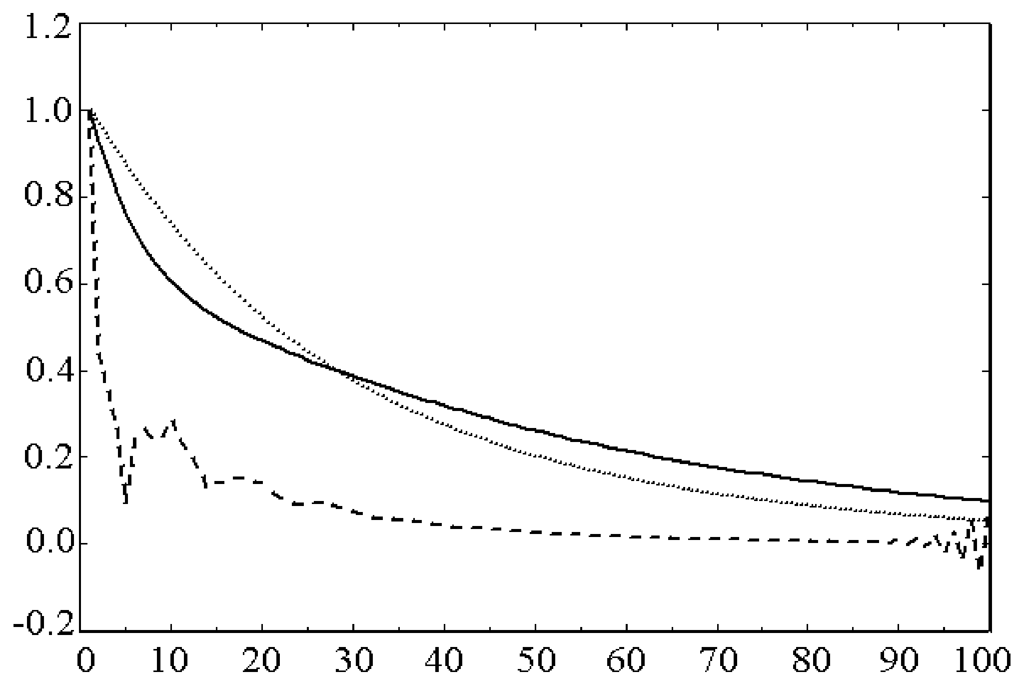
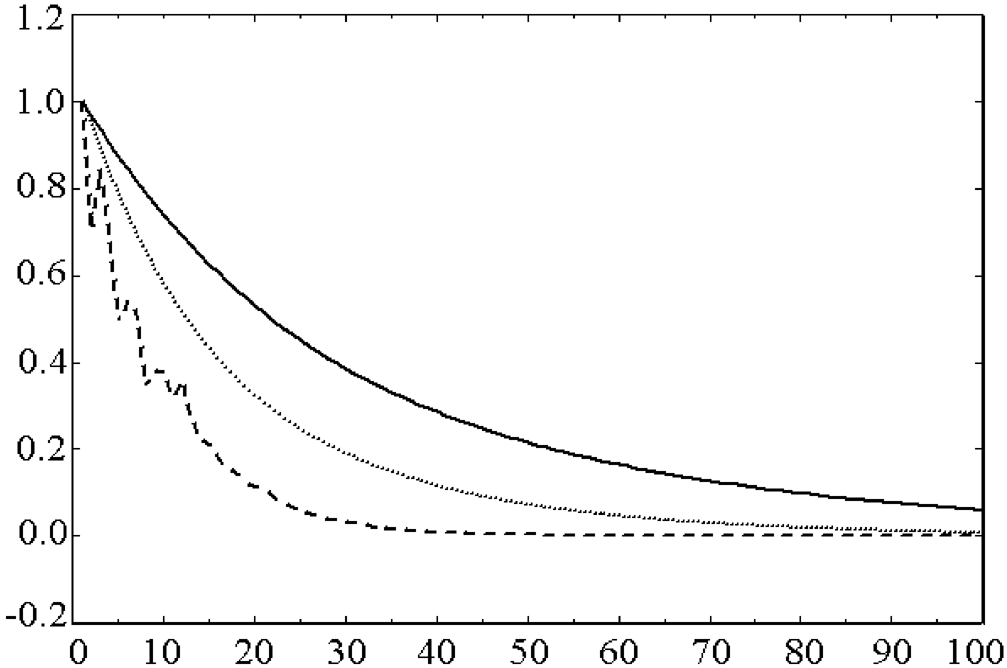


Figure 2.2. Generalized impulse response functions (GIs) (continued)

(a) 35 highest TI currency pairs

(i) TRY/CHF, (ii) KRW/AUD, (iii) GBP/NZD



(i) USD/NOK, (ii) CHF/SEK

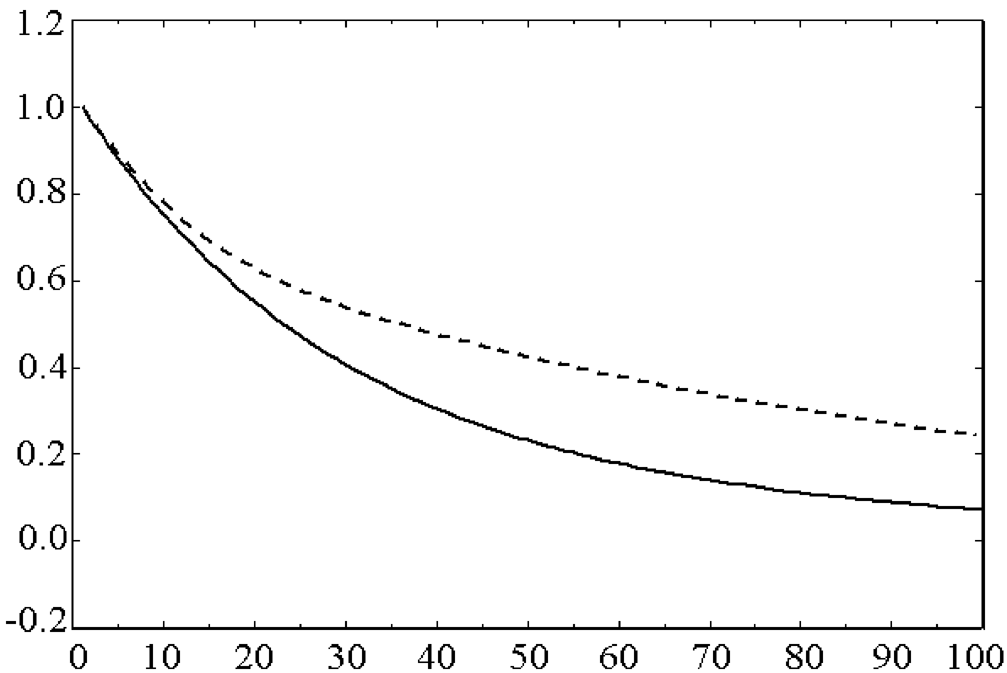
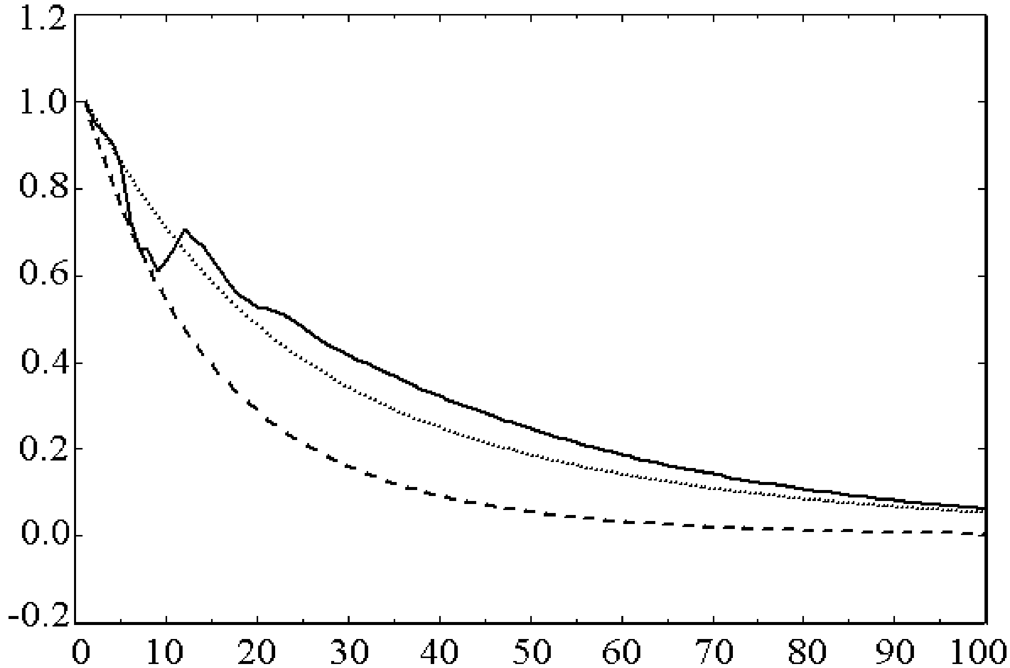


Figure 2.2. Generalized impulse response functions (GIs) (continued)

(b) 35 lowest TI currency pairs

(i) CHF/NOK, (ii) CAD/AUD, (iii) TRY/DKK



(i) MXN/CAD, (ii) SEK/CAD, (iii) TRY/CAD

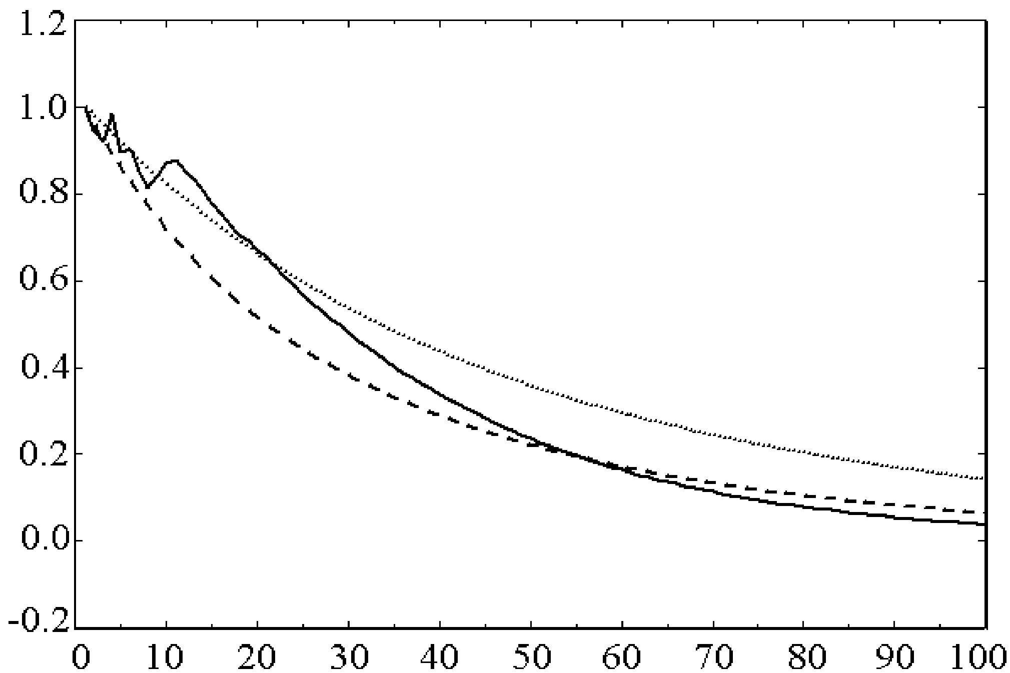
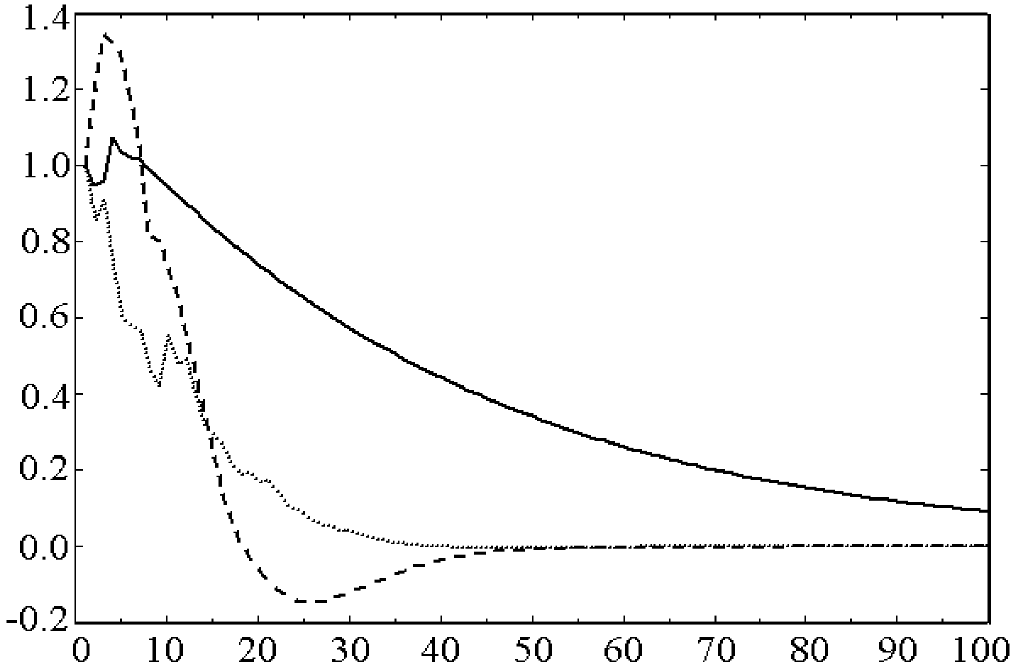


