Trade Intensity, Carry Trades and Exchange Rate Volatility*

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Abstract

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 for 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.

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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 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 Burnside et al. (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. (2008), 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

[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".

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 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 coun-

[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.

tries 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, we describe our data. In Section 3, we provide preliminary evidence of a linkage between trade intensity and exchange rate volatility. In Section 4, we introduce the *ESTAR* model, and describe how to estimate half-lives of deviations from PPP. In Section 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 6, we define carry trade returns, and the performance statistics for carry trade strategies is presented. In Section 7, we conclude.

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 (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 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.

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

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.

3.1 Measuring exchange rate volatility

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

$$q_t \equiv s_t - p_t + p_t^* \tag{1}$$

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 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 Rodrick (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

[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.

the bilateral real exchange rate as

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

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.

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

$$tradeint^{\max}_{X,Y,t} = \max \left[\begin{array}{c} \left(\frac{export_{X,Y,t} + export_{Y,X,t}}{\sum\limits_{all} export_{X,i,t} + \sum\limits_{all} export_{i,X,t}} \right), \\ \\ \left(\frac{export_{X,Y,t} + export_{Y,X,t}}{\sum\limits_{all} export_{Y,i,t} + \sum\limits_{all} export_{i,Y,t}} \right) \end{array} \right] \tag{3}$$

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 (3), and is defined as (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

$$tradeint^{\text{avg}}_{X,Y,t} = \text{avg}\left[\begin{array}{c} \left(\frac{export_{X,Y,t}+export_{Y,X,t}}{\sum\limits_{all} export_{X,i,t}+\sum\limits_{all} export_{i,X,t}}\right), \\ \\ \left(\frac{export_{X,Y,t}+export_{Y,X,t}}{\sum\limits_{all} export_{Y,i,t}+\sum\limits_{all} export_{i,Y,t}}\right) \end{array}\right] \quad (4)$$

This definition uses the average of two fractions in any bilateral trade relationship. If we apply the definition in (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 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 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. 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 the next two sections, we introduce the *ESTAR* model, and demonstrate how to measure half-lives of deviations from PPP.

[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.

4 Econometric Framework

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 (1) may be written as

$$(q_t - \mu) = \sum_{j=1}^{p} \theta_j \left(q_{t-j} - \mu\right) + \left[\sum_{j=1}^{p} \theta_j^* \left(q_{t-j} - \mu\right)\right] \Phi\left(q_{t-d} - \mu; \gamma, c\right) + \varepsilon_t \tag{5}$$

where $\{q_t\}$ is a stationary and ergodic process, $\varepsilon_t \sim iid\left(0, \sigma^2\right)$, and $\Phi\left(\cdot\right)$ 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 (5) may also be written, reparameterized in a first difference form as

$$\Delta q_t = \alpha + \rho q_{t-1} + \sum_{j=1}^{p-1} \beta_j \Delta q_{t-j} + \left[\alpha^* + \rho^* q_{t-1} + \sum_{j=1}^{p-1} \beta_j^* \Delta q_{t-j}\right] \Phi\left(q_{t-d}; \gamma, c\right) + \varepsilon_t \tag{6}$$

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

$$\Phi\left(q_{t-d}; \gamma, c\right) = 1 - \exp\left[-\gamma\left(q_{t-d} - c\right)^2 / \sigma_{q_{t-d}}\right] \quad \text{with } \gamma > 0 \tag{7}$$

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 (7), Equation (6) is called the exponential *STAR* (*ESTAR*) model. The exponential function in Equation (7) is bounded between

0 and 1, and depends on the transition variable q_{t-d}. The exponential function also has the properties that $\Phi(q_{t-d};\gamma,c) \rightarrow 1$ both as $q_{t-d} \rightarrow -\infty$ and $q_{t-d} \rightarrow \infty$ whereas $\Phi(q_{t-d};\gamma,c) = 0$ for $q_{t-d} = c$, and is symmetrically inverse-bell shaped around zero. For either $\gamma \rightarrow 0$ or $\gamma \rightarrow \infty$, the exponential function given by Equation (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 (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 (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 (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 et al. (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 Terä svirta (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. (2002), 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 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 (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.

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

$$GI_q\left(h,\delta,\omega_{t-1}\right)=E\left[q_{t+h}\mid\varepsilon_t=\delta,\omega_{t-1}\right]-E\left[q_{t+h}\mid\omega_{t-1}\right] \tag{8}$$

for $h=0,1,2,....$ In Equation (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

$$GI_q\left(h,\varepsilon_t,\Omega_{t-1}\right)=E\left[q_{t+h}\mid\varepsilon_t,\Omega_{t-1}\right]-E\left[q_{t+h}\mid\Omega_{t-1}\right] \tag{9}$$

Equation (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 (8) for all observations in the estimation sample and value of the initial shock. For the history and the initial shock, we compute $GI_{\Delta q}\left(h,\delta,\omega_{t-1}\right)$ for horizons $h=0,1,2,...,100$. The conditional expectations in Equation (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

[6] Kiliç (2009) 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.

obtained by accumulating the impulse responses for the first differences as

$$GI_q(h, \delta, \omega_{t-1}) = \sum_{i=1}^{h} GI_{\Delta q}(i, \delta, \omega_{t-1}) \tag{10}$$

The estimated GIs for both high and low trade intensity currency pairs are depicted in Figures 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.

5 Empirical Results

5.1 Preliminary Analysis

5.1.1 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 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 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.

5.1.2 Robustness checks

In Table 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 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 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 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 3 (c), the results in both subsamples are almost exactly equal to each other and to the overall results reported in Table 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 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

[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.

and exchange rate volatility holds up well across the different robustness tests.

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 4, we report estimation results from *ESTAR* models as given by (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 (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 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 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 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

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

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 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 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.

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 ϵ, $\Delta F/F$, respectively. The absolute value of the change in interest rate is given by Δi $(= i_t - i_{t-1})$. 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 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.

[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 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.

Table 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 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.

6 Application to carry trades

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

$$\mathrm{ER}_{t+h} = (i_t - i_t^*) - \Delta s_{t+h} \tag{11}$$

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

[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.

that uncovered interest rate parity (UIP) condition holds, there should be no excess return to the carry trade strategy on average

$$E_t\left(\mathrm{ER}_{t+h}\right) = 0 \tag{12}$$

or

$$E_t\left(\Delta s_{t+h}\right) = \left(i_t - i_t^*\right) \tag{13}$$

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.

6.2 Portfolio Analysis

6.2.1 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 Jordá 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 Jordá 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 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 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 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

[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.

from 0.031 for the naïve strategy to 0.061 for the PPP-augmented strategy. Likewise, in Table 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 Jordá and Taylor (2009).

Trade intensity begins to play a role as we raise the threshold τ. Figure 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 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 $1 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 Jordá 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.

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.

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TABLE 1. (A) TRADE INTENSITY (MAXIMUM) MATRIX

	Australia	Canada	Denmark	Great Britain	Japan	Korea	Mexico	New Zealand	Norway	Singapore	Sweden	Switzerland	Turkey	United States
Australia		0.02764	0.01137	0.09094	0.34581	0.07703	0.00311	0.33937	0.00447	0.07216	0.01873	0.02201	0.01581	0.25361
Canada	0.02764		0.01499	0.05067	0.05158	0.03307	0.02039	0.02432	0.04402	0.01191	0.02259	0.03185	0.02521	0.87729
Denmark	0.01137	0.01499		0.26804	0.08363	0.01777	0.00376	0.00538	0.15497	0.01061	0.23205	0.05136	0.02113	0.13960
Great Britain	0.09094	0.05067	0.26804		0.11318	0.04104	0.01430	0.10653	0.36061	0.07012	0.25688	0.24083	0.24172	0.40134
Japan	0.34581	0.05158	0.08363	0.11318		0.35287	0.05148	0.21447	0.04868	0.31455	0.06674	0.13382	0.09902	0.55988
Korea	0.07703	0.03307	0.01777	0.04104	0.35287		0.01076	0.03854	0.01697	0.07729	0.01627	0.02723	0.04457	0.42104
Mexico	0.00311	0.02039	0.00376	0.01430	0.05148	0.01076		0.00800	0.00156	0.00528	0.00781	0.01570	0.00291	0.88868
New Zealand	0.33937	0.02432	0.00538	0.10653	0.21447	0.03854	0.00800		0.00173	0.03684	0.00872	0.00796	0.00299	0.20582
Norway	0.00447	0.04402	0.15497	0.36061	0.04868	0.01697	0.00156	0.00173		0.01004	0.26542	0.01724	0.01369	0.10938
Singapore	0.07216	0.01191	0.01061	0.07012	0.31455	0.07729	0.00528	0.03684	0.01004		0.01134	0.02667	0.01529	0.40240
Sweden	0.01873	0.02259	0.23205	0.25688	0.06674	0.01627	0.00781	0.00872	0.26542	0.01134		0.06099	0.04504	0.19891
Switzerland	0.02201	0.03185	0.05136	0.24083	0.13382	0.02723	0.01570	0.00796	0.01724	0.02667	0.06099		0.09941	0.35509
Turkey	0.01581	0.02521	0.02113	0.24172	0.09902	0.04457	0.00291	0.00299	0.01369	0.01529	0.04504	0.09941		0.37323
United States	0.25361	0.87729	0.13960	0.40134	0.55988	0.42104	0.88868	0.20582	0.10938	0.40240	0.19891	0.35509	0.37323	

