PIP testing noise traders: New evidence on the volatility of exchange rates.

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Abstract

This research explores a new aspect of noise trading, never addressed in the past that should have a direct impact on volatility. Assuming that currency traders (and particularly unsophisticated traders) measure their gains and losses in terms of PIPs and if the USD PIP value is variable, their willingness to enter the market should be affected. The reason is that if the USD PIP value is low, an additional PIP will not translate into high gains or losses, reducing the perceived risk of entering the market for noise traders. This in turn, following Black (1986)'s rationale, would clearly affect the variance of exchange rates. This study presents an empirical use for a particular class of Nelson's (1991) EGARCH type of volatility model where the lagged PIP value variation is incorporated as an exogenous component of the variance equation. The main sample was divided into three sub-samples. The first one corresponded to currencies that switched to the EUR in 1999. This first sub-sample permitted to assess not only the PIP effect on the standard variance equation but also permitted to assess the effect on noise trading of a quoted currency that turned into the base (reversed quotation). The PIP effect was correctly signed and significant for most of the EUR currencies, providing new evidence that the PIP value affected the conditional variance of exchange rate returns. The Euro effect, in turn, was inversely signed and diminished the PIP effect. The results for the remaining two subsamples, including major Asian currencies, were also interesting. Non EUR European currencies such as the Canadian Dollar, the South African Rand, the Singapore Dollar, the Chilean Peso and the Mexican Peso evidenced the correct sign and magnitude for the PIP value effect, indicating that a rise in PIP value diminishes the conditional variance and that US based noise traders do potentially have these currencies in their portfolios.

Keywords: Exchange rates, Noise, EGARCH, International finance, Volatility.

*This is a first draft version of this paper. Comments are encouraged and welcome.

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1 Introduction.

It is well known for those familiar with the foreign exchange markets that traders assess their profits, spreads and any other transaction costs in terms of PIPs before they translate their wins or losses to their particular local currency. The issue I present in this paper is that a change in the PIP value (measured in local currency terms) should have a direct effect on the willingness of noise traders to enter the market given that a higher PIP value should discourage them due to the fact that they will perceive a higher amount of wealth at stake if they eventually loose money against informed traders. Briefly speaking, one PIP gain or loss will result in a higher amount of local currency at risk. This in turn, should affect volatility. Indeed, as Black (1986) stated,

> anything that changes the amount or character of noise trading will change the volatility of price

The hypothesis here is that both,, the amount and character of noise traders, should be affected by a change in PIP value and if this statement is true, volatility should also be affected by these unsophisticated traders [as De Long, Shleifer, Summers & Waldmann (1989, 1990, 1991) or Palomino (1996), among others, demonstrated].

1.1 Some basic definitions.

Let's begin with some preliminaries. "Ticks" are usually referred to the minimum price increment according to the prevailing counting system in major financial markets. Nevertheless, in the foreign exchange markets, ticks are called **PIP**s simply because **ticks** are reserved to describe the minimum amount of time elapsed between one currency trade and the following.

In order to calculate PIPs, it is also important to consider that practitioners are rigorous in the interpretation of the notation of a currency pair. For instance, in the academic field, USD/JPY or JPY/USD can be treated interchangeably (so interpretation must be provided by the author as is typically the case in the literature) but in the practitioner's arena, the order in which the currency pair is provided is crucial for interpretation. USD/JPY means that the US dollar is the base currency and that the Japanese Yen is the quoted currency, or in simple terms, that the commodity is the USD and the price is quoted in JPY (it should also be noted that symbols are chosen according to international standards). In general terms, CUR1/CUR2 means that CUR1 is the base currency and CUR2 the quoted currency. This article will be consistent with this notation.

Independently of the position of the trader (long or short), currency pairs are always provided in a particular order in the dealer market. For instance, USD/JPY indicates that the USD is the base currency against the Yen and dealers will always quote in that order.

Let's define the **PIP value** as the punctual nominal amount of a PIP in terms of a full lot, or 100,000 units of the base currency . For a US investor, if the base is the foreign currency, the PIP value will be constant and equal to 0.0001*100,000=10 USD. Many unsophisticated traders will rather consider a minilot for their calculations (i.e., 10,000 units of the base currency) so that the PIP value reduces to 1 USD (0.0001*10,000). Now, if the investor is located in the base currency's economy, the PIP value will be variable, given that for this particular trader, the commodity is the USD. We will provide more insight on the variable/static properties of PIPs below.