Figure 2.2. Generalized impulse response functions (GIs) (continued)

(b) 35 lowest TI currency pairs

(i) NZD/CAD, (ii) SEK/KRW, (iii) NOK/KRW



(i) GBP/MXN, (ii) KRW/DKK, (iii) CHF/MXN

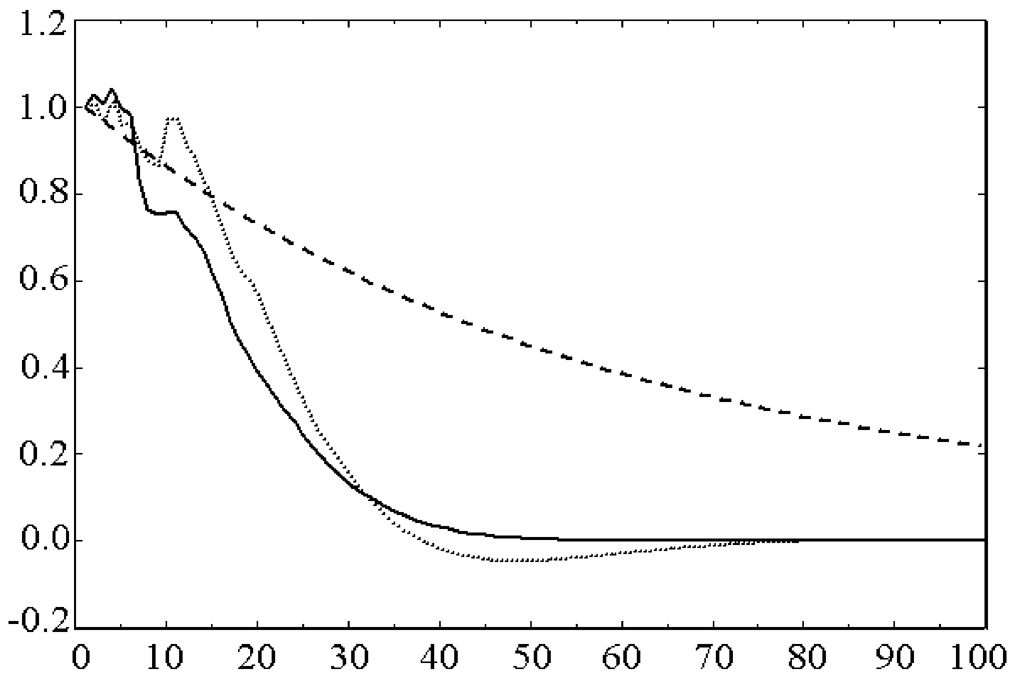
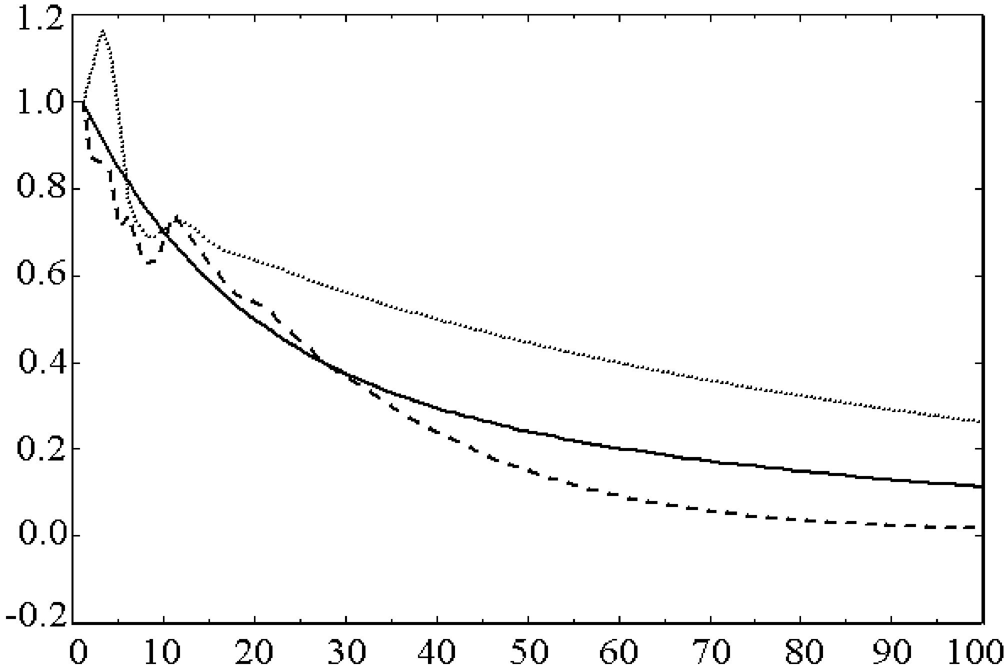


Figure 2.2. Generalized impulse response functions (GIs) (continued)

(b) 35 lowest TI currency pairs

(i) SEK/SGD, (ii) MXN/KRW, (iii) TRY/AUD



(i) TRY/NOK, (ii) TRY/SGD, (iii) DKK/AUD

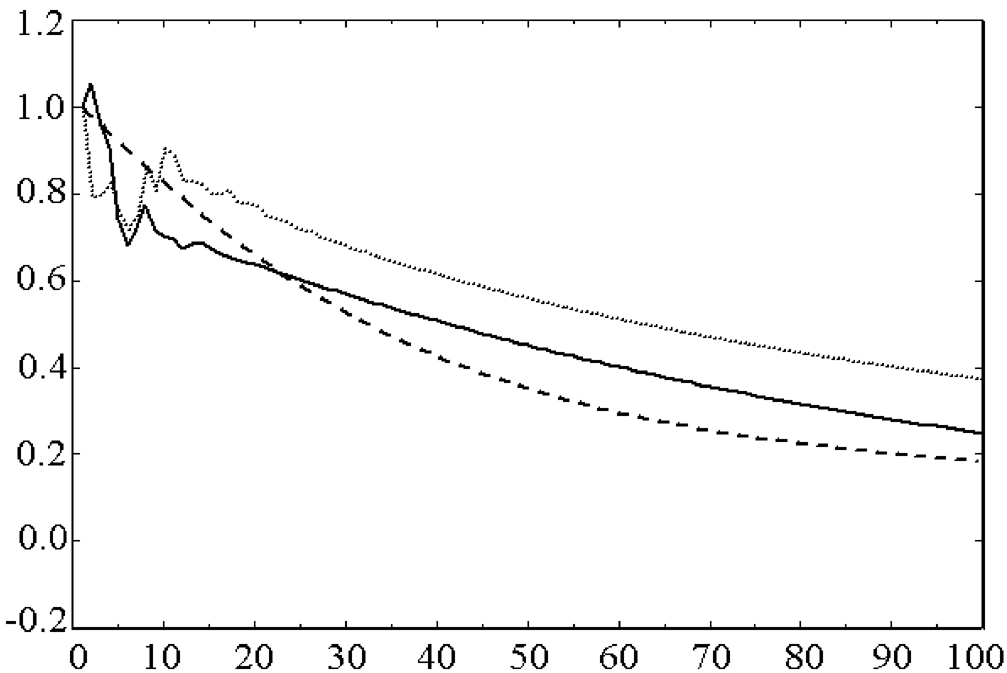
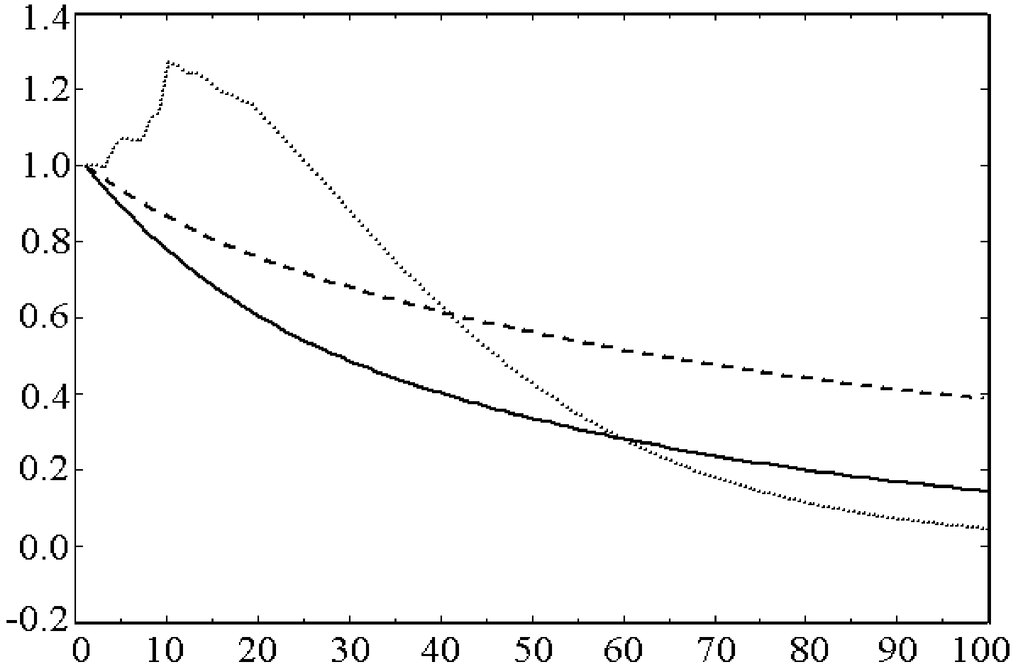


Figure 2.2. Generalized impulse response functions (GIs) (continued)

(b) 35 lowest TI currency pairs

(i) SGD/NOK, (ii) DKK/CAD, (iii) SGD/DKK



(i) SGD/CAD, (ii) SEK/MXN, (iii) SEK/NZD

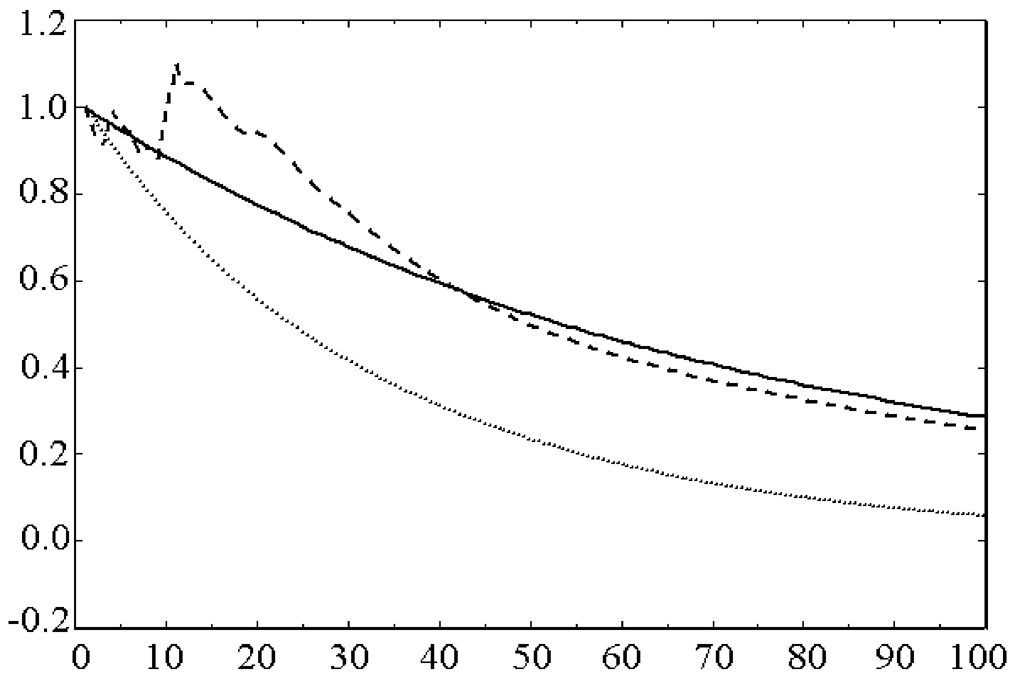
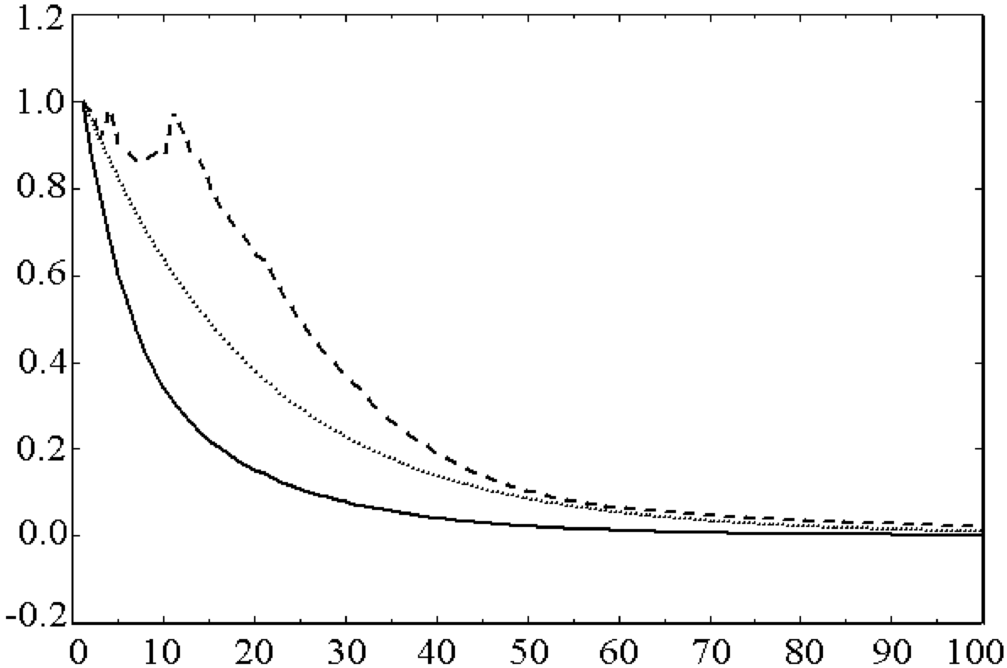