Note. Trade intensity (maximum) is calculated as an average value over the sample period, 1980-2005, using Equation (3). Betts and Kehoe (2008) use this measure of trade intensity in the paper.

TABLE 1. (B) TRADE INTENSITY (AVERAGE) MATRIX

	Australia	Canada	Denmark	Great Britain	Japan	Korea	Mexico	New Zealand	Norway	Singapore	Sweden	Switzerland	Turkey	United States
Australia		0.01677	0.00845	0.06404	0.20883	0.06166	0.00232	0.21375	0.00367	0.07051	0.01718	0.01816	0.00952	0.13779
Canada	0.01677		0.00824	0.03852	0.05050	0.02199	0.01412	0.01284	0.02477	0.00720	0.01330	0.01808	0.01307	0.61978
Denmark	0.00845	0.00824		0.16024	0.04589	0.01150	0.00237	0.00413	0.13585	0.00778	0.18393	0.04479	0.01504	0.07270
Great Britain	0.06404	0.03852	0.16024		0.08491	0.03422	0.01173	0.05860	0.22838	0.05040	0.17220	0.15197	0.13077	0.24254
Japan	0.20883	0.05050	0.04589	0.08491		0.23560	0.03416	0.11301	0.02752	0.19133	0.03908	0.07574	0.05140	0.39799
Korea	0.06166	0.02199	0.01150	0.03422	0.23560		0.00969	0.02224	0.01218	0.06446	0.01236	0.01897	0.02509	0.23907
Mexico	0.00232	0.01412	0.00237	0.01173	0.03416	0.00969		0.00457	0.00109	0.00390	0.00578	0.01069	0.00160	0.51808
New Zealand	0.21375	0.01284	0.00413	0.05860	0.11301	0.02224	0.00457		0.00121	0.02355	0.00572	0.00559	0.00265	0.10522
Norway	0.00367	0.02477	0.13585	0.22838	0.02752	0.01218	0.00109	0.00121		0.00825	0.23490	0.01715	0.00904	0.05765
Singapore	0.07051	0.00720	0.00778	0.05040	0.19133	0.06446	0.00390	0.02355	0.00825		0.01039	0.02126	0.00897	0.21903
Sweden	0.01718	0.01330	0.18393	0.17220	0.03908	0.01236	0.00578	0.00572	0.23490	0.01039		0.05397	0.02796	0.10659
Switzerland	0.01816	0.01808	0.04479	0.15197	0.07574	0.01897	0.01069	0.00559	0.01715	0.02126	0.05397		0.06326	0.18717
Turkey	0.00952	0.01307	0.01504	0.13077	0.05140	0.02509	0.00160	0.00265	0.00904	0.00897	0.02796	0.06326		0.18952
United States	0.13779	0.61978	0.07270	0.24254	0.39799	0.23907	0.51808	0.10522	0.05765	0.21903	0.10659	0.18717	0.18952	

Note. Trade intensity (average) is calculated as an average value over the sample period, 1980-2005, using Equation (4). This is an alternative measure to Trade intensity (maximum) in Betts and Kehoe (2008).

TABLE 2. EFFECTS OF TRADE INTENSITY ON REAL EXCHANGE RATE VOLATILITY

: INSTRUMENTAL VARIABLE ESTIMATION USING PANEL DATA

	[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 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 3. (A) EFFECTS OF TRADE INTENSITY ON REAL EXCHANGE RATE VOLATILITY : ROBUSTNESS CHECKS 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 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 3. (B) EFFECTS OF TRADE INTENSITY ON REAL EXCHANGE RATE VOLATILITY

: ROBUSTNESS CHECKS 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 absolute 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 for robustness checks. 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 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 3. (C) EFFECTS OF TRADE INTENSITY ON REAL EXCHANGE RATE VOLATILITY

: ROBUSTNESS CHECKS 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 absolute 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 for robustness checks. 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 3. (D) EFFECTS OF TRADE INTENSITY ON REAL EXCHANGE RATE VOLATILITY

: ROBUSTNESS CHECKS 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 absolute 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 for robustness checks. 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 4. (a) Estimation results from *ESTAR* models: 35 highest TI currency pairs