In this paper, a **sophisticated trader** will be considered as a hedger, an international investor, the Central Bank, or an exporter/importer buying or selling a basket of currencies relevant for her business. **Unsophisticated traders** will be referred to as traders that are partly informed or uninformed and will trade with the sole purpose of speculating (i.e., they take uncovered positions). The latter will also be referred to as **noise traders** and **volatility feeders**. These noise traders's behavior will be characterized in a similar fashion as that described by Black (1986). Informed speculators will be referred to as sophisticated traders, for example, the Central Bank, private dealers and informed customers.

1.2 The mechanics in PIPs.

The fact that a currency is quoted against the dollar or if it rather turns out to be the base should have important implications on the behavior of traders and especially unsophisticated traders, but to understand why, an example can come in handy.

Briefly speaking, it is relevant to ask which currency is the base and which one is the quoted one, as to understand what the smallest increment really means for a particular trader. For instance, if the USD/JPY is quoted (at two decimal places) as 120.00Y, it means that it takes 120 Yen to buy one dollar (long position) or that if you sell (short) one dollar you will receive 120Y in exchange. But let's imagine for a minute that the dealer rather provides prices for the JPY/USD pair, so the current price would be inverted as 1/120 = \$0.0083. Using four decimal places instead of two would become more useful but needless to say, further decimal places would be lost (including any price information in those decimals). In the former case, one PIP would translate into 0.01 Yen but in the latter, a PIP would be equivalent to 0.01 cents of a dollar. Although the dealer is providing quotes for the same currency pair, the price is quoted in different PIP currency denominations depending on which side the base currency is and its interpretation (or variable/fixed property) will, in turn, depend on where the trader is geographically located and what currencies are in his portfolio.

Let's now move on to another currency pair to better explain this last argument, say, the AUD/USD, where in this case a one PIP variation is equivalent to 0.0001 USD (or 0.01 cents). On December 14th 2005, the spot exchange rate was quoted at 0.7567 and diminished to 0.7430 the next day, a variation of -0.0137 USD or simply 137 PIPs. For the latter case, a US based trader made a total loss of 137 PIPs per AUD if long on AUD between December 14th and December 15th. Each PIP corresponded to 0.01 cents, so in this case, the loss expressed in PIPs had a constant USD equivalent amount. Whatever the notional lot size is, the PIP value is this case is simply constant! But in the same example, an Australian trader long in USD (short in AUD) would make a gain equivalent to 137 PIPs but the problem for her is that the PIP value is expressed in USD. This trader will simply calculate that one full lot PIP value is rather (0.0001/0.7567)*100,000=AUD 13.22 on the first trading day and (0.0001/0.7430)*100,000=AUD 13.46 on the closing day (trading is considered on a realistic discrete time path and not in a continuous setting). Although this trader made a win, she might be tempted to close her position because of the higher perceived stake at risk on the closing day, as we will see in the following paragraphs. Truth is that rounding to 4 decimal places, the translation between USD to AUD would yield AUD 0.0001 as the pip increment, but given that traders use full or mini lots to do their calculations, the outcome is variable.

To provide even more insight, let's consider now that the currency pair is the USD/CAD where the US dollar is the base currency and the Canadian dollar the quoted currency (so the dealers will always respect that order for quotation purposes), a US based trader will now face a fluctuating PIP value (as opposed to the case for the AUD). Indeed, a PIP is now defined as 0.0001 CAD (or 0.01 cents of a Canadian dollar), so to calculate the PIP value in terms of USD it is required to replicate the algebra for the Australian trader. For instance, if the exchange rate on December 23rd 2005 was 1.1649, then (0.0001/1.1649)*100,000=USD 8.58 is the PIP value on that day for a full lot. The interpretation is straightforward, one PIP increment would yield a marginal ex-ante $8.58 profit and one PIP reduction would lead to a marginal loss of $8.58 per full lot. It should also be noticed that these increments/reductions change as exchange rates fluctuate and that is the key to the problem.

1.3 The issue.

In this research paper, unsophisticated investors are assumed to compute and understand the PIP value to assess their wins and losses. This statement would imply that a larger PIP value will be interpreted as more stake at risk and noise traders would tend to close their positions (or will be discouraged from opening new ones). This in turn, would reduce volatility.