Figure 2.2. Generalized impulse response functions (GIs) (continued)

(b) 35 lowest TI currency pairs

(i) CHF/NZD, (ii) NZD/MXN, (iii) NZD/DKK



(i) SGD/MXN, (ii) NOK/AUD, (iii) TRY/NZD

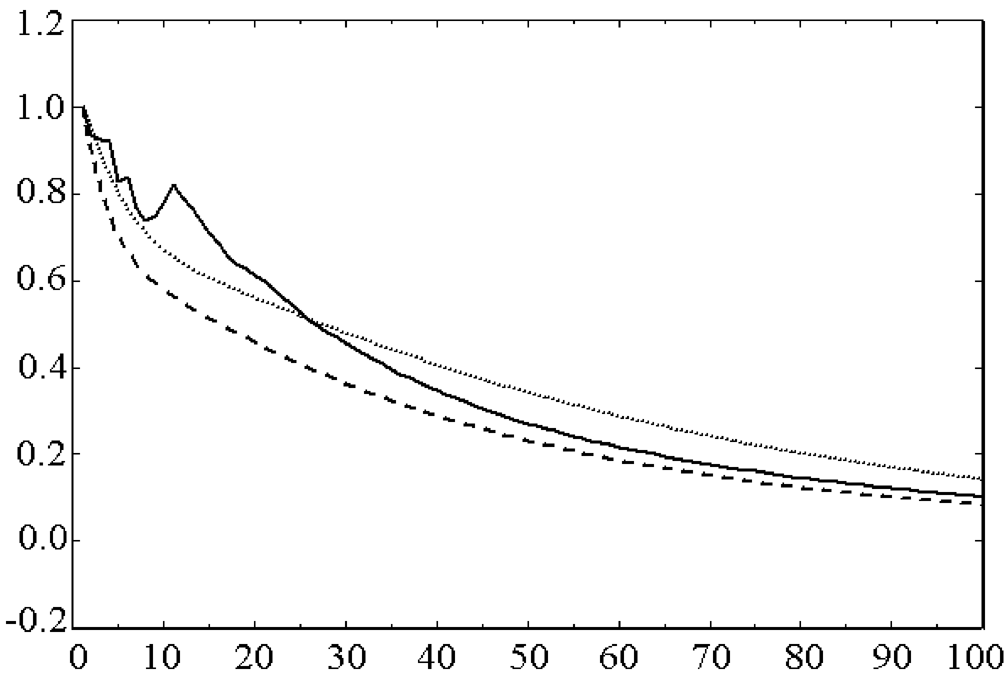
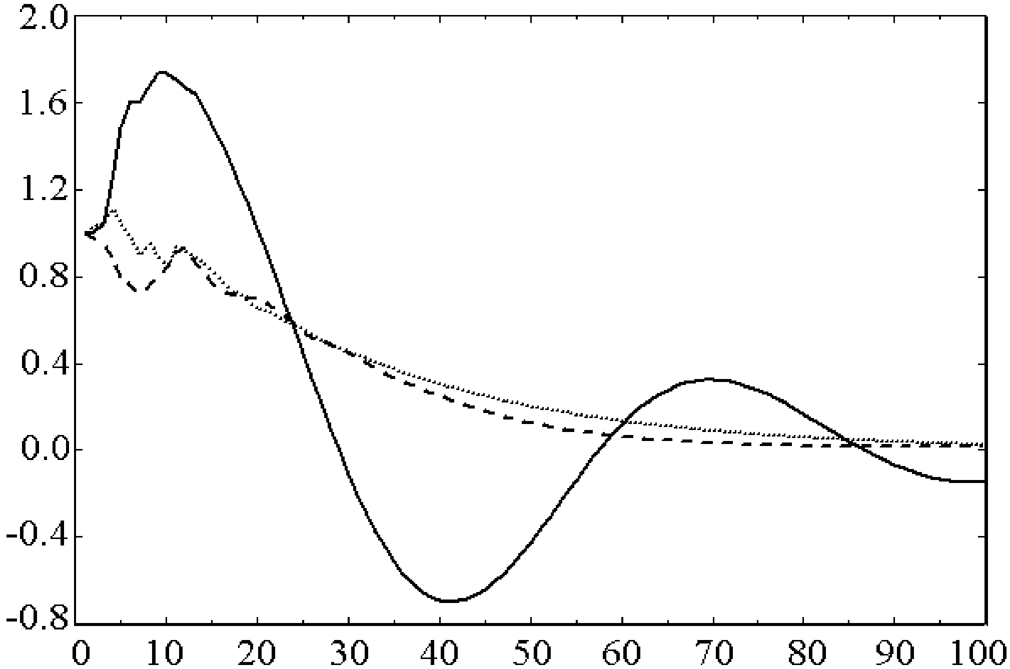


Figure 2.2. Generalized impulse response functions (GIs) (continued)

(b) 35 lowest TI currency pairs

(i) MXN/DKK, (ii) MXN/AUD, (iii) TRY/MXN



(i) NOK/NZD, (ii) NOK/MXN

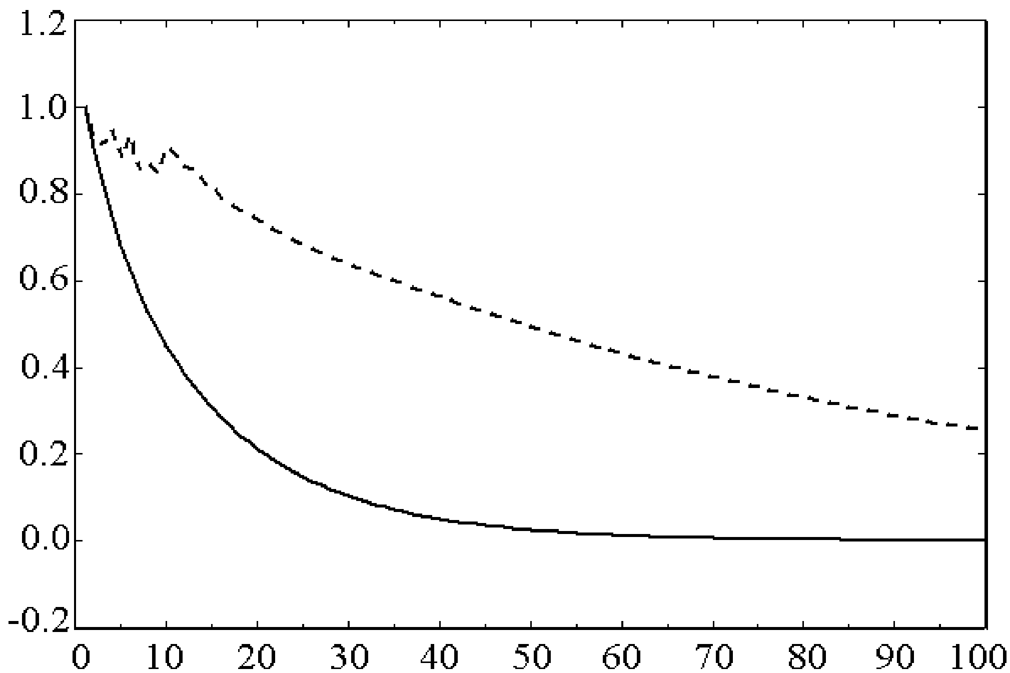
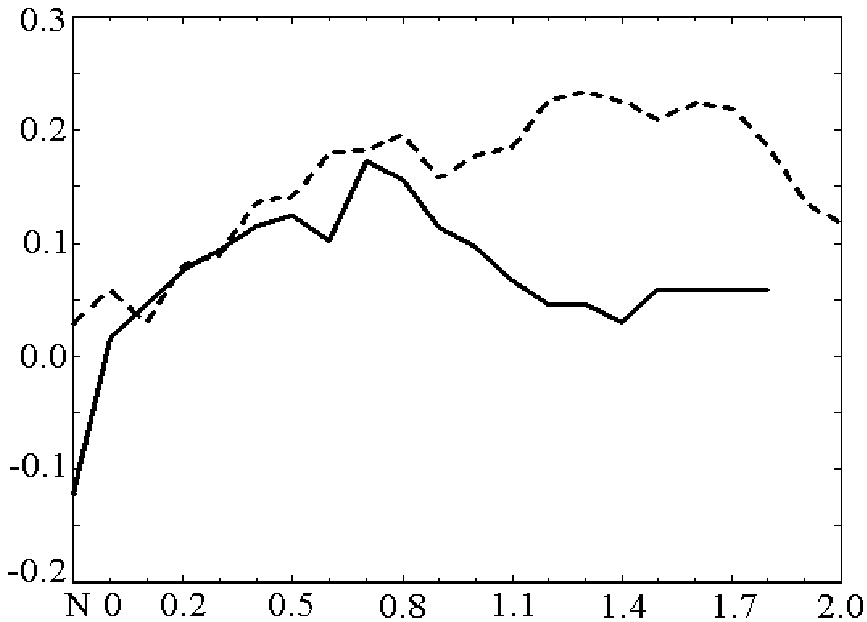
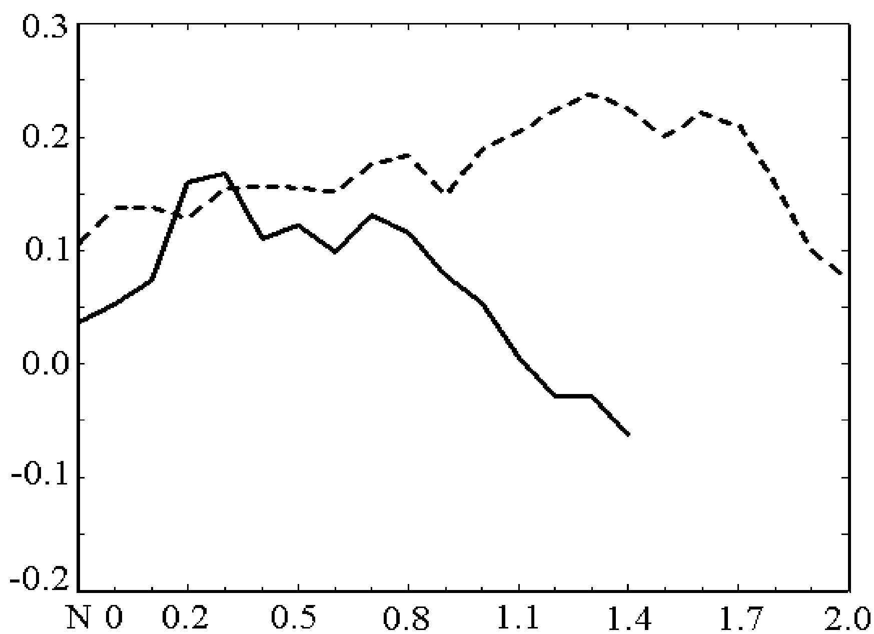


Figure 2.3. Sharpe ratios without and with a momentum trading strategy

(a) Sharpe ratios *without* a momentum trading strategy



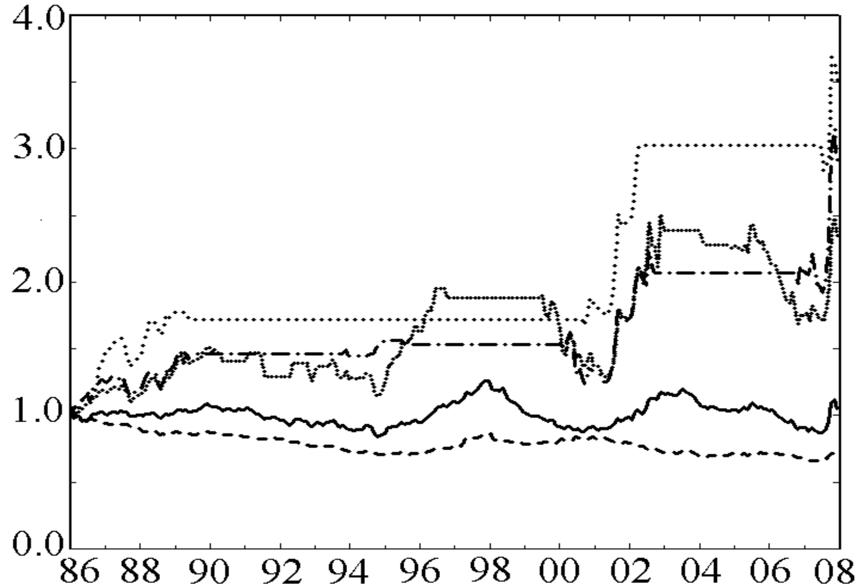
(b) Sharpe ratios *with* a momentum trading strategy

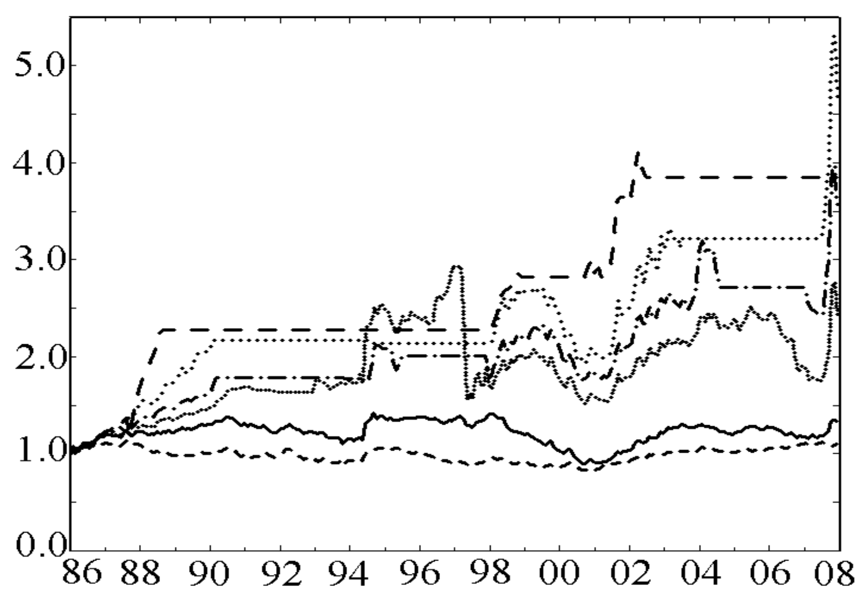


Note. The x-axis refers to a threshold, and the y-axis refers to a Sharpe ratio. "N" refers to the naïve carry trade strategy. The solid line denotes high trade intensity pairs, and the dashed line denotes low trade intensity pairs.