	USD/CAD	USD/MXN	USD/JPY	USD/GBP	USD/KRW	KRW/JPY	SEK/NOK	GBP/NOK	USD/SGD	NZD/AUD	JPY/AUD	SGD/JPY	USD/TRY	SEK/DKK	USD/CHF	GBP/SEK	GBP/DKK	GBP/CHF
p	8	11	2	1	10	4	1	12	1	4	12	1	4	12	12	1	4	1
d	1	3	5	5	2	3	2	3	6	6	2	6	4	1	2	5	6	4
Linear part																		
ρ	0.002	0.080	0.139	-0.027	0.062	0.096	0.239	-0.028	0.360	-0.062	-0.042	0.119	0.208	0.004	0.109	-0.053	0.050	0.162
	(0.129)	(0.547)	(0.132)	(0.047)	(0.048)	(0.086)	(0.141)	(0.043)	(0.083)	(0.093)	(0.027)	(0.096)	(0.199)	(0.015)	(0.088)	(0.049)	(0.119)	(0.246)
β_1	0.368	-1.196	-0.222		1.353	0.435		0.052		-0.010	0.211		0.355	0.001	-0.112		-0.875	
	(0.173)	(0.674)	(0.250)		(0.250)	(0.203)		(0.100)		(0.200)	(0.091)		(0.296)	(0.080)	(0.130)		(0.301)	
β_2	0.367	-0.548			-0.094	0.181		0.127		-0.040	-0.055		-0.095	0.120	0.069		-0.278	
	(0.186)	(0.612)			(0.175)	(0.186)		(0.105)		(0.165)	(0.078)		(0.274)	(0.070)	(0.096)		(0.250)	
β_3	-0.132	-0.237			0.488	0.137		-0.057		0.223	0.117		-0.069	0.016	-0.141		-0.590	
	(0.096)	(0.274)			(0.196)	(0.155)		(0.104)		(0.187)	(0.073)		(0.204)	(0.111)	(0.119)		(0.441)	
β_4	0.670	-0.332			-0.510			-0.029			-0.194			-0.031	-0.043			
	(0.198)	(0.228)			(0.205)			(0.080)			(0.093)			(0.083)	(0.093)			
β_5	0.005	-0.147			0.495			-0.151			0.226			-0.105	0.098			
	(0.154)	(0.185)			(0.235)			(0.100)			(0.097)			(0.097)	(0.099)			
β_6	-0.288	-0.296			-0.577			-0.066			-0.128			-0.050	-0.105			
	(0.189)	(0.240)			(0.246)			(0.091)			(0.090)			(0.064)	(0.097)			
β_7	0.846	-0.190			0.015			0.025			-0.015			0.003	0.196			
	(0.216)	(0.293)			(0.175)			(0.092)			(0.076)			(0.063)	(0.094)			
β_8		-0.010			0.201			0.073			0.022			0.090	-0.047			
		(0.253)			(0.258)			(0.078)			(0.082)			(0.093)	(0.099)			
β_9		0.447			0.574			-0.031			-0.050			0.074	0.051			
		(0.247)			(0.232)			(0.086)			(0.080)			(0.117)	(0.094)			
β_{10}		0.918						0.072			-0.015			-0.011	0.028			
		(0.069)						(0.096)			(0.081)			(0.068)	(0.083)			
β_{11}								0.112			0.206			-0.005	0.248			
								(0.089)			(0.092)			(0.079)	(0.091)			
Nonlinear part																		
ρ	-0.018	-0.125	-0.166	-0.011	-0.113	-0.131	-0.267	-0.048	-0.372	-0.057	-0.003	-0.149	-0.229	-0.282	-0.150	-0.075	-0.068	-0.185
	(0.128)	(0.550)	(0.132)	(0.054)	(0.065)	(0.089)	(0.141)	(0.086)	(0.084)	(0.111)	(0.043)	(0.097)	(0.200)	(4.097)	(0.091)	(0.081)	(0.120)	(0.248)
β_1^*	-0.362	1.201	0.355		-1.830	-0.525		-0.275		0.004	-0.194		-0.348	5.365	0.299		1.093	
	(0.186)	(0.671)	(0.263)		(0.293)	(0.254)		(0.245)		(0.243)	(0.236)		(0.324)	(77.248)	(0.158)		(0.307)	
β_2^*	-0.384	0.554			0.110	-0.139		-0.527		0.182	0.073		0.057	-5.339	-0.155		0.310	
	(0.199)	(0.612)			(0.206)	(0.225)		(0.257)		(0.204)	(0.210)		(0.302)	(80.042)	(0.143)		(0.263)	
β_3^*	0.133	0.309			-0.591	-0.347		-0.036		-0.133	0.086		0.012	2.995	0.336		0.721	
	(0.125)	(0.288)			(0.220)	(0.202)		(0.252)		(0.214)	(0.158)		(0.212)	(43.880)	(0.153)		(0.446)	
β_4^*	-0.708	0.252			0.320			-0.011			0.272			-3.506	0.031			
	(0.215)	(0.256)			(0.264)			(0.241)			(0.200)			(48.676)	(0.164)			
β_5^*	-0.029	0.180			-0.539			0.484			-0.654			3.513	-0.127			
	(0.175)	(0.189)			(0.253)			(0.276)			(0.240)			(52.839)	(0.148)			
β_6^*	0.242	0.255			0.755			0.255			0.283			2.994	0.128			
	(0.216)	(0.250)			(0.267)			(0.252)			(0.218)			(43.558)	(0.162)			
β_7^*	-0.845	0.188			-0.161			0.280			0.002			-1.375	-0.174			
	(0.243)	(0.297)			(0.227)			(0.225)			(0.193)			(20.813)	(0.157)			
β_8^*		0.017			-0.224			-0.085			0.339			-5.227	0.044			
		(0.257)			(0.329)			(0.194)			(0.197)			(75.456)	(0.153)			
β_9^*		-0.393			-0.484			-0.092			0.275			-6.763	0.091			
		(0.256)			(0.272)			(0.212)			(0.212)			(97.367)	(0.151)			
β_{10}^*		-0.845						-0.263			0.025			3.328	-0.138			
		(0.089)						(0.230)			(0.204)			(48.932)	(0.146)			
β_{11}^*								-0.018			-0.273			-2.714	-0.184			
								(0.220)			(0.239)			(41.236)	(0.145)			
γ	41.509	500.000	20.795	10.444	8.534	10.753	50.519	4.166	371.426	6.369	1.195	13.220	39.991	0.135	13.537	3.507	500.000	500.000
	(1.073)	(3.058)	(1.379)	(1.256)	(0.177)	(0.634)	(1.302)	(0.221)	(25.787)	(1.046)	(0.363)	(1.149)	(0.939)	(0.185)	(0.635)	(0.438)	(4.587)	(9.712)
c	-0.735	-3.075	-5.545	-0.166	-7.449	2.038	0.057	-2.369	-0.898	-1.484	5.102	-4.488	-1.212	0.104	-0.971	-2.285	-2.414	-0.782
	(0.002)	(0.0001)	(0.009)	(0.016)	(0.005)	(0.015)	(0.002)	(0.021)	(0.001)	(0.036)	(0.116)	(0.013)	(0.004)	(18.662)	(0.007)	(0.034)	(0.0001)	(0.0004)
$\hat{\sigma}_\varepsilon$	0.017	0.045	0.032	0.030	0.022	0.040	0.019	0.023	0.015	0.027	0.045	0.029	0.040	0.020	0.032	0.026	0.024	0.028
LM(4)	1.043	0.852	1.043	2.332	8.674	4.493	0.503	0.322	5.320	2.080	0.345	1.063	1.945	8.488	0.892	0.620	2.992	1.725
	(0.385)	(0.493)	(0.385)	(0.056)	(0.001)	(0.002)	(0.733)	(0.863)	(0.001)	(0.083)	(0.847)	(0.375)	(0.103)	(0.001)	(0.469)	(0.649)	(0.019)	(0.144)
LM(8)	3.424	0.680	0.937	1.665	5.985	2.757	0.657	0.452	2.694	1.110	0.540	1.211	1.626	6.634	0.749	0.594	1.787	1.852
	(0.001)	(0.709)	(0.486)	(0.106)	(0.001)	(0.006)	(0.729)	(0.889)	(0.007)	(0.356)	(0.826)	(0.292)	(0.117)	(0.001)	(0.648)	(0.783)	(0.079)	(0.067)
pRNL	0.632	0.152	0.767	0.183	0.194	0.427	0.701	0.854	0.519	0.771	0.840	0.995	0.751	0.874	0.962	0.975	0.401	0.096
SSR	0.098	0.686	0.358	0.313	0.163	0.546	0.123	0.179	0.079	0.241	0.682	0.281	0.558	0.128	0.342	0.224	0.189	0.269
AIC	-8.032	-6.039	-6.813	-6.959	-7.490	-6.367	-7.895	-7.367	-8.337	-7.183	-6.030	-7.068	-6.345	-7.704	-6.719	-7.294	-7.430	-7.111
BIC	-7.807	-5.743	-6.723	-6.892	-7.218	-6.232	-7.827	-7.049	-8.270	-7.048	-5.711	-7.000	-6.210	-7.385	-6.401	-7.227	-7.295	-7.043
T	348	348	348	348	348	348	348	348	348	348	348	348	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 coefficients. $\hat{\sigma}_\varepsilon$ 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 4. (A) ESTIMATION RESULTS FROM *ESTAR* MODELS: 35 HIGHEST TI CURRENCY PAIRS (CONTINUED)