So several questions arise from the above claim. First of all, are noise traders really sensitive to changes in PIP value? Furthermore, are these unsophisticated traders more sensitive to PIP value because it is their most reliable source for measuring their exposure to informed traders? One straightforward hypothesis will be to claim that if noise traders are really sensitive to changes in PIP value, the conditional variance of exchange rates returns should depend on PIPs.

The problem is that the above hypothesis strictly relies on the variability of PIPs. If most noise traders are located in the US and if they face a fixed PIP currency, no effect on volatility should be noticed but if we are dealing with a variable PIP, the statement above should hold true. Nevertheless, if we observe exactly the opposite, two alternative explanations would arise. (i) Noise traders are not located in the US but overseas, so when a US trader faces a fixed PIP, a noise trader overseas will face a variable PIP and those are the agents really causing the change in the conditional variance of currency returns (ii) Noise traders are really based in the US and hold portfolios of foreign currencies but are not sensitive to changes in PIP value. Of course, both alternatives strictly depend on initial assumptions for the model. Intuition leads us to think that most noise traders are actually located in the US because roughly 89% of currency turnover[1] includes the USD on either side of a transaction. Furthermore, the geographical location of USD based reported turnover corresponds to 19.2% of the total in 2004 which locates the USD in second place after the GBP (31.3%). Secondly, the US implemented several flexibilities in the forex market the late nineties, which may have attracted even more US based noise traders in the market given the improved availability of online brokers[2]. In this paper, we will assume that if there is no statistically significant effect of the PIP value on the conditional variance of exchange rates returns, it will be a sign of explanation (ii), if it is a significant positive effect instead of a negative effect, it will be interpreted as if it is more likely that explanation (i) holds.

The eurozone provides a good lab to test the hypothesis described above. Most Euro currencies were quoted as USD/EUR before the birth of the Euro in 1999, considering here the DEM, FRF, PTE among others. Then, the US dollar and Euro pair was quoted as EUR/USD. First of all, this currency quote swap provides an easy way to assess whether a switch from a variable to a fixed PIP (assuming noise traders are US based traders) reduces the volatility of exchange rates. If it does, more US based traders are participating in the market and the proportion of those who are unsophisticated (noise traders) would be explaining the structural change. Concretely speaking, US noise traders holding a basket of European currencies quoted against the USD (the latter as base) and faced with variable PIPs, later switched to fixed PIP value (because the EUR is the base) and their risk measured in terms of PIPs is no longer a determinant for the conditional variance.

To get a bit more of intuition on the issue, let's consider the following story. Traders that enter the market with the sole purpose to buy or sale currencies obtained from sales/costs or returns on investment abroad or furthermore, to make coupon payments for debt issued overseas, should not be worried about PIP values or any other similar indicator of perceived risk since they are not tak-

[1] BIS triennial Central Bank survey 2004. Percentage includes both sides of the market (i.e., total market turnover equals 200%).

[2] Doing a simple Internet search, the author found more than 51 different brokers and all of them offered a margin account in USD (i.e., assumed to be the local currency).

ing uncovered positions (their position is "naturally" covered) and their trading is clearly motivated by their economic activity. These traders will be referred to as *hedgers*. Now, turning attention towards *speculators*[3], there are two groups among these traders. The first group includes *informed traders* and they will enter the market to profit from private information against dealers [Glosten-Milgrom (1985), Easley-O'Hara (1987)] or uninformed traders (in case it is a brokered market). Since they have a signal or reliable information on what the fundamental exchange rate is, they will not necessarily be intimidated by a larger PIP value, unless our setting involves limits to arbitrage in the sense of Shleifer & Vishny (1997), among other frictions that may involve additional risk for these traders. The second group of speculators are *noise traders* [such as those defined by Kyle (1985) and Black (1986)], these traders are not necessarily random players but could eventually obey to specific psychological biases [Shiller (2003)]. So, these individuals, if interested in computing PIP values (as it is assumed for this group), should be concerned about PIPs because it will determine their willingness to participate in the market. This means that noise traders can't just enter the market at random, because they are concerned about their risk in terms of PIPs, so departures from standard Kyle (1985) (i.e., where noise traders are just random players) type of models is required at this stage. Low PIP values are an indicator of low risk of making a loss whereas a high value would indicate a high risk of making a loss. This means that more noise traders will enter the market when PIP value is low, implying higher volatility (the opposite is also true).

Section II describes the data and sample, section III deals with