Figure 2.4. Performance of portfolios without and with a momentum trading strategy

(a) Performance of portfolios *without* a momentum trading strategy: High TI (top) vs. Low TI (bottom)

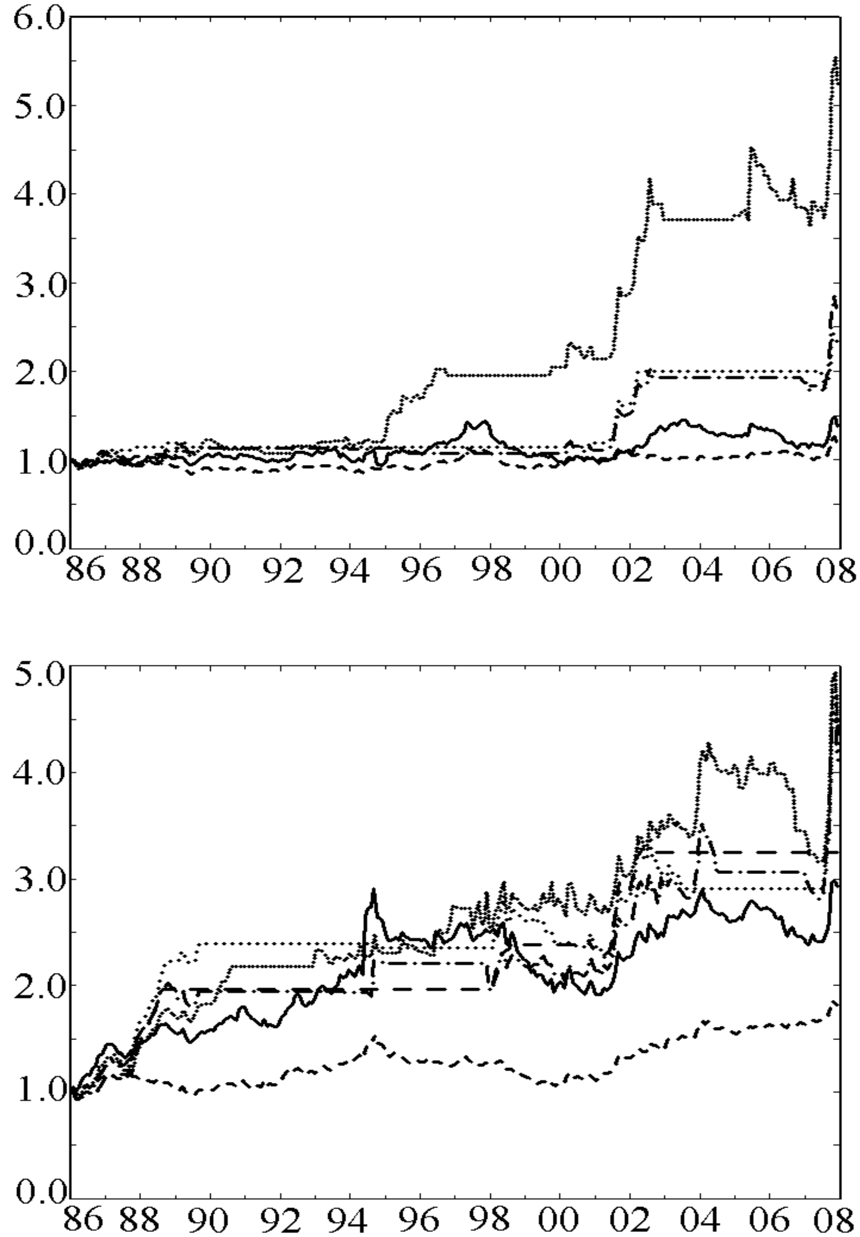




Note. The x-axis refers to time, and the y-axis refers to an amount of dollars. The short-dashed, solid, and circle-marker lines denote the naïve carry trade strategy, the PPP-augmented carry trade strategy with a threshold of 0 percent, and of 30 percent, respectively. Also, the dash-dotted, dotted, and long-dashed lines denote the PPP-augmented carry trade strategy with a threshold of 50 percent, of 70 percent, and of 130 percent, respectively.

Figure 2.4. Performance of portfolios without and with a momentum trading strategy (continued)

(b) Performance of portfolios *with* a momentum trading strategy: High TI (top) vs. Low TI (bottom)



Note. As for Figure 2.4 (a).

Chapter 3

Nonlinear Long Memory Properties and Mean Reversion of Real Exchange Rates in the Post-Bretton Woods Era

3.1 Introduction

While real exchange rates are known to be remarkably volatile, they consistently tend to revert back to long-run equilibrium levels. Although deviations from Purchasing Power Parity (PPP) in the short run are broadly observed, researchers believe that some form of PPP holds at least as a long-run relationship (see, e.g., Rogoff (1996) and Taylor et al. (2001)). The mean reverting behavior of real exchange rates is well documented in many previous studies. A considerable amount of literature (see, e.g., Abuaf and Jorion (1990) [1973-1987], Frankel and Rose (1996a) [1948-1992], Diebold et al. (1991) [1832-1913], Froot and Rogoff (1995) [1913-1988], Lothian and Taylor (1996) [1791-1990], Papell (1997) [1973-

1994], Rogoff (1996) [1972-1995], Taylor and Sarno (1998) [1973-1996], and Wu (1996) [1974-1993], among others. The sample period is also reported in brackets.) has examined whether real exchange rates exhibit mean reversion, and whether there is evidence of PPP in the long run under the recent float. The results have generally been mixed with less evidence of stationarity in the post-Bretton Woods period. Lothian and Taylor (1996) found strong evidence of significant mean reverting behavior of real exchange rates using the annual data spanning two centuries. The authors argued that the slow adjustment and the low power of conventional unit root tests do account for the widespread failure of such tests to reject the null hypothesis of a unit root in the data for the recent floating rate period alone. Abuaf and Jorion (1990), Murray and Papell (2005), and Rossi (2005) have used the data for exchange rates in the post-Bretton Woods Era since 1973. However, Froot and Rogoff (1995), Rogoff (1996) and many others found that it is notably much harder to detect mean reversion in real exchange rates during the post-Bretton Woods period. Many other studies including the aforementioned articles have mainly attempted to explain the puzzling inability to reject the null hypothesis of nonstationarity using standard unit root tests.

There has also been a large amount of literature to study mean reversion in real exchange rates by employing nonlinear models. Taylor et al. (2001) estimate a smooth transition autoregressive ($STAR$) model, which allows the speed at which exchange rates converge to their long-run equilibrium values to depend on the size of the deviations, and provide evidence of nonlinear mean reversion in a number of major real exchange rates. The model thus allows for the possibility that real exchange rates may behave like unit root processes when close to their long-run equilibrium levels, while becoming increasingly mean-reverting the further they move away from equilibrium. Cheung and Lai (2000) examine dollar-based real exchange rates using fractional integration analysis which estimates a standard *ARFIMA* model, and present evidence of mean reversion for many series. Furthermore, Cheung and Lai (2001) show that the puzzling behavior of yen-based real exchange rates may stem from long memory dynamics undermining unit root tests in their ability to identify mean reversion.

Recent evidence reveals that many univariate economic and financial time series possess both nonlinear and long memory properties. Motivated by this recent evidence, Baillie and Kapetanios (2008) developed a general nonlinear, smooth transition regime autoregression which is embedded within a strongly dependent, long memory process. The authors also found that a fractionally integrated, nonlinear autoregressive *ESTAR* (*FI-NLAR-ESTAR*) model is quite successful in representing the nonlinear structures and strong dependencies within six monthly forward premia for the periods, December 1978 through December 1998 or January 2002 depending on whether the currency is included in the Eurozone, and the historical yearly USD/GBP real exchange rate for the periods, 1791 through 1994. In their paper, it has been shown that the time domain MLE is generally superior to the two step estimator which is an alternative procedure of first estimating the long memory parameter by using the Local Whittle estimator to obtain a fractionally integrated filtered series, before estimating the remaining parameters. Also, van Dijk et al. (2002a) proposed a fractionally integrated smooth transition autoregressive (*FI-STAR*) model to jointly capture both long memory and nonlinear features, and found evidence of both long memory and nonlinear behavior for three decades of monthly US unemployment. Hence, the article by Baillie and Kapetanios (2008) aims to jointly model both nonlinearity and long memory for economic and financial time series which include forward premia, real exchange rates, and many others.

This paper examines nonlinear and long memory properties and mean reverting dynamics of real exchange rates. The purpose of this paper is to find evidence which is supportive of mean reversion in real exchange rates by estimating the *FI-NLAR-ESTAR* model that is capable of representing both nonlinear and long memory features for the various economic and financial time series. It has been found that the *FI-NLAR-ESTAR* model is quite successful in detecting the mean reverting dynamics of real exchange rates. While the nonlinear long memory model has been found to be more supportive of strong empirical evidence for the presence of slow mean reversion in real exchange rates, the linear fractionally integrated model has not for all of the currencies considered in this study over the recent float.

The contribution of this paper to the existing literature is that a model that is capable of capturing both nonlinear and long memory characteristics may help identifying mean reversion in real exchange rates. In particular, the fractional integration analysis reveals that the null hypothesis of the presence of a unit root is rejected at least at the 5 percent significance level for all of the currencies considered in this study. This implies that a linear fractionally integrated model such as *ARFIMA* can be improved by adding nonlinear properties in terms of its ability to detect mean reversion to the long run equilibrium level in real exchange rates.

The rest of the paper is organized as follows: Section 3.2 introduces the time series model representing both nonlinearity and long memory. Section 3.3 presents empirical results from the estimation of the model. Section 3.4 describes the data, and provides some summary statistics. Section 3.5 concludes.

3.2 The *FI-NLAR-ESTAR* model

A univariate time series process with fractional integration in its conditional mean is represented by

$$(1-L)^d y_t = u_t, \quad t = 1, 2, ..., T \tag{3.1}$$

where L is the lag operator, d is the long memory parameter and u_t is a short memory I(0) process. The time series y_t is said to be a fractionally integrated process of order d, or I(d) (see Granger and Joyeux (1980), Granger (1980) and Hosking (1981)). Long memory, fractionally integrated processes are associated with hyperbolically decaying autocorrelations and impulse response weights. Baillie (1996) provides detailed surveys of these models and discussions of the applications to economics and finance. The parameter d is possibly noninteger, and represents the degree of "long memory" behavior or persistence in the series. For noninteger d, the operator $(1-L)^d$ in equation (1) is through the binomial expansion

$$(1-L)^d = 1 - dL + \frac{d\,(d-1)}{2!}L^2 - \frac{d\,(d-1)\,(d-2)}{3!}L^3 + \cdots . \tag{3.2}$$

For $d = 1$, $(1-L)^d$ is the usual first-differencing operator. For $-0.5 < d < 0.5$, the process is covariance stationary and invertible. For $0 < d < 0.5$, the process possesses long memory, and its autocorrelations are all positive and decay at a hyperbolic rate. For $-0.5 < d < 0$, the sum of absolute values of the processes autocorrelations tends to a constant so that it has short memory. For $0.5 \leq d < 1$, the process does not have a finite variance, but still has a cumulative impulse response function with a finite sum, which implies that shocks to the level of the series are mean reverting. The mean reverting property depends on whether $d < 1$. For $d = 1$, the time series is a unit root process which implies the effect of a shock does not die out. However, a fractionally integrated process with $d < 1$ exhibits shock-dissipating behavior. If the short memory process u_t is represented as an *ARMA*(p,q) process, equation (1) becomes the *ARFIMA*(p,d,q) model

$$\Phi(L)(1-L)^d y_t = \Theta(L)\epsilon_t, \tag{3.3}$$

where $\Phi(L) = 1 - \phi_1 L - \cdots - \phi_p L^p$, $\Theta(L) = 1 + \theta_1 L + \cdots + \theta_q L^q$, and all roots of $\Phi(L)$ and $\Theta(L)$ lie outside the unit circle.