	USD/AUD	NOK/DKK	GBP/TRY	NZD/JPY	USD/SEK	USD/NZD	GBP/JPY	CHF/JPY	USD/DKK	SGD/AUD	SGD/KRW	GBP/AUD	TRY/CHF	KRW/AUD	GBP/NZD	USD/NOK	CHF/SEK
p	1	1	1	1	8	8	2	1	4	1	10	1	1	10	1	1	1
d	2	4	2	5	5	5	3	2	6	2	2	2	3	2	1	1	4
Linear part																	
ρ	0.144	0.073	0.856	0.173	-0.033	-0.033	0.461	0.335	0.038	0.078	0.029	0.537	0.297	0.073	0.133	0.253	0.093
	(0.101)	(0.041)	(0.477)	(0.123)	(0.028)	(0.060)	(0.155)	(0.141)	(0.054)	(0.075)	(0.038)	(0.302)	(0.162)	(0.105)	(0.257)	(0.344)	(0.051)
β_1					-0.026	0.047	-0.236		-0.212		0.710			0.559			
					(0.114)	(0.113)	(0.363)		(0.167)		(0.307)			(0.378)			
β_2					0.010	0.102			0.214		0.015			-0.095			
					(0.082)	(0.110)			(0.184)		(0.148)			(0.120)			
β_3					0.040	0.073			0.010		-0.130			-0.169			
					(0.100)	(0.104)			(0.142)		(0.118)			(0.119)			
β_4					0.157	-0.167					-0.190			0.085			
					(0.112)	(0.110)					(0.111)			(0.135)			
β_5					0.144	-0.181					0.187			-0.161			
					(0.083)	(0.152)					(0.091)			(0.126)			
β_6					0.045	0.187					-0.124			-0.030			
					(0.076)	(0.124)					(0.117)			(0.114)			
β_7					0.082	0.187					0.133			0.010			
					(0.071)	(0.111)					(0.096)			(0.105)			
β_8											-0.079			0.006			
											(0.110)			(0.105)			
β_9											0.247			0.161			
											(0.101)			(0.134)			
Nonlinear part																	
ρ	-0.182	-0.138	-0.901	-0.207	-0.054	-0.058	-0.489	-0.378	-0.080	-0.171	-0.273	-0.570	-0.328	-0.196	-0.198	-0.285	-0.140
	(0.100)	(0.041)	(0.477)	(0.122)	(0.093)	(0.077)	(0.155)	(0.142)	(0.052)	(0.068)	(0.089)	(0.301)	(0.161)	(0.121)	(0.254)	(0.343)	(0.051)
β_1^*					0.561	0.024	0.369		0.385		-1.690			-0.737			
					(0.471)	(0.168)	(0.369)		(0.181)		(0.432)			(0.402)			
β_2^*					-0.195	-0.131			-0.191		0.088			0.263			
					(0.187)	(0.167)			(0.203)		(0.324)			(0.165)			
β_3^*					0.329	0.219			0.056		0.450			0.184			
					(0.280)	(0.172)			(0.170)		(0.181)			(0.202)			
β_4^*					-0.442	0.273					0.200			-0.254			
					(0.381)	(0.156)					(0.171)			(0.193)			
β_5^*					-0.185	0.396					-0.278			0.222			
					(0.306)	(0.189)					(0.172)			(0.156)			
β_6^*					-0.332	-0.179					0.544			0.149			
					(0.344)	(0.177)					(0.138)			(0.161)			
β_7^*					0.047	-0.077					-0.323			-0.142			
					(0.202)	(0.158)					(0.158)			(0.205)			
β_8^*											0.290			-0.015			
											(0.150)			(0.180)			
β_9^*											-0.490			-0.051			
											(0.177)			(0.184)			
γ	23.338	5.658	500.000	277.480	0.997	4.140	120.424	62.657	8.003	4.715	2.066	121.028	58.695	13.780	21.151	33.520	8.679
	(1.692)	(0.730)	(5.087)	(3.862)	(0.823)	(0.330)	(3.370)	(1.524)	(0.795)	(1.068)	(0.084)	(2.097)	(2.022)	(0.372)	(2.140)	(1.540)	(0.721)
c	-0.624	0.038	-1.089	-6.581	-2.808	0.828	-5.347	-4.265	-2.788	0.473	-6.434	-0.499	0.287	6.776	1.137	-2.730	-1.650
	(0.006)	(0.016)	(0.0003)	(0.001)	(0.262)	(0.026)	(0.001)	(0.001)	(0.020)	(0.032)	(0.036)	(0.001)	(0.003)	(0.005)	(0.010)	(0.005)	(0.011)
$\hat{\sigma}_\varepsilon$	0.032	0.017	0.046	0.040	0.031	0.033	0.034	0.031	0.031	0.029	0.024	0.036	0.048	0.034	0.036	0.030	0.025
LM(4)	0.998	1.227	2.027	1.329	1.573	0.444	1.239	1.238	0.869	1.230	8.436	0.594	1.310	4.248	0.641	1.825	1.422
	(0.409)	(0.299)	(0.090)	(0.259)	(0.181)	(0.777)	(0.294)	(0.295)	(0.483)	(0.298)	(0.001)	(0.667)	(0.266)	(0.002)	(0.634)	(0.124)	(0.226)
LM(8)	1.060	1.388	1.345	1.606	1.507	2.214	0.880	0.951	0.813	0.776	6.443	0.814	1.349	2.187	0.598	1.393	1.405
	(0.391)	(0.201)	(0.220)	(0.122)	(0.154)	(0.026)	(0.534)	(0.474)	(0.591)	(0.625)	(0.001)	(0.591)	(0.218)	(0.028)	(0.780)	(0.198)	(0.193)
pRNL	0.758	0.957	0.638	0.674	0.717	0.815	0.423	0.574	0.818	0.975	0.375	0.999	0.412	0.121	0.912	0.629	0.132
SSR	0.339	0.098	0.732	0.553	0.319	0.365	0.397	0.320	0.318	0.295	0.195	0.443	0.793	0.401	0.436	0.308	0.208
AIC	-6.880	-8.116	-6.109	-6.388	-6.852	-6.717	-6.709	-6.936	-6.908	-7.018	-7.314	-6.612	-6.028	-6.592	-6.627	-6.974	-7.368
BIC	-6.812	-8.049	-6.042	-6.321	-6.626	-6.491	-6.619	-6.869	-6.773	-6.950	-7.042	-6.544	-5.961	-6.320	-6.560	-6.906	-7.300
T	348	348	348	348	348	348	348	348	348	348	348	348	348	348	348	348	348

TABLE 4. (B) ESTIMATION RESULTS FROM *ESTAR* MODELS: 35 LOWEST TI CURRENCY PAIRS

	CHF/NOK	CAD/AUD	TRY/DKK	MXN/CAD	SEK/CAD	TRY/CAD	NZD/CAD	SEK/KRW	NOK/KRW	GBP/MXN	KRW/DKK	CHF/MXN	SEK/SGD	MXN/KRW	TRY/AUD	TRY/NOK	TRY/SGD	DKK/AUD
p	12	1	1	11	1	1	4	10	10	11	1	11	1	11	6	9	1	10
d	5	3	4	2	5	4	6	2	6	3	2	4	2	3	1	1	1	3
Linear part																		
ρ	0.362	0.383	0.517	0.129	-0.031	0.522	0.012	0.050	0.057	0.045	0.520	0.214	0.062	0.176	0.201	0.189	0.341	0.212
	(0.850)	(0.255)	(0.149)	(0.912)	(0.068)	(0.292)	(0.156)	(0.152)	(0.729)	(0.567)	(0.292)	(1.147)	(0.074)	(0.435)	(0.227)	(0.191)	(0.277)	(0.115)
β_1	-0.257			-0.390			0.577	-0.422	0.914	-0.618		-0.909		-0.337	0.663	0.183		-0.440
	(0.875)			(1.032)			(0.408)	(0.230)	(0.789)	(0.806)		(1.165)		(0.695)	(0.306)	(0.116)		(0.187)
β_2	0.153			0.940			-0.048	-0.097	0.209	-0.193		-1.365		-0.157	-0.340	0.659		0.076
	(0.925)			(0.317)			(0.203)	(0.152)	(0.762)	(0.566)		(1.681)		(0.385)	(0.199)	(0.269)		(0.176)
β_3	-0.146			-0.681			-0.332	0.264	0.728	1.437		-0.384		0.271	0.264	-0.048		0.077
	(0.820)			(0.340)			(0.370)	(0.187)	(0.804)	(0.456)		(1.108)		(0.300)	(0.258)	(0.143)		(0.171)
β_4	-0.450			-0.293				-0.293	-0.056	0.690		0.354		0.588	0.193	-0.003		-0.069
	(0.806)			(0.317)				(0.137)	(0.658)	(0.361)		(0.340)		(0.357)	(0.225)	(0.188)		(0.128)
β_5	-1.367			-0.396				0.220	-0.550	-0.183		0.874		0.480	0.209	-0.304		0.037
	(0.406)			(0.268)				(0.165)	(0.742)	(0.240)		(0.477)		(0.401)	(0.171)	(0.189)		(0.179)
β_6	0.149			0.696				0.059	-0.640	0.144		0.496		0.135		0.067		0.075
	(0.367)			(0.312)				(0.176)	(0.316)	(0.251)		(0.456)		(0.437)		(0.208)		(0.152)
β_7	0.284			-0.164				0.129	-0.891	-0.386		-0.642		0.010		0.159		0.389
	(0.457)			(0.346)				(0.146)	(0.228)	(0.427)		(0.600)		(0.384)		(0.204)		(0.200)
β_8	-0.173			0.389				-0.160	-0.997	0.210		1.193		-0.472		0.026		0.229
	(0.247)			(0.239)				(0.205)	(0.413)	(0.378)		(1.001)		(0.742)		(0.151)		(0.162)
β_9	0.392			-0.633				0.189	0.303	0.154		2.427		0.269				-0.035
	(0.282)			(0.346)				(0.136)	(0.268)	(0.412)		(0.630)		(0.254)				(0.163)
β_{10}	-0.585			1.217						1.307		1.752		2.528				
	(0.401)			(0.093)						(0.143)		(0.342)		(1.913)				
β_{11}	0.681																	
	(0.207)																	
Nonlinear part																		
ρ	-0.398	-0.456	-0.553	-0.158	-0.020	-0.542	-0.034	-0.740	-0.144	-0.091	0.535	-0.264	-0.118	-0.208	-0.212	-0.202	-0.365	-0.253
	(0.851)	(0.255)	(0.150)	(0.913)	(0.071)	(0.292)	(0.157)	(0.766)	(0.732)	(0.570)	(0.290)	(1.152)	(0.067)	(0.437)	(0.227)	(0.194)	(0.276)	(0.119)
β_1^*	0.261			0.364			-0.637	-0.152	-0.981	0.726		0.984		0.249	-0.651	-0.121		0.538
	(0.878)			(1.034)			(0.408)	(0.153)	(0.797)	(0.819)		(1.157)		(0.699)	(0.316)	(0.187)		(0.204)
β_2^*	-0.147			-0.942			0.076	0.707	-0.086	0.214		1.392		0.174	0.450	-0.755		-0.228
	(0.859)			(0.317)			(0.240)	(0.278)	(0.775)	(0.573)		(1.685)		(0.390)	(0.214)	(0.277)		(0.217)
β_3^*	0.160			0.775			0.479	0.311	-0.804	-1.380		0.494		-0.272	-0.327	0.022		-0.005
	(0.795)			(0.351)			(0.376)	(0.197)	(0.803)	(0.462)		(1.118)		(0.314)	(0.276)	(0.193)		(0.213)
β_4^*	0.449			0.235				-0.247	-0.023	-0.697		-0.371		-0.698	-0.360	-0.161		0.053
	(0.812)			(0.338)				(0.223)	(0.659)	(0.374)		(0.354)		(0.363)	(0.244)	(0.221)		(0.163)
β_5^*	1.301			0.428				0.362	0.633	0.220		-0.828		-0.469	-0.390	0.289		-0.132
	(0.409)			(0.269)				(0.159)	(0.748)	(0.244)		(0.481)		(0.402)	(0.196)	(0.201)		(0.210)
β_6^*	-0.199			-0.731				-0.218	0.730	-0.251		-0.523		-0.165		-0.039		-0.043
	(0.372)			(0.318)				(0.196)	(0.330)	(0.258)		(0.456)		(0.441)		(0.219)		(0.183)
β_7^*	-0.283			0.160				-0.035	0.852	0.394		0.679		-0.051		-0.122		-0.421
	(0.468)			(0.349)				(0.212)	(0.241)	(0.433)		(0.605)		(0.399)		(0.226)		(0.230)
β_8^*	0.145			-0.348				-0.211	1.010	-0.190		-1.188		0.493		-0.109		-0.317
	(0.258)			(0.243)				(0.188)	(0.416)	(0.381)		(1.004)		(0.749)		(0.171)		(0.196)
β_9^*	-0.376			0.700				0.342	-0.111	-0.100		-2.300		-0.214				0.209
	(0.292)			(0.347)				(0.224)	(0.282)	(0.419)		(0.632)		(0.254)				(0.184)
β_{10}^*	0.647			-1.187				-0.150		-1.320		-1.733		-2.496				
	(0.400)			(0.103)				(0.167)		(0.149)		(0.341)		(1.909)				
β_{11}^*	-0.656																	
	(0.219)																	
γ	500.000	500.000	238.526	500.000	26.375	348.676	165.502	26.083	286.582	56.800	32.866	216.122	15.383	51.056	51.563	53.757	13.029	6.832
	(1.462)	(3.892)	(3.674)	(3.204)	(2.196)	(3.892)	(3.233)	(0.677)	(2.334)	(1.139)	(0.879)	(1.968)	(2.314)	(0.886)	(0.880)	(1.664)	(0.652)	(0.290)
c	-1.563	0.237	-1.191	2.203	1.606	0.364	-1.887	-5.006	-4.757	-2.772	4.768	-1.947	1.376	-4.274	0.891	-1.311	-0.024	2.044
	(0.0001)	(0.0002)	(0.001)	(0.0002)	(0.008)	(0.0004)	(0.001)	(0.002)	(0.0002)	(0.001)	(0.003)	(0.001)	(0.015)	(0.004)	(0.002)	(0.002)	(0.011)	(0.011)
$\hat{\sigma}_\varepsilon$	0.020	0.027	0.043	0.046	0.031	0.040	0.032	0.039	0.035	0.052	0.043	0.059	0.028	0.052	0.043	0.043	0.041	0.035
LM(4)	1.280	2.255	3.309	1.182	2.168	2.073	0.857	0.823	3.911	0.881	1.216	0.542	2.721	1.298	0.998	1.852	2.206	0.877
	(0.278)	(0.063)	(0.011)	(0.319)	(0.072)	(0.084)	(0.490)	(0.511)	(0.004)	(0.475)	(0.304)	(0.705)	(0.030)	(0.271)	(0.409)	(0.119)	(0.068)	(0.478)
LM(8)	1.256	1.897	2.575	0.861	2.362	1.549	1.048	1.030	2.634	0.756	0.648	0.491	2.112	1.053	1.258	1.456	1.382	1.033
	(0.266)	(0.060)	(0.010)	(0.550)	(0.018)	(0.140)	(0.400)	(0.413)	(0.008)	(0.642)	(0.737)	(0.863)	(0.034)	(0.396)	(0.265)	(0.173)	(0.204)	(0.411)
*p*RNL	0.650	0.080	0.654	0.403	0.484	0.836	0.901	0.099	0.295	0.640	0.559	0.729	0.377	0.795	0.485	0.836	0.584	0.984
SSR	0.132	0.248	0.620	0.696	0.336	0.553	0.356	0.506	0.402	0.917	0.642	1.163	0.271	0.917	0.618	0.621	0.585	0.408
AIC	-7.674	-7.193	-6.275	-6.024	-6.886	-6.388	-6.794	-6.360	-6.590	-5.749	-6.240	-5.512	-7.101	-5.749	-6.220	-6.169	-6.334	-6.573
BIC	-7.355	-7.125	-6.207	-5.729	-6.819	-6.321	-6.659	-6.088	-6.317	-5.454	-6.173	-5.216	-7.033	-5.454	-6.040	-5.920	-6.266	-6.301
T	348	348	348	348	348	348	348	348	348	348	348	348	348	348	348	348	348	348

Note. As for Table 4. (a).

Table 4. (b) Estimation results from *ESTAR* models: 35 lowest TI currency pairs (continued)