A model that is capable of capturing both nonlinear and long memory features is the *FI-NLAR-ESTAR* model developed by Baillie and Kapetanios (2008). In the paper, the authors consider a general nonlinear, smooth transition regime autoregression which is embedded within a strongly dependent, long memory process. They consider situations where the short memory process u_t is allowed to be a nonlinear process, rather than a pure *ARMA* process. To be more specific, by allowing for general nonlinear processes and from equation (3.1)

$$u_t = F\left(u_{t-1}, \cdots, u_{t-p}\right) + \epsilon_t, \tag{3.4}$$

so that the short memory component of the process is a possibly nonlinear autoregression involving the last p lags of the variable, u_t. The strong dependent component is represented by a fractionally integrated process as in equation (3.1), and the stationary I(0) component is composed of an autoregression with a linear part of order p and a nonlinear part of order k where the nonlinearity involves the use of a smooth transition function. The *FI*(d)-*NLAR*(p,k) -*ESTAR* model is represented as

$$\begin{aligned} (1-L)^d y_t &= u_t, & (3.5)\\ u_t &= \alpha(L) u_{t-1} + \beta(L) u_{t-1}\phi(u_{t-D}) + \epsilon_t, \end{aligned}$$

where the polynomials in the lag operator are $\alpha(L) = \alpha_0 + \sum_{i=0}^{p-1} \alpha_i L^i$, $\beta(L) = \beta_0 + \sum_{i=0}^{k-1} \beta_i L^i$, $\phi(u_{t-D})$ is the smooth transition autoregression function, D is a delay parameter, and ϵ_t is a white noise process. The most widely used nonlinear model is the Exponential Smooth Transition Autoregressive (*ESTAR*) model introduced by Granger and Teräsvirta (1993) and Teräsvirta (1994). A transition function suggested by Granger and Teräsvirta (1993) is the exponential function

$$\phi(u_{t-D}) = 1 - \exp\left(-\gamma(u_{t-D} - c)^2\right) \quad \text{with } \gamma > 0, \tag{3.6}$$

where u_{t-D} is a transition variable, γ is a slope parameter, and c is a location parameter. The restriction on the parameter ($\gamma > 0$) is an identifying restriction. Thus, the *NLAR*(*p*,*k*) -*ESTAR* part is represented as

$$\begin{aligned} u_t = {} & \alpha_0 + \beta_0 \left[1 - \exp\left(-\gamma(u_{t-D} - c)^2\right)\right] \\ & + \sum_{i=1}^{p} \alpha_i u_{t-i} + \sum_{i=1}^{k} \beta_i u_{t-i} \left[1 - \exp\left(-\gamma(u_{t-D} - c)^2\right)\right] + \epsilon_t, \end{aligned} \tag{3.7}$$

and this is the form of the model that is used for the empirical analysis of real exchange rates in this study. The estimation of the model is implemented through the use of a time domain MLE for a stationary, fractionally integrated, nonlinear autoregression with smooth transition regimes.[1] The model can be estimated by approximate MLE in the time domain. Baillie and Kapetanios (2008) show that an alternative procedure of first estimating the long memory parameter by using the Local Whittle estimator to obtain a fractionally filtered series, before estimating the remaining parameters, is generally found to be inferior to the

[1] Baillie and Kapetanios (2008) show that the use of a time domain MLE for stationary, fractionally integrated, nonlinear autoregression with smooth transition regimes has desirable asymptotic properties and possesses $T^{1/2}$ consistent parameter estimates with a limiting Normal distribution.

full MLE.

Several previous studies including Diebold et al. (1991), Cheung (1993) and Cheung and Lai (2000, 2001) have considered fractionally integrated, or long memory behavior of real exchange rates. However, a recent paper by Baillie and Kapetanios (2007) constructs the application of the tests based on logistic approximations and Artificial Neural Networks (ANN), and suggests the widespread presence of both nonlinear and long memory components in many economic and financial time series such as the rate of inflation and real exchange rates. For example, as mentioned earlier, van Dijk et al. (2002a) propose a time series model to describe long memory and nonlinearity at the same time, and find evidence of both nonlinear and long memory properties for US unemployment. Hence, Baillie and Kapetanios (2008) aim to jointly model both nonlinear and long memory characteristics for strongly dependent processes, and include some applications of the methodology and estimation of a fractionally integrated, nonlinear autoregressive $ESTAR$ model to forward premia for six different currencies and the yearly USD/GBP real exchange rate. They find that the estimated $FI(d)$-$NLAR(p,k)$-$ESTAR$ models appear to be successful in representing the nonlinear structures and strong dependencies.

3.3 Data and Summary Statistics

This study uses monthly price levels measured by consumer price indices (CPI), and monthly spot exchange rates for the Swiss Franc (CHF), Great British Pound (GBP), Japanese Yen (JPY), Norwegian Krone (NOK) and Swedish Krona (SEK) vis-à-vis the US Dollar. The data used in this empirical study are collected from the *International Financial Statistics*

(*IFS*) and spot exchange rates are measured as mid rates at the end of the month, from January 1970 through October 2010, comprising a total of 490 monthly observations for each currency.

The real exchange rate, q_t, is defined in logarithmic form as

$$q_t \equiv s_t - p_t + p_t^* \tag{3.8}$$

where s_t is the logarithm of the nominal exchange rate which is measured as the price of the domestic currency in terms of the foreign currency, and p_t and p_t^* denote the logarithms of the domestic and foreign price levels, respectively. If PPP held continuously, q_t would be a constant that reflects differences in units of measurement. As noted in particular by Taylor et al. (2001), the real exchange rate may be interpreted as a measure of the deviation from PPP. Since the real exchange rate is the nominal exchange rate which is adjusted for relative price levels between two countries, variations in the real exchange rate may represent deviations from PPP. Lothian and Taylor (1996) also noted that failure to reject the hypothesis of nonstationarity in the real exchange rate has been evidence against long-run PPP.

Figure 3.1 shows the logarithms of monthly real exchange rates over the periods, January 1970 through October 2010. Most of the sample periods fall into the post-Bretton Woods floating exchange rate system. In all cases, it is observed that real exchange rates exhibit large appreciations and depreciations against the US Dollar over the entire sample periods. Table 1 presents some preliminary summary statistics for the time series data of real exchange rates. The first two rows show the mean and standard deviation of real exchange rates as defined in equation (3.8). It is interesting to note that the Swiss Franc (CHF) and Japanese

Yen (JPY)–two currencies that are most widely used as funding currencies for carry trades–appear to exhibit higher exchange rate volatility than other three currencies, as indicated by standard deviations of 0.21 and 0.25, respectively. In Table 3.1, ACF1 through ACF 6 denote autocorrelation functions up to lag 6. It is clearly indicated that real exchange rates are strongly dependent processes. Many economic and financial time series including real exchange rates and forward premia are strongly persistent, and display slowly decaying hyperbolic autocorrelations. The Ljung-Box test statistics for autocorrelations up to 20 lags also reveal that there is significant evidence that there is autocorrelation between the series for each currency. In Figure 3.2 (a), the first 120 autocorrelations of the logarithms of real exchange rates are plotted. Also, the autocorrelations of first-differenced real exchange rates are displayed in Figure 3.2 (b). The autocorrelations of real exchange rates show a slow decay associated with fractionally integrated processes. The autocorrelations of first-differenced real exchange rates display some negative values at low lags, which strongly suggests overdifferencing.

3.4 Empirical Results

The results from estimating *FI-NLAR-ESTAR* models for different currencies are reported in Table 3.2. The tests for nonlinearity denoted by *TLG* (proposed by Teräsvirta et al. (1993)) and *ANN* (proposed by Lee et al. (1993)), respectively indicate the necessity of the nonlinear long memory model. The p-values for these nonlinearity tests are reported in Table 3.2, and provide significant evidence for nonlinearity. The chosen orders, p and k of the models that optimized the information criteria are different across the currencies. In most cases, the lag orders selected by each information criterion were the same. Otherwise, following Baillie and Kapetanios (2008), the choice from the Akaike criterion was used. The most appropriate order of the linear autoregressive part varies between 8 for JPY and SEK, and 12 for GBP, while the optimum order for the nonlinear autoregressive part is one for all currencies. The long memory parameter d from MLE is relatively close to the Local Whittle estimate for most currencies.[2] It is in the range between 0.5 and 1 for most currencies which implies nonstationarity of the process, but nevertheless existence of a cumulative impulse response function with a finite sum, which implies that shocks to the level of the series are mean reverting. It is in the range between 0 and 0.5 for GBP and SEK, which implies covariance stationarity of the process. As noted by Baillie and Kapetanios (2008), two of the estimated models have the first nonlinear autoregressive coefficient β_1 being small and not significantly different from zero. However, the effect of nonlinearity enters through the statistically significant constant term β_0. Since the estimated long memory parameter exceeds 0.5 in most cases, the models were also estimated after having first-differenced the data. It appeared that this did not change the results after having added unity to the estimate of the long memory parameter. In the last three rows of Table 3.2, the estimation results from Autoregressive Fractionally Integrated Moving Average (*ARFIMA*) models are reported. The long memory parameter, d along with the chosen order, p of the model is displayed.

Following Cheung and Lai (2000, 2001), the fractional integration analysis is implemented. The results from *ARFIMA* models and *FI-NLAR-ESTAR* models are displayed in Tables 3.3

[2] It was not possible to find an appropriate model for the Canadian Dollar (CAD), since the estimate of γ was very large, and both the Local Whittle and MLE methods were not able to reject the hypothesis of $d = 1$.

and 3.4, respectively. In each Table, the MLE of the long memory parameter d along with its corresponding standard error is reported. The t-statistics for each hypothesis testing is also reported. In Table 3.3, the results from *ARFIMA* models indicate that the null hypothesis of $d = 0$ is rejected in favor of the alternative hypothesis of $d > 0$ at the 5 percent significance level for CHF and SEK, and at 1 percent significance level for other currencies. However, the null hypothesis of $d = 1$ (a unit root) cannot be rejected in favor of the alternative hypothesis of $d < 1$ (mean reversion) at the any significance level for CHF, JPY, and NOK, while it is rejected at the 10 percent significance level for GBP, and at 1 percent level for SEK. For the *ARFIMA* model, these results provide no evidence of mean reversion at all for three out of five currencies. In Table 3.4, the results from *FI-NLAR-ESTAR* models indicate that all the currencies have an integration order of neither zero nor unity. The null hypothesis of $d = 0$ is rejected in favor of the alternative hypothesis of $d > 0$ at the 1 percent significance level for all the currencies. Furthermore, the null hypothesis of $d = 1$ (a unit root) is also rejected in favor of the alternative hypothesis of $d < 1$ (mean reversion) at the 5 percent significance level only for NOK, and at the 1 percent level for all other currencies. This finding is consistent with the result in Baillie and Kapetanios (2008). The authors considered the historical series of the annual USD/GBP real exchange rate for the periods spanning from 1791 through 1994, and found that the estimated nonlinear and long memory model provides evidence of slow mean reversion of the historical series. Overall, the results from *FI-NLAR-ESTAR* models suggest significant empirical evidence of slow mean reversion in real exchange rates for all the currencies in this study.

An investigation of the fractional integration analysis for two models clearly reveals the fact that the model that is capable of capturing both nonlinear and long memory characteristics outperforms the linear fractionally integrated model. That is, the *FI-NLAR-ESTAR* model works better in terms of its ability to identify mean reversion to the long run equilibrium level in real exchange rates. The need for the nonlinear model for strongly persistent processes is apparently indicated by the fractional integration analysis which strongly supports the mean reverting process of real exchange rates.

3.5 Conclusion

Although deviations from Purchasing Power Parity (PPP) in the short run are broadly observed, researchers believe that some form of PPP holds at least as a long-run relationship. Several previous studies have examined whether real exchange rates exhibit mean reversion, and whether there is evidence of PPP in the long run. This paper investigates both nonlinear and long memory characteristics and mean reverting behavior of real exchange rates. The paper estimates a fractionally integrated, nonlinear autoregressive *ESTAR* (*FI-NLAR-ESTAR*) model for strongly dependent processes developed by Baillie and Kapetanios (2008). It has been found that the *FI-NLAR-ESTAR* model is quite successful in identifying the mean reverting dynamics of real exchange rates. While the nonlinear long memory model has been found to be more supportive of strong empirical evidence for the presence of slow mean reversion in real exchange rates, the linear fractionally integrated model has not for all of the currencies considered in this study over the recent float. Overall, the results suggest that the model that is capable of representing both nonlinear and long memory characteristics may help identifying mean reversion in real exchange rates. That is, the *FI-NLAR-ESTAR* model works better than the linear fractionally integrated model such as *ARFIMA* in terms of its ability to detect mean reversion to the long run equilibrium level in real exchange rates. The need for the nonlinear model for strongly persistent processes is apparently indicated by the fractional integration analysis which is strongly supportive of the mean reverting process of real exchange rates. In general, this study illustrates that the puzzling behavior of real exchange rates may be due to both nonlinear and long memory dynamics, which weaken the ability of standard unit root tests to detect mean reversion to the long run equilibrium level.

Table 3.1. Summary statistics

	Real exchange rate				
Currency	CHF	GBP	JPY	NOK	SEK
Mean	0.3187	-0.4267	4.7431	1.9121	1.8851
Standard dev.	0.2092	0.1484	0.2518	0.1413	0.1873
ACF1	0.9768	0.9757	0.9843	0.9724	0.9853
ACF2	0.9524	0.9474	0.9672	0.9433	0.9688
ACF3	0.9280	0.9182	0.9493	0.9123	0.9521
ACF4	0.9028	0.8889	0.9306	0.8811	0.9338
ACF5	0.8789	0.8591	0.9125	0.8524	0.9143
ACF6	0.8549	0.8291	0.8950	0.8228	0.8944
LB	5733.92	5461.51	6736.65	5292.47	6703.80
T	490	490	490	490	490

Note. Real exchange rates are in logs. ACF1-ACF6 denote autocorrelation functions up to lag 6. LB denotes the Ljung-Box test statistic for autocorrelations up to 20 lags. T denotes the sample size.