	SGD/NOK	DKK/CAD	SGD/DKK	SGD/CAD	SEK/MXN	SEK/NZD	CHF/NZD	NZD/MXN	NZD/DKK	SGD/MXN	NOK/AUD	TRY/NZD	MXN/DKK	MXN/AUD	TRY/MXN	NOK/NZD	NOK/MXN
p	1	1	10	1	11	1	1	11	1	11	1	1	11	12	11	1	11
d	3	6	3	3	1	4	4	4	3	4	2	1	6	5	2	3	4
Linear part																	
ρ	0.157	0.077	0.010	0.301	0.192	0.054	0.047	0.226	0.749	0.423	0.125	0.071	0.365	0.623	0.053	-0.094	0.138
	(0.166)	(0.104)	(0.159)	(0.133)	(0.378)	(0.223)	(0.090)	(0.166)	(0.283)	(0.280)	(0.140)	(0.172)	(0.655)	(0.698)	(0.883)	(0.069)	(0.366)
β_1			-0.459		-0.480			-0.184		-0.356			-0.279	0.631	-0.236		-0.302
			(0.351)		(0.365)			(0.169)		(0.251)			(0.638)	(1.086)	(0.744)		(0.469)
β_2			0.405		-1.926			-0.258		0.060			-2.142	-0.567	0.312		-0.327
			(0.344)		(0.896)			(0.197)		(0.331)			(0.946)	(0.932)	(1.003)		(0.703)
β_3			-0.110		0.284			-0.689		-0.239			0.088	-0.989	1.080		-0.155
			(0.305)		(0.754)			(0.413)		(0.305)			(0.845)	(0.810)	(0.458)		(0.512)
β_4			-0.372		0.682			-0.072		0.555			-1.299	-1.249	0.538		-1.532
			(0.339)		(0.547)			(0.350)		(0.427)			(0.683)	(1.151)	(0.847)		(1.175)
β_5			0.046		-0.793			0.797		-0.545			0.157	-0.617	-1.656		-0.028
			(0.328)		(0.729)			(0.389)		(0.424)			(0.549)	(0.490)	(0.958)		(0.493)
β_6			0.712		0.240			-0.292		-0.394			0.226	-1.332	-1.085		-0.032
			(0.291)		(0.458)			(0.313)		(0.698)			(0.242)	(1.262)	(0.801)		(0.280)
β_7			0.525		0.459			0.336		0.530			0.760	-0.636	1.616		0.177
			(0.352)		(0.370)			(0.355)		(0.387)			(0.234)	(0.453)	(0.916)		(0.275)
β_8			0.037		0.433			0.102		-0.0002			1.027	-0.590	-2.321		0.125
			(0.264)		(0.647)			(0.344)		(0.491)			(0.239)	(0.287)	(1.512)		(0.177)
β_9			0.053		-0.524			-0.199		-0.224			0.033	-0.170	-1.640		-0.016
			(0.275)		(0.205)			(0.260)		(0.421)			(0.416)	(0.171)	(1.281)		(0.217)
β_{10}					1.113			1.186		1.475			1.074	1.113	1.608		
					(0.547)			(0.270)		(0.156)			(0.121)	(0.185)	(0.660)		
β_{11}														0.366			
														(0.156)			
Nonlinear part																	
ρ	-0.187	-0.104	-0.023	-0.313	-0.215	-0.091	-0.157	-0.266	-0.798	-0.459	-0.241	-0.145	-0.403	-0.662	-0.089	-0.026	-0.172
	(0.164)	(0.101)	(0.161)	(0.133)	(0.377)	(0.224)	(0.087)	(0.166)	(0.284)	(0.282)	(0.134)	(0.149)	(0.658)	(0.699)	(0.880)	(0.085)	(0.368)
β^*_1			0.499		0.530			0.228		0.334			0.322	-0.635	0.334		0.389
			(0.357)		(0.372)			(0.184)		(0.270)			(0.641)	(1.092)	(0.763)		(0.476)
β^*_2			-0.422		1.979			0.245		-0.048			2.206	0.567	-0.292		0.366
			(0.349)		(0.898)			(0.214)		(0.333)			(0.948)	(0.934)	(1.007)		(0.737)
β^*_3			0.193		-0.187			0.837		0.275			0.018	0.984	-1.030		0.251
			(0.327)		(0.765)			(0.424)		(0.309)			(0.848)	(0.821)	(0.460)		(0.523)
β^*_4			0.410		-0.721			0.027		-0.629			1.245	1.192	-0.592		1.571
			(0.360)		(0.558)			(0.370)		(0.436)			(0.694)	(1.176)	(0.861)		(1.178)
β^*_5			-0.033		0.856			-0.806		0.585			-0.112	0.636	1.686		0.067
			(0.343)		(0.730)			(0.391)		(0.428)			(0.553)	(0.498)	(0.958)		(0.499)
β^*_6			-0.712		-0.291			0.308		0.357			-0.258	1.330	1.088		-0.010
			(0.302)		(0.464)			(0.320)		(0.700)			(0.265)	(1.271)	(0.802)		(0.290)
β^*_7			-0.456		-0.420			-0.294		-0.551			-0.756	0.697	-1.564		-0.153
			(0.365)		(0.374)			(0.357)		(0.390)			(0.240)	(0.466)	(0.917)		(0.283)
β^*_8			-0.0001		-0.460			-0.047		0.027			-1.031	0.670	2.315		-0.140
			(0.278)		(0.655)			(0.345)		(0.495)			(0.242)	(0.298)	(1.513)		(0.185)
β^*_9			0.101		0.682			0.238		0.290			0.110	0.237	1.671		0.120
			(0.292)		(0.216)			(0.262)		(0.417)			(0.422)	(0.185)	(1.285)		(0.231)
β^*_{10}					-1.032			-1.071		-1.437			-1.028	-1.029	-1.524		
					(0.556)			(0.276)		(0.160)			(0.134)	(0.199)	(0.660)		
β^*_{11}														-0.301			
														(0.188)			
γ	30.028	13.847	26.892	297.821	45.770	500.000	14.142	34.497	500.000	68.666	13.971	10.587	120.667	293.130	52.107	7.836	77.307
	(1.072)	(1.644)	(0.642)	(3.632)	(0.737)	(6.104)	(1.374)	(1.386)	(3.892)	(1.133)	(0.686)	(3.254)	(1.149)	(1.594)	(0.660)	(1.384)	(0.924)
c	-1.491	1.913	-1.645	0.159	-0.248	3.649	2.029	-4.063	-3.693	-2.082	2.134	2.589	0.442	2.701	-1.617	3.593	-0.597
	(0.005)	(0.020)	(0.003)	(0.0003)	(0.002)	(0.0003)	(0.012)	(0.006)	(0.0002)	(0.002)	(0.010)	(0.031)	(0.001)	(0.0002)	(0.002)	(0.020)	(0.002)
$\hat{\sigma}_\varepsilon$	0.026	0.032	0.026	0.021	0.055	0.036	0.038	0.056	0.036	0.046	0.034	0.049	0.055	0.052	0.055	0.034	0.060
LM(4)	0.682	1.474	1.333	0.253	2.736	1.347	0.707	1.897	0.640	0.831	0.465	2.918	2.858	1.803	2.403	1.053	0.903
	(0.605)	(0.210)	(0.258)	(0.908)	(0.029)	(0.252)	(0.587)	(0.111)	(0.634)	(0.506)	(0.761)	(0.021)	(0.024)	(0.128)	(0.050)	(0.380)	(0.463)
LM(8)	0.924	1.370	1.353	0.393	1.439	1.264	0.731	1.179	0.831	0.503	0.824	2.664	1.565	1.225	1.946	0.715	0.646
	(0.497)	(0.209)	(0.217)	(0.924)	(0.180)	(0.262)	(0.664)	(0.311)	(0.576)	(0.854)	(0.582)	(0.008)	(0.135)	(0.284)	(0.053)	(0.679)	(0.738)
pRNL	0.703	0.803	0.280	0.939	0.165	0.933	0.519	0.462	0.970	0.855	0.656	0.439	0.864	0.807	0.612	0.736	0.667
SSR	0.239	0.356	0.227	0.151	1.030	0.444	0.495	1.037	0.431	0.717	0.406	0.748	1.009	0.907	1.003	0.404	1.208
AIC	-7.227	-6.829	-7.162	-7.690	-5.633	-6.608	-6.501	-5.626	-6.639	-5.995	-6.699	-6.086	-5.654	-5.744	-5.659	-6.702	-5.488
BIC	-7.159	-6.761	-6.890	-7.623	-5.338	-6.541	-6.433	-5.331	-6.572	-5.699	-6.632	-6.019	-5.358	-5.425	-5.364	-6.635	-5.216
T	348	348	348	348	348	348	348	348	348	348	348	348	348	348	348	348	348

TABLE 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 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 7. (A) PERFORMANCE STATISTICS FOR CARRY TRADE PORTFOLIOS

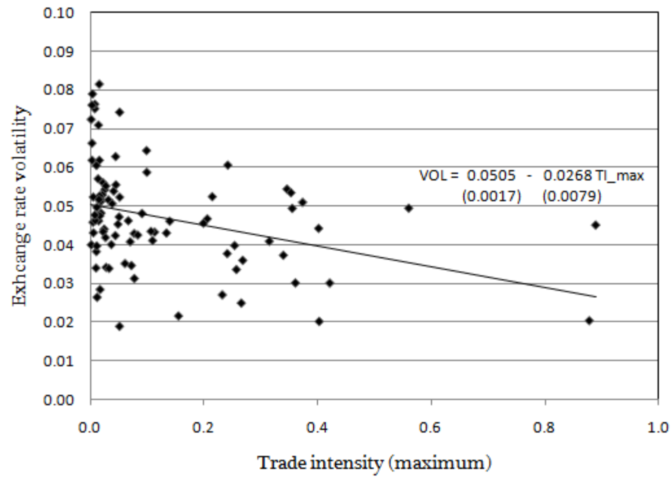
	High trade intensity currency pairs			Low trade intensity currency pairs		
Strategy	Return	Std. Dev.	Sharpe Ratio	Return	Std. Dev.	Sharpe Ratio
Naïve carry	-0.016	0.011	-0.121	0.006	0.016	0.031
PPP - $\tau = 0$	0.004	0.020	0.018	0.015	0.021	0.061
PPP - $\tau = 0.1$	0.019	0.034	0.048	0.011	0.027	0.032
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.

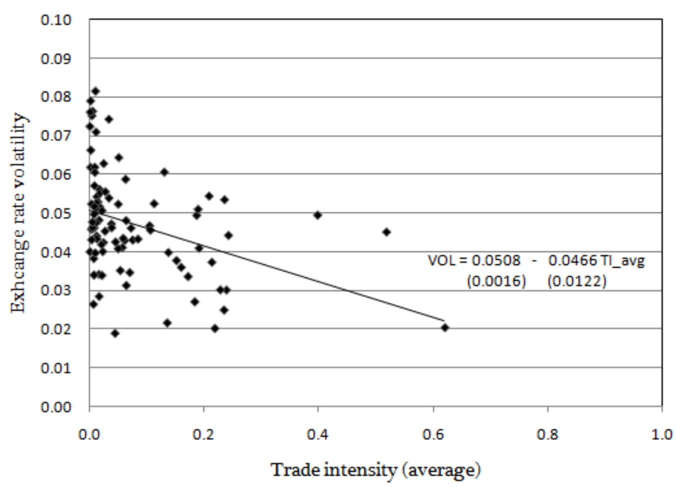
TABLE 7. (B) PERFORMANCE STATISTICS FOR CARRY TRADE PORTFOLIOS

	High trade intensity currency pairs			Low trade intensity currency pairs		
Strategy	Return	Std. Dev.	Sharpe Ratio	Return	Std. Dev.	Sharpe Ratio
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 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.



(A) SCATTER PLOT OF EXCHANGE RATE VOLATILITY AGAINST TRADE INTENSITY (MAXIMUM)



(B) SCATTER PLOT OF EXCHANGE RATE VOLATILITY AGAINST TRADE INTENSITY (AVERAGE)

FIGURE 1. SCATTER PLOTS OF EXCHANGE RATE VOLATILITY AGAINST TRADE INTENSITY 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. THE OLS ESTIMATES ARE REPORTED ABOVE, AND THE CORRESPONDING STANDARD ERRORS ARE IN PARENTHESES.