Table 3.2. Estimated *FI-NLAR-ESTAR* models for monthly real exchange rates

	Real exchange rate				
Currency	CHF	GBP	JPY	NOK	SEK
LW	0.9075	0.8757	0.6165	0.6244	0.6592
Nonlinearity tests					
TLG	0.002	0.026	0.137	0.000	0.009
ANN	0.001	0.037	0.110	0.000	0.012
Estimation of *FI-NLAR-ESTAR* model					
p	9	12	8	10	8
k	1	1	1	1	1
Linear *AR* parameters					
α_0	0.9356	-0.1033	-1.0460	-0.1208	-0.1715
	(0.5044)	(0.1319)	(0.0442)	(0.2618)	(0.3652)
α_1	-0.1081	0.8497	-1.6554	1.4066	0.6528
	(0.2741)	(0.3548)	(0.2921)	(0.0578)	(0.5183)
α_2	0.0823	0.0842	0.1162	-0.2432	0.0605
	(0.0572)	(0.0552)	(0.4743)	(0.1600)	(0.1194)
α_3	0.0867	0.0385	0.0875	-0.1522	0.1011
	(0.0566)	(0.0552)	(0.3395)	(0.0940)	(0.1166)
α_4	-0.0027	0.0388	-0.0444	-0.0208	0.0084
	(0.0690)	(0.0551)	(0.5132)	(0.1023)	(0.1289)
α_5	0.0455	0.0152	0.0116	0.0759	0.0145
	(0.0666)	(0.0556)	(0.1902)	(0.0829)	(0.1241)
α_6	-0.0665	-0.0661	-0.0611	-0.1280	-0.1231
	(0.0657)	(0.0537)	(0.6066)	(0.0817)	(0.1137)
α_7	0.0848	0.0043	0.0413	0.1338	0.0785
	(0.0691)	(0.0508)	(0.4822)	(0.0882)	(0.1158)
α_8	-0.0171	0.0416	0.1279	-0.0936	0.0676
	(0.0987)	(0.0538)	(0.5507)	(0.0820)	(0.0983)
α_9	0.1002	0.0450		0.0774	
	(0.0594)	(0.0556)		(0.0923)	
α_{10}		-0.0739		-0.0705	
		(0.0557)		(0.0511)	
α_{11}		0.1457			
		(0.0555)			
α_{12}		-0.0787			
		(0.0467)			

Table 3.2. Estimated *FI-NLAR-ESTAR* models for monthly real exchange rates (continued)

	Real exchange rate				
Currency	CHF	GBP	JPY	NOK	SEK
Nonlinear *AR* parameters					
β_0	-1.9401	0.2132	2.0330	0.1577	2.5712
	(0.4007)	(0.1489)	(0.2350)	(0.2311)	(0.4284)
β_1	-0.0105	-0.2141	0.0633	-0.0008	-0.6328
	(0.3192)	(0.3443)	(1.2233)	(0.1223)	(0.5509)
θ	0.2382	0.3091	1.7287	0.6007	0.0439
	(0.1571)	(0.9293)	(0.0237)	(1.2970)	(0.0216)
c	1.7175	0.1865	-0.6452	-2.5684	-0.8524
	(0.0747)	(0.3622)	(0.0528)	(0.2799)	(0.0544)
d	0.6729	0.4182	0.6414	0.5907	0.4635
	(0.0763)	(0.0207)	(0.0244)	(0.1860)	(0.0361)
LBR	10.56	13.45	6.09	8.76	11.07
Results from *ARFIMA* models					
p	9	9	10	11	8
d	0.9243	0.6485	0.7685	0.9008	0.2952
	(0.4141)	(0.2550)	(0.2770)	(0.2450)	(0.1618)

Note. *LW* denotes the Local Whittle estimate. *TLG* and *ANN* denote the tests for nonlinearity developed by Teräsvirta et al. (1993) and Lee et al. (1993), respectively. *LBR* denotes the Ljung-Box statistic for residual autocorrelation.

Table 3.3. Fractional integration analysis for *ARFIMA* models

Results from *ARFIMA* models				
Currency	d	Standard error	Testing H_0:$d = 0$ against H_1:$d > 0$	Testing H_0:$d = 1$ against H_1:$d < 1$
CHF	0.9243	0.4141	2.2321**	-0.1828
GBP	0.6485	0.2550	2.5431***	-1.3784*
JPY	0.7685	0.2770	2.7744***	-0.8357
NOK	0.9008	0.2450	3.6767***	-0.4049
SEK	0.2952	0.1618	1.8245**	-4.3560***

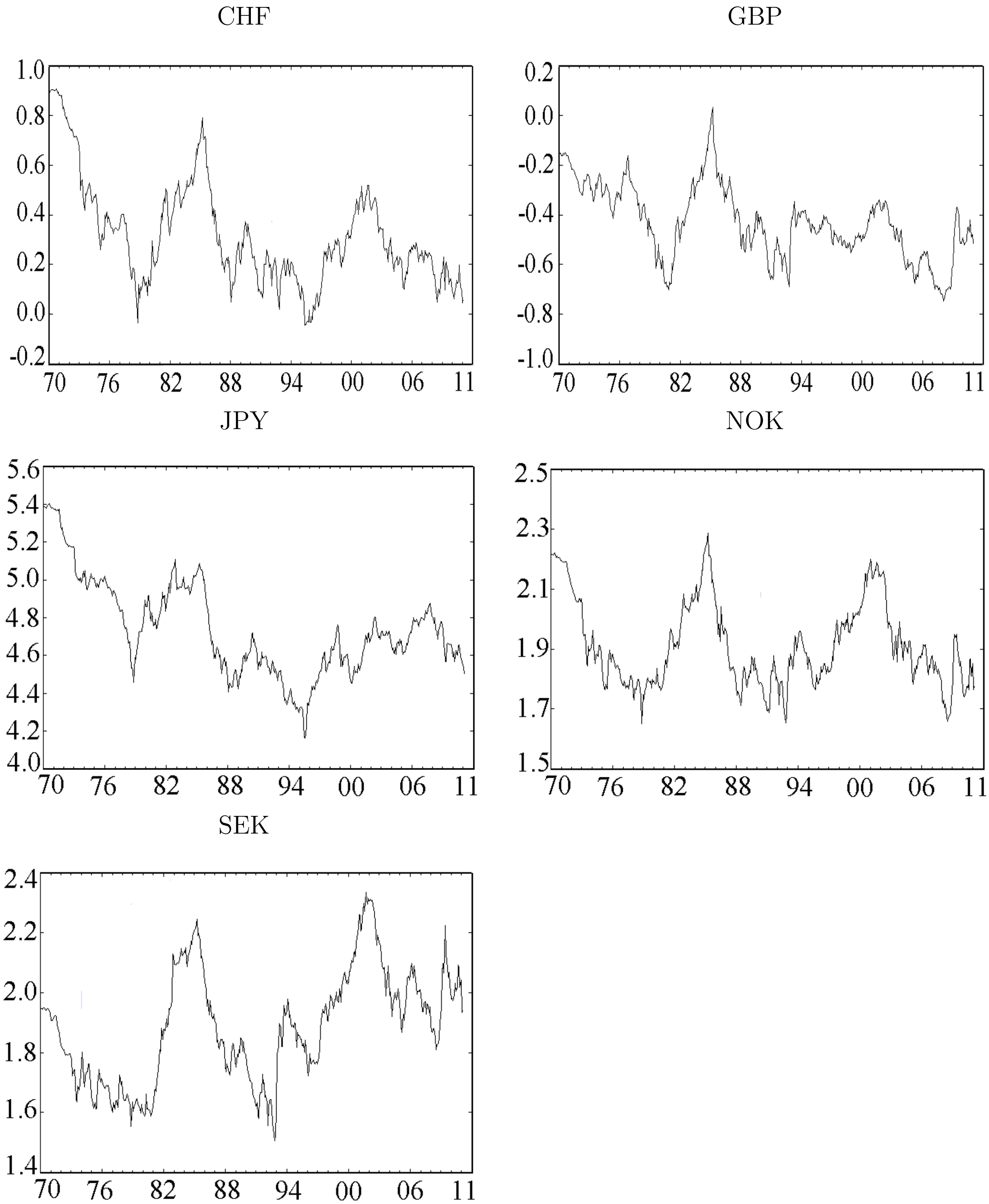
Note. d denotes the *MLE* of the long memory parameter. The t-statistics for each hypothesis testing are reported. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 3.4. Fractional integration analysis for *FI-NLAR-ESTAR* models

Results from *FI-NLAR-ESTAR* models				
Currency	d	Standard error	Testing H_0:$d = 0$ against H_1:$d > 0$	Testing H_0:$d = 1$ against H_1:$d < 1$
CHF	0.6729	0.0763	8.8191***	-4.2870***
GBP	0.4182	0.0207	20.2029***	-28.1063***
JPY	0.6414	0.0244	26.2869***	-14.6967***
NOK	0.5907	0.1860	3.1758***	-2.2005**
SEK	0.4635	0.0361	12.8393***	-14.8615***

Note. As for Table 3.3.

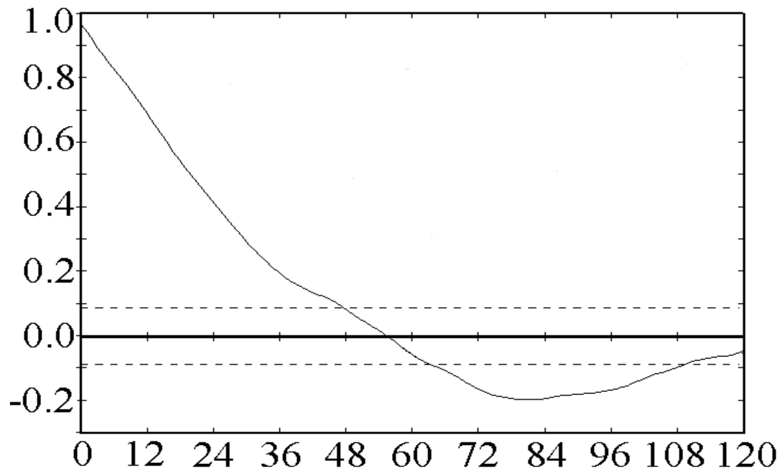
Figure 3.1. Logarithms of monthly real exchange rates vis-à-vis the US Dollar over time



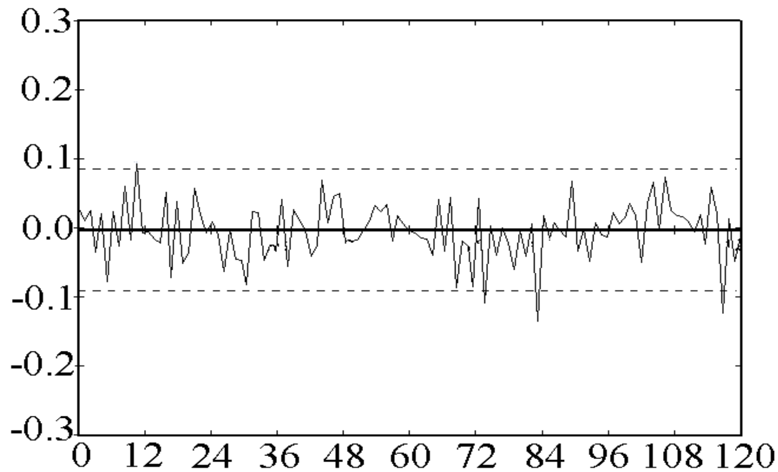
Note. The sample period is from January 1970 through October 2010.

Figure 3.2. Autocorrelations

(a) CHF



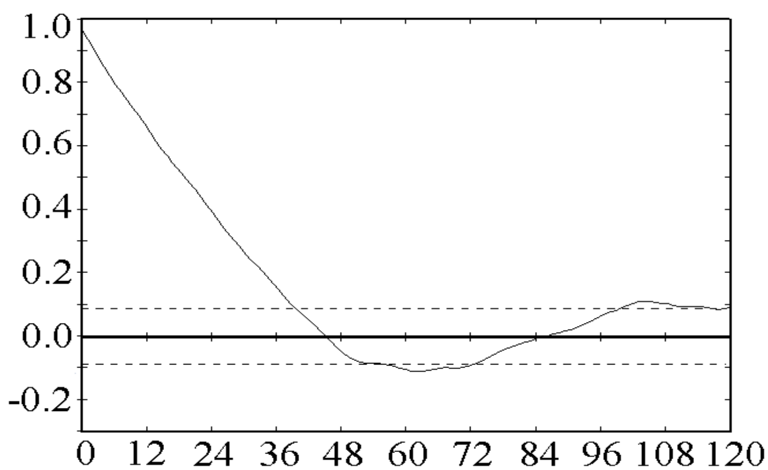
(b) CHF



Note. (a) Autocorrelations of the logarithms of real exchange rates. The horizontal axis represents the first 120 lags of the autocorrelations of monthly real exchange rates. (b) Autocorrelations of differenced real exchange rates. The horizontal line represents the first 120 lags of the autocorrelations of the first differences of monthly real exchange rates. The dashed lines indicate the Bartlett 95 percent confidence intervals.

Figure 3.2. Autocorrelations (continued)

(a) GBP



(b) GBP

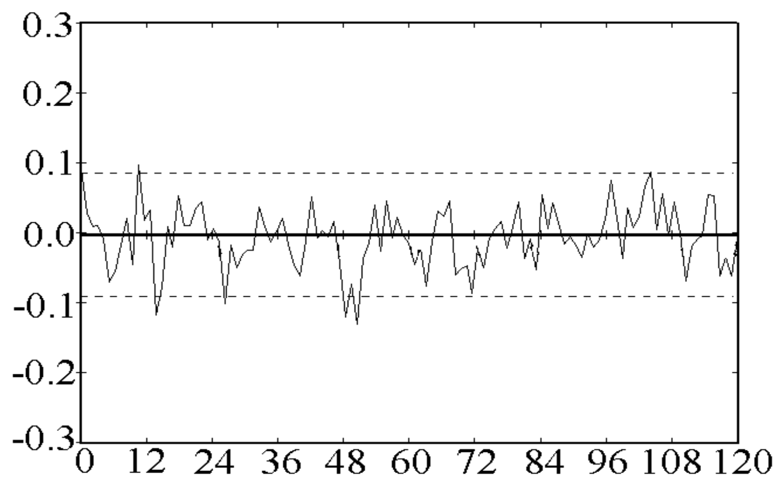
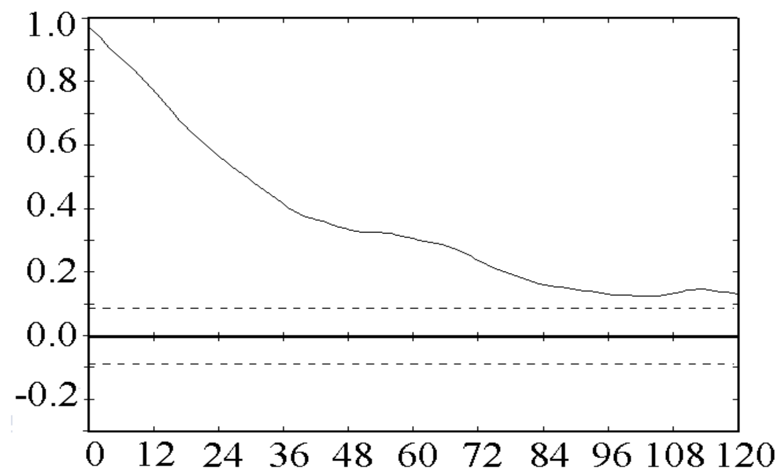


Figure 3.2. Autocorrelations (continued)

(a) JPY



(b) JPY

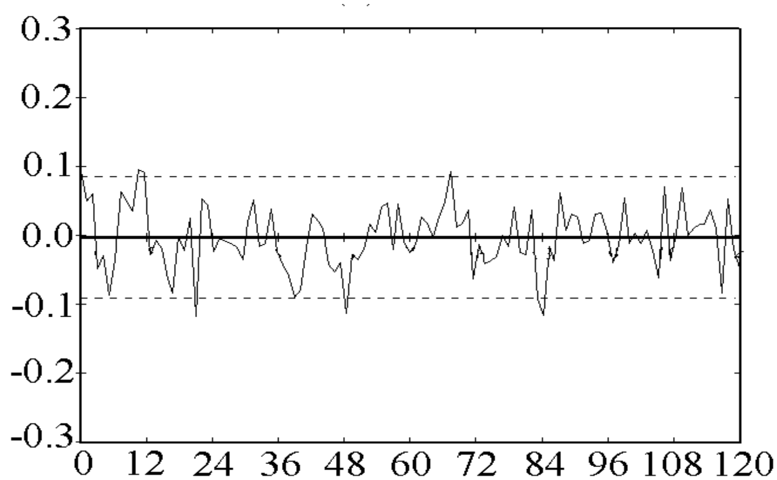
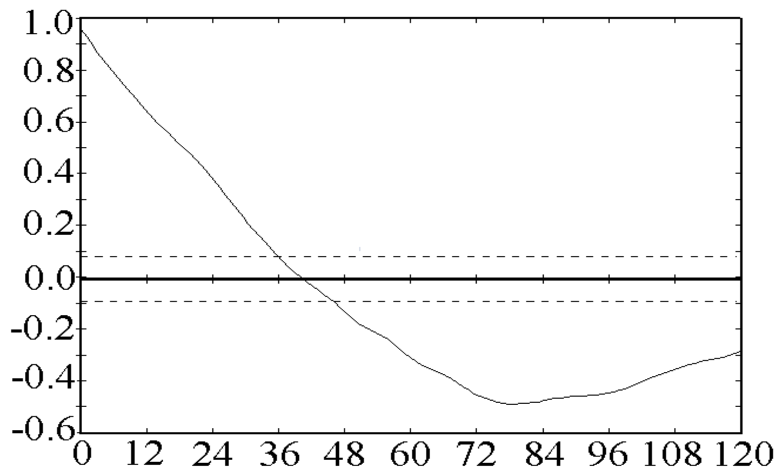


Figure 3.2. Autocorrelations (continued)

(a) NOK



(b) NOK

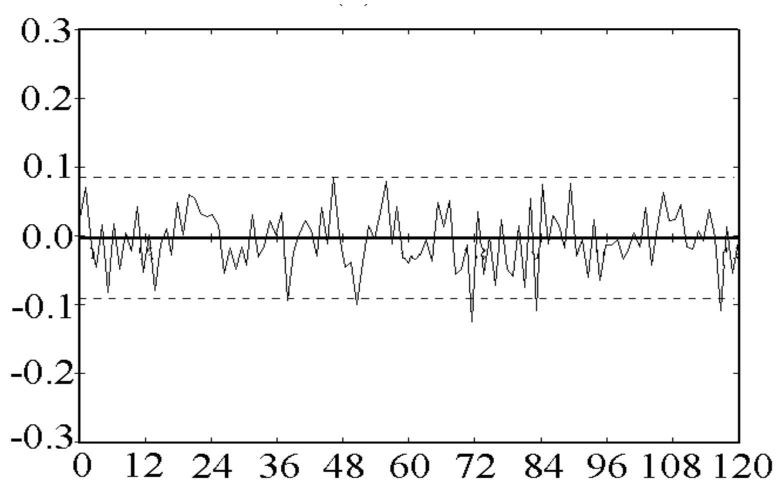
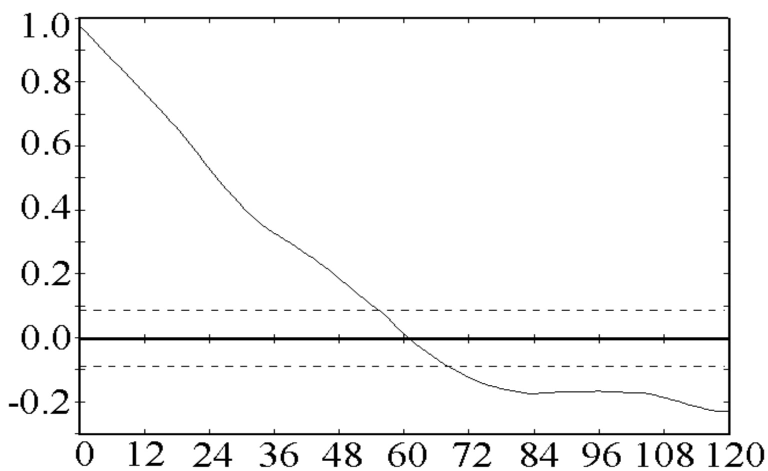
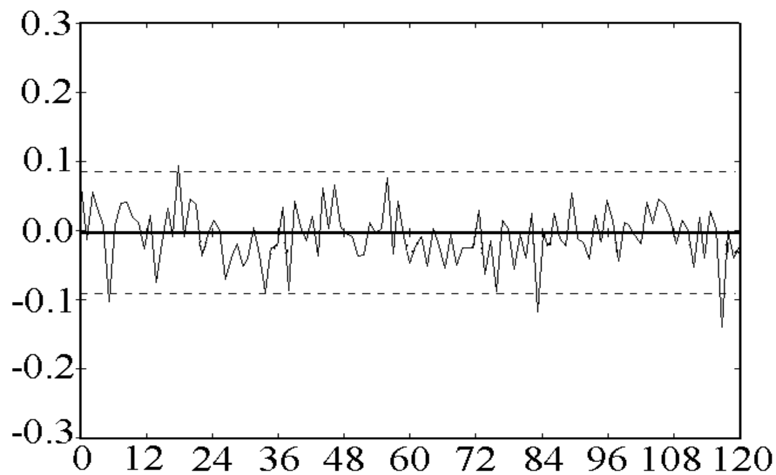


Figure 3.2. Autocorrelations (continued)

(a) SEK



(b) SEK



BIBLIOGRAPHY

Bibliography

Abreu, D. and Brunnermeier, M. K. (2003). Bubbles and Crashes. *Econometrica*, 71:173–204.

Abuaf, N. and Jorion, P. (1990). Purchasing power parity in the long run. *Journal of Finance*, 45:157–174.

Ahearne, A., Kydland, F. E., and Wynne, M. (2006). Ireland's Great Depression. *The Economic and Social Review*, 37:215–243.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Labys, P. (2003). Modelling and Forecasting Realised Volatility. *Econometrica*, 71:579–625.

Asness, C., Moskowitz, T. J., and Pedersen, L. H. (2009). Value and Momentum Everywhere. *AFA 2010 Atlanta Meetings Paper*.

Baillie, R. T. (1996). Long memory processes and fractional integration in econometrics. *Journal of Econometrics*, 73:5–59.

Baillie, R. T. and Bollerslev, T. (1994). The long memory of the forward premium. *Journal of International Money and Finance*, 13:565–571.

Baillie, R. T., Chung, C. F., and Tieslau, M. A. (1996). Analysing inflation by the fractionally integrated ARFIMA-GARCH model. *Journal of Applied Econometrics*, 11:23–40.

Baillie, R. T. and Kapetanios, G. (2007). Testing for Neglected Nonlinearity in Long- Memory Models. *Journal of Business and Economic Statistics*, 25:447–461.

Baillie, R. T. and Kapetanios, G. (2008). Nonlinear models for strongly dependent processes with financial applications. *Journal of Econometrics*, 147:60–71.

Baillie, R. T. and Kapetanios, G. (2010). Estimation and Inference for Impulse Response Weights for Strongly Persistent Processes. *Michigan State University, Working paper*.

Baillie, R. T. and Kiliç, R. (2006). Do asymmetric and nonlinear adjustments explain the forward premium anomaly? *Journal of International Money and Finance*, 25:22–47.

Bansal, R. and Dahlquist, M. (2000). The Forward Premium Puzzle: Different tales from Developed and Emerging Economies. *Journal of International Economics*, 51:115–144.

Baum, C. F., Barkoulas, J. T., and Caglayan, M. (2001). Nonlinear adjustment to purchasing power parity in the post-Bretton Woods era. *Journal of International Money and Finance*, 20:379–399.

Benjamin, D. and Meza, F. (2009). Total Factor Productivity and Labor Reallocation: The Case of the Korean 1997 Crisis. *The B.E. Journal of Macroeconomics (Advances)*, 9:1–39.

Bergoeing, R., Kehoe, P. J., Kehoe, T. J., and Soto, R. (2002). A Decade Lost and Found: Mexico and Chile in the 1980s. *Review of Economic Dynamics*, 5:166–205.

Bernanke, B., Gertler, M., and Gilchrist, S. (1999). *The Financial Accelerator in a Quantitative Business Cycle Framework*. In Handbook of Macroeconomics, Taylor, J. and Woodford, M. (Eds.), North-Holland, Amsterdam.

Betts, C. M. and Kehoe, T. J. (2008). Real Exchange Rate Movements and the Relative Price of Non-traded Goods. *Research Department Staff Report 415, Federal Reserve Bank of Minneapolis*.

Bhansali, V. (2007). Volatility and the Carry Trade. *Journal of Fixed Income*, 17:72–84.

Broda, C. and Romalis, J. (2009). Identifying the Relationship Between Trade and Exchange Rate Volatility. *Commodity Prices and Markets, East Asia Seminar on Economics*, 20.

Brodsky, D. A. (1984). Fixed Versus Flexible Exchange Rates and the Measurement of Exchange Rate Instability. *Journal of International Economics*, 16:295–306.

Brunnermeier, M. K., Nagel, S., and Pedersen, L. H. (2008). Carry Trades and Currency Crashes. *NBER Macroeconomics Annual*, 23:313–347.

Brunnermeier, M. K. and Pedersen., L. H. (2009). Market Liquidity and Funding Liquidity. *Review of Financial Studies*, 22:2201–2238.

Burnside, C., Eichenbaum, M., Kleshchelski, I., and Rebelo, S. (2011). Do Peso Problems explain the returns to the Carry Trade? *Review of Financial Studies*, 24:853–891.

Burnside, C., Eichenbaum, M., and Rebelo, S. (2001). Prospective deficits and the Asian currency crisis. *Journal of Political Economy*, 109:1155–1197.

Burnside, C., Eichenbaum, M., and Rebelo, S. (2007). The Returns to Currency Speculation in Emerging Markets. *American Economic Review Papers and Proceedings*, 97:333–338.

Calvo, G. A. (2000). *Balance of Payments Crises in Emerging Markets: Large Capital Inflows and Sovereign Governments*. In Currency crises, Krugman, P. R. (Eds.), University of Chicago Press, Chicago, IL.

Calvo, G. A. and Reinhart, C. M. (2002). Fear of floating. *Quarterly Journal of Economics*, 107:379–408.

Cargill, T. F. and Parker, E. (2002). Asian finance and the role of bankruptcy: a model of the transition costs of financial liberalization. *Journal of Asian Economics*, 13:297–318.

Chakraborty, S. (2009). The boom and the bust of the Japanese economy: A quantitative look at the period 1980-2000. *Japan and the World Economy*, 21:116–131.

Chari, V. V., Kehoe, P. J., and McGrattan, E. R. (2002). Accounting for the Great Depression. *American Economic Review Papers and Proceedings*, 92:22–27.

Chari, V. V., Kehoe, P. J., and McGrattan, E. R. (2005). Sudden Stops and Output Drops. *American Economic Review*, 95:381–387.

Chari, V. V., Kehoe, P. J., and McGrattan, E. R. (2006). Appendices: Business Cycle Accounting. *Federal Reserve Bank of Minneapolis Research Department Staff Report*, 362:1–53.

Chari, V. V., Kehoe, P. J., and McGrattan, E. R. (2007). Business Cycle Accounting. *Econometrica*, 75:781–836.

Cheung, Y. W. (1993). Long memory in foreign exchange rates. *Journal of Business and Economic Statistics*, 11:93–101.

Cheung, Y. W. and Lai, K. S. (2000). On cross-country differences in the persistence of real exchange rates. *Journal of International Economics*, 50:375–397.

Cheung, Y. W. and Lai, K. S. (2001). Long Memory and Nonlinear Mean Reversion in Japanese Yen-Based Real Exchange Rates. *Journal of International Money and Finance*, 20:115–132.