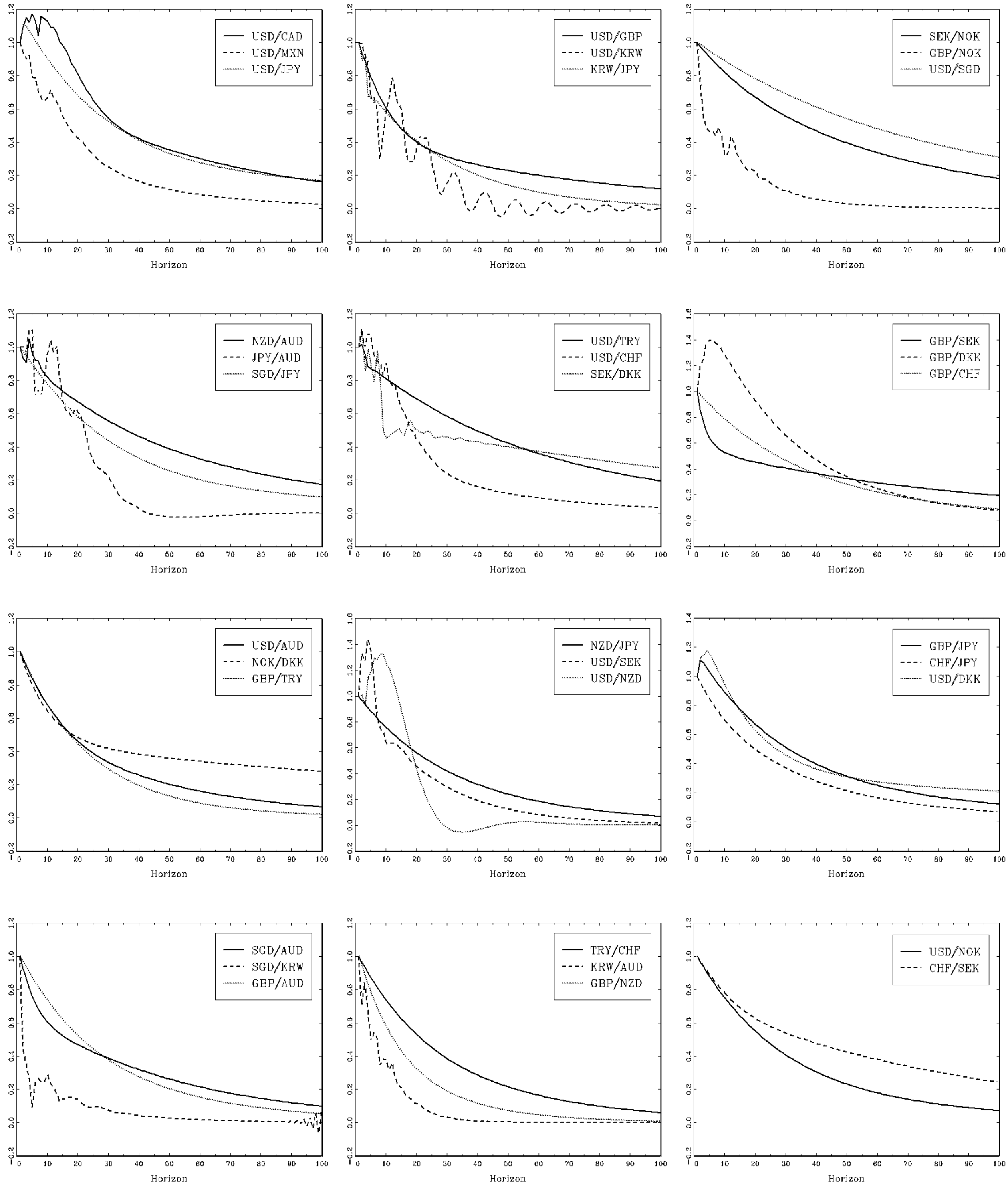


FIGURE 2. (A) GENERALIZED IMPULSE RESPONSE FUNCTIONS (GIS) FOR 35 HIGHEST TI CURRENCY PAIRS

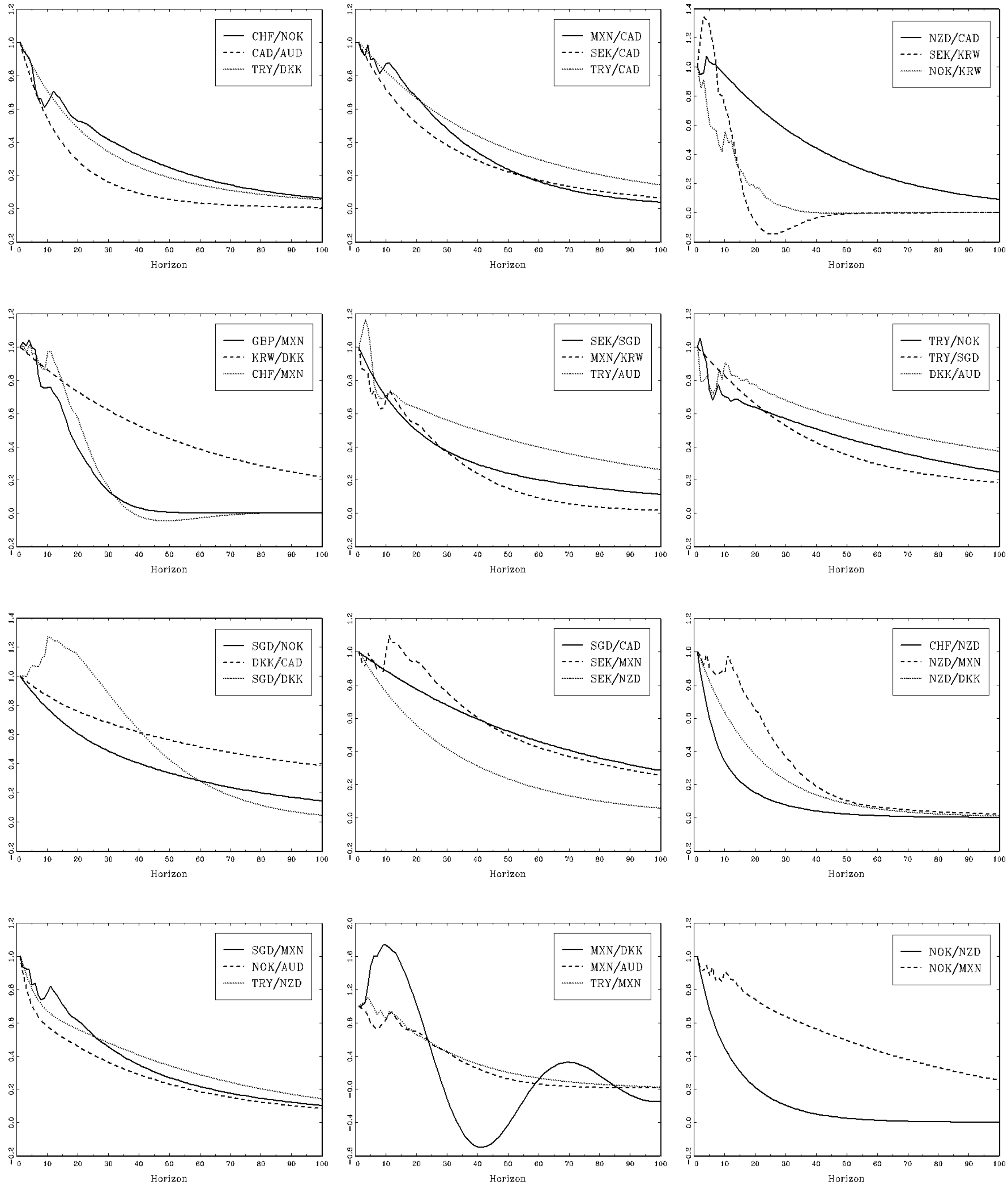
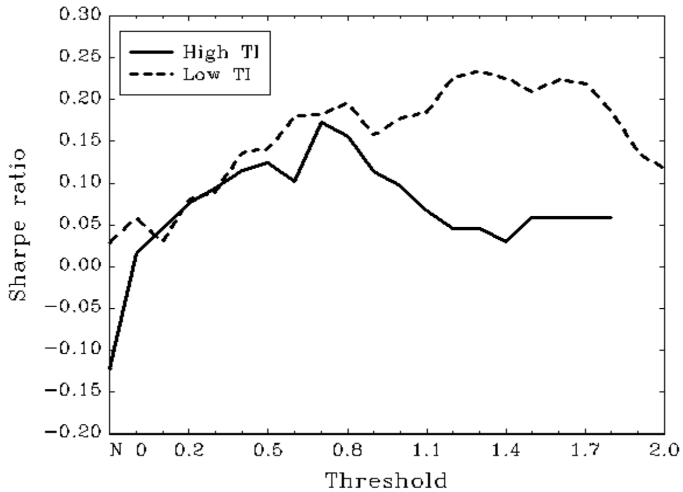
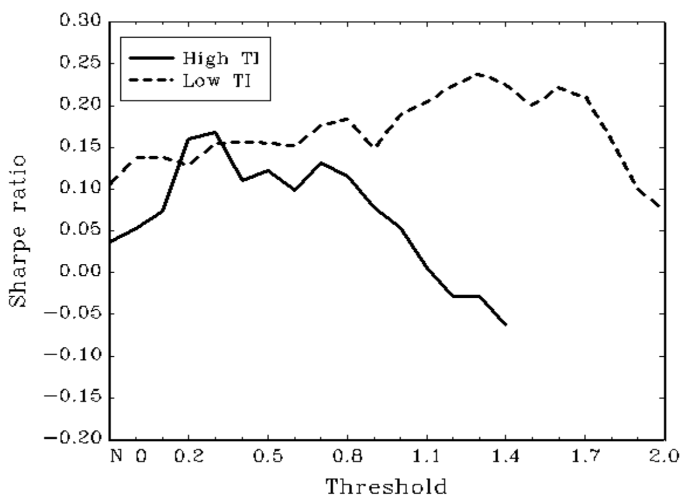


Figure 2. (b) Generalized impulse response functions (GIs) for 35 lowest TI currency pairs

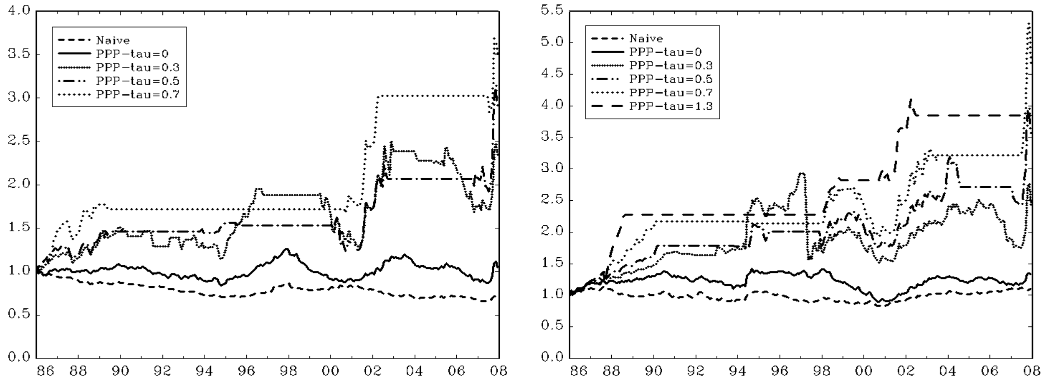


(A) SHARPE RATIOS WITHOUT A MOMENTUM TRADING STRATEGY

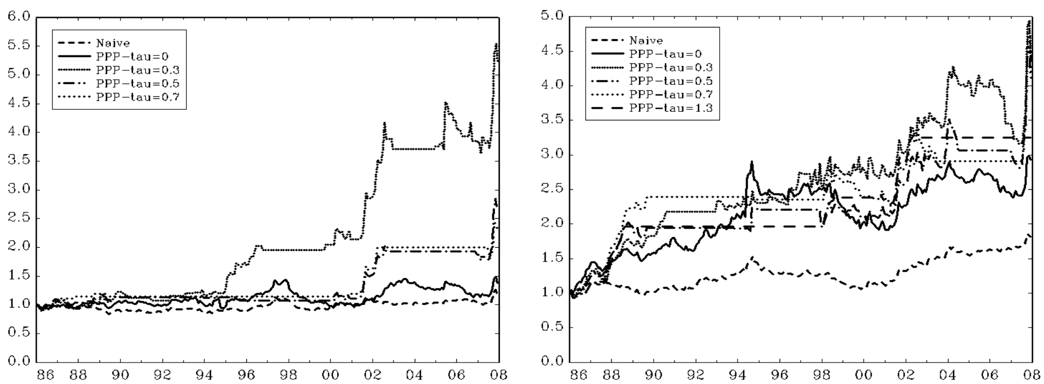


(B) SHARPE RATIOS WITH A MOMENTUM TRADING STRATEGY

FIGURE 3. SHARPE RATIOS WITHOUT AND WITH A MOMENTUM TRADING STRATEGY. "N" REFERS TO THE NAÏVE CARRY TRADE STRATEGY.



(A) PERFORMANCE OF PORTFOLIOS WITHOUT A MOMENTUM TRADING STRATEGY: HIGH TI (LEFT) VS. LOW TI (RIGHT)



(B) PERFORMANCE OF PORTFOLIOS WITH A MOMENTUM TRADING STRATEGY: HIGH TI (LEFT) VS. LOW TI (RIGHT)

FIGURE 4. PERFORMANCE OF PORTFOLIOS WITHOUT AND WITH A MOMENTUM TRADING STRATEGY