Choi, K., Yu, W., and Zivot, E. (2010). Long Memory versus Structural Breaks in Modeling and Forecasting Realized Volatility. *Journal of International Money and Finance*, 29:857–875.

Christiano, L. J. and Davis, J. M. (2006). Two flaws in business cycle accounting. *NBER Working Papers*, 12647.

Clark, P., Tamirisa, N., Wei, S. J., Sadikov, A., and Zeng, L. (2004). A New Look at Exchange Rate Volatility and Trade Flows. *IMF Occasional Paper*, 235.

Cociuba, S. E. and Ueberfeldt, A. (2008). Driving forces of the Canadian economy: an accounting exercise. *Manuscript, Bank of Canada*.

Cole, H. L. and Kehoe, T. J. (1996). A self-fulfilling model of Mexico's 1994-1995 debt crisis. *Journal of International Economics*, 41:309–330.

Cole, H. L. and Kehoe, T. J. (2000). Self-fulfilling debt crises. *Review of Economic Studies*, 67:91–116.

Conesa, J. C., Kehoe, T. J., and Ruhl, K. J. (2007). Modeling Great Depressions: The Depression in Finland in the 1990s. *Federal Reserve Bank of Minneapolis Quarterly Review*, 31:16–44.

Dell'Ariccia, G. (1999). Exchange Rate Fluctuations and Trade Flows: Evidence from the European Union. *IMF Staff Papers*, 46:315–334.

Diebold, F. X., Husted, S., and Rush, M. (1991). Real Exchange Rates Under the Gold Standard. *Journal of Political Economy*, 99:1252–1271.

Diebold, F. X. and Inoue, A. (2001). Long Memory and Regime Switching. *Journal of Econometrics*, 105:131–159.

Dornbusch, R. (1976). Expectations and Exchange Rate Dynamics. *Journal of Political Economy*, 84:11611176.

Engel, C. (1996). The Forward Discount Anomaly and the Risk Premium: A Survey of Recent Evidence. *Journal of Empirical Finance*, 3:123–192.

Engel, C. and West, K. D. (2005). Exchange rates and Fundamentals. *Journal of Political Economy*, 113:485–517.

Fabio, K. (2004). Real interest rates and Brazilian business cycles. *Review of Economic Dynamics*, 7:436–455.

Fama, E. F. (1984). Forward and Spot Exchange rates. *Journal of Monetary Economics*, 14:319–338.

Flood, R. P. and Garber, P. M. (1984). Collapsing exchange rate regimes: Some linear examples. *Journal of International Economics*, 17:1–13.

Frankel, J. A. and Rose, A. K. (1996a). A panel project on purchasing power parity: mean reversion within and between countries. *Journal of International Economics*, 40:209–224.

Frankel, J. A. and Rose, A. K. (1996b). Currency Crashes in emerging markets: An empirical treatment. *Journal of International Economics*, 41:351–366.

Frankel, J. A. and Wei, S. J. (1993). Trade Blocs and Currency Blocs. *NBER Working Paper*.

Froot, K. A. and Rogoff, K. (1995). *Perspectives on PPP and long-run real exchange rates*. In Handbook of International Economics 3, Grossman, G., Rogoff, K. (Eds.), North-Holland, New York, NY.

Froot, R. A. and Thaler, R. H. (1990). Anomalies: Foreign exchange. *Journal of Economic Perspectives*, 4:179–192.

Gallant, A. R., Rossi, P. E., and Tauchen, G. (1993). Nonlinear Dynamic Structures. *Econometrica*, 61:871–908.

Ghosh, S. (2006). East Asian finance: The road to robust markets. *The World Bank*, pages 1–217.

Granger, C. W. J. (1980). Long Memory Relationships and the Aggregation of Dynamic Models. *Journal of Econometrics*, 14:227–238.

Granger, C. W. J. and Joyeux, R. (1980). An introduction to long memory time series models and fractional differencing. *Journal of Time Series Analysis*, 1:15–39.

Granger, C. W. J. and Teräsvirta, T. (1993). *Modelling Nonlinear Economic Relationships.* Oxford University Press, New York, NY.

Gregoriou, A. and Kontonikas, A. (2009). Modeling the behaviour of inflation deviations from the target. *Economic Modelling*, 26:90–95.

Hansen, L. P. and Hodrick, R. J. (1980). Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis. *Journal of Political Economy*, 88:829–853.

Hau, H. (2002). Real Exchange Rate Volatility and Economic Openness: Theory and Evidence. *Journal of Money, Credit and Banking*, 34:611–630.

Hodrick, R. J. (1987). *The Empirical Evidence on the Efficiency of Forward and Futures Foreign Exchange Markets.* Harwood Academic Publishers, London.

Hodrick, R. J. (1989). Risk, uncertainty and exchange rates. *Journal of Monetary Economics*, 23:433–459.

Hornstein, A. and Prescott, E. C. (1993). *The Firm and the Plant in General Equilibrium Theory.* In General Equilibrium, Growth, and Trade, Becker R. et al. (Eds.), San Diego: Academic Press, San Diego, CA.

Hosking, J. R. M. (1981). Fractional differencing. *Biometrika*, 65:15–39.

Imbs, J. M., Mumtaz, H., Ravn, M. O., and Rey, H. (2005). PPP Strikes Back: Aggregation and the real exchange rate. *Quarterly Journal of Economics*, 120:1–43.

Jordà, O. and Taylor, A. M. (2009). The Carry Trade and Fundamentals: Nothing to Fear But FEER Itself. *NBER Working Paper.*

Kaminsky, G. L. (2006). Currency crises: Are they all the same? *Journal of International Money and Finance*, 25:503–527.

Kaminsky, G. L. and Reinhart, C. M. (1999). The Twin Crises: The Causes of Banking and Balance-Of-Payments Problems. *American Economic Review*, 89:473–500.

Kapetanios, G. (2003). Threshold Models for Trended Time Series. *Empirical Economics*, 28:687–707.

Kapetanios, G., Shin, Y., and Snell, A. (2003). Testing for a Unit Root in the Nonlinear STAR Framework. *Journal of Econometrics*, 112:359–379.

Kehoe, T. J. (2003). What can we learn from the current crisis in Argentina? *Scottish Journal of Political Economy*, 50:609–633.

Kehoe, T. J. and Ruhl, K. J. (2009). Sudden Stops, Sectoral Reallocations, and the Real Exchange Rate. *Journal of Development Economics*, 89:235–249.

Kenen, P. and Rodrik, D. (1986). Measuring and Analysing the Effects of Short-Term Volatility on Real Exchange Rates. *Review of Economics and Statistics*, 68:311–315.

Kersting, E. (2008). The 1980s recession in the UK: A business cycle accounting perspective. *Review of Economic Dynamics*, 11:179–191.

Kilian, L. and Zha, T. (2002). Quantifying the uncertainty about the half-life of deviations from PPP. *Journal of Applied Econometrics*, 17:107–125.

Kiliç, R. (2009a). Further on nonlinearity, persistence, and integration properties of real exchange rates. *Journal of International Financial Market, Institutions and Money*, 19:207–211.

Kiliç, R. (2009b). Nonlinearity and Persistence in PPP: Does Controlling for Nonlinearity Solve the PPP Puzzle? *Review of International Economics*, 17:570–587.

Koop, G., Pesaran, M. H., and Potter, S. (1996). Impulse Response Analysis in Nonlinear Multivariate Models. *Journal of Econometrics*, 74:119–147.

Krugman, P. R. (1979). A model of balance-of-payments crises. *Journal of Money, Credit and Banking*, 11:311–325.

Kydland, F. E. and Prescott, E. C. (1988). The Workweek of Capital and Its Cyclical Implications. *Journal of Monetary Economics*, 21:343–360.

Kydland, F. E. and Zarazaga, C. E. J. M. (2002). Argentina's Lost Decade. *Review of Economic Dynamics*, 5:152–165.

Kydland, F. E. and Zarazaga, C. E. J. M. (2004). Argentina's Capital Gap Puzzle. *Manuscript, Federal Reserve Bank of Dallas, Center for Latin American Economics.*

Laeven, L. and Valencia, F. (2008). Systematic Banking Crises: A New Database. *IMF Working Paper.*

Lama, R. (2011). Accounting for Output Drops in Latin America. *Review of Economic Dynamics*, 14:295–316.

Lee, T. H., White, H., and Granger, C. W. J. (1993). Testing for Neglected Nonlinearity in Time Series Models: A Comparison of Neural Network Methods and Alternative Tests. *Journal of Econometrics*, 56:269–290.

Lothian, J. R. and Taylor, M. P. (1996). Real Exchange Rate Behavior: the Recent Float from the Perspective of the Past Two Centuries. *Journal of Political Economy*, 104:488–509.

Mark, N. C. (1995). Exchange Rates and Fundamentals: Evidence on Long-Horizon Predictability. *American Economic Review*, 85:201–218.

Mark, N. C. and Wu, Y. (1997). Rethinking deviations from uncovered interest rate parity: the role of covariance risk and noise. *The Economic Journal*, 108:1686–1706.

McGrattan, E. R. (1994). The macroeconomic effects of distortionary taxation. *Journal of Monetary Economics*, 33:573–601.

McGrattan, E. R. (1996). Solving the stochastic growth model with a finite element method. *Journal of Economic Dynamics and Control*, 20:19–42.

Meese, R. C. and Rogoff, K. (1983). Empirical exchange rate models of the seventies : Do they fit out of sample? *Journal of International Economics*, 14:3–24.

Meza, F. (2008). Financial Crisis, Fiscal Policy and the 1995 GDP Contraction in Mexico. *Journal of Money, Credit and Banking*, 40:1239–1261.

Michael, P., Nobay, A. R., and Peel, D. A. (1997). Transactions Costs and Nonlinear Adjustment in Real Exchange Rates: An Empirical Investigation. *Journal of Political Economy*, 105:862–879.

Molodtsova, T. and Papell, D. H. (2009). Out-of-Sample Exchange Rate Predictability with Taylor Rule Fundamentals. *Journal of International Economics*, 77:137–276.

Murray, C. J. and Papell, D. H. (2005). Do Panels Help Solve the Purchasing Power Parity Puzzle? *Journal of Business and Economic Statistics*, 23:410–415.

Neumeyer, P. A. and Reny, F. (2005). Business cycles in emerging economies: The role of interest rates. *Journal of Monetary Economics*, 52:345–380.

Nozaki, M. (2010). Do Currency Fundamentals Matter for Currency Speculators? *IMF Working paper.*

Obstfeld, M. (1994). The logic of currency crises. *Banque de France – Cahiers économiqueset monétaires*, 43:189–213.

Otsu, K. (2008). A neoclassical analysis of the Korean crisis. *Review of Economic Dynamics*, 11:449–471.

Papell, D. H. (1997). Searching for stationarity: Purchasing power parity under the current float. *Journal of International Economics*, 43:313–332.

Parke, W. R. (1999). What is Fractional Integration? *Review of Economics and Statistics*, 81:632–638.

Ranaldo, A. and Söderland, P. (2010). Safe Haven Currencies. *Review of Finance*, 14:385–407.

Reinhart, C. M. and Rogoff, K. S. (2009). *This Time Is Different: Eight Centuries of Financial Folly.* Princeton University Press, Princeton, NJ.

Rogoff, K. (1996). The Purchasing Power Parity Puzzle. *Journal of Economic Literature*, 34:647–668.

Rose, A. K. (2000). One Money, One Market: The Effect of Common Currencies on Trade. *Economic Policy*, April:9–45.

Rossi, B. (2005). Confidence intervals for half-life deviations from Purchasing Power Parity. *Journal of Business and Economic Statistics*, 23:432–442.

Sarantis, N. (1999). Modelling Nonlinearities in Real Effective Exchange Rates. *Journal of International Money and Finance*, 18:27–45.

Sarno, L. (2001). The behavior of US public debt: a nonlinear perspective. *Economics Letters*, 74:119–125.

Schneider, M. and Tornell, A. (2004). Balance Sheet Effects, Bailout Guarantees and Financial Crises. *Review of Economic Studies*, 71:883–913.

Simonovska, I. and Soderling, L. (2008). Business Cycle Accounting For Chile. *IMF Working Paper*.

Sustek, R. (2011). Monetary business cycle accounting. *Review of Economic Dynamics*, Forthcoming.

Taylor, M. P., Peel, D. A., and Sarno, L. (2001). Nonlinear mean-reversion in real exchange rates: Toward a solution to the purchasing power parity puzzles. *International Economic Review*, 42:1015–1042.

Taylor, M. P. and Sarno, L. (1998). The behavior of real exchange rates during the post-Bretton Woods period. *Journal of International Economics*, 46:281–312.

Taylor, M. P. and Sarno, L. (2001). Real Exchange Rate Dynamics in Transition Economies: A Nonlinear Analysis. *Studies in Nonlinear Dynamics and Econometrics*, 5:153–177.

Teräsvirta, T. (1994). Specification, estimation and evaluation of smooth transition autoregressive models. *Journal of the American Statistical Association*, 89:208–218.

Teräsvirta, T., Lin, C. F., and Granger, C. W. J. (1993). Power of the Neural Network Linearity Test. *Journal of Time Series Analysis*, 14:209–220.

van Dijk, D., Frances, P. H., and Paap, R. (2002a). Nonlinear Long Memory Model with Application to US Unemployment. *Journal of Econometrics*, 110:135–165.

van Dijk, D., Teräsvirta, T., and Franses, P. H. (2002b). Smooth transition autoregressive models - A survey of recent developments. *Econometric Reviews*, 21:1–47.

Wu, Y. (1996). Are real exchange rates nonstationary? Evidence from a panel-data test. *Journal of Money, Credit and Banking*, 28:54–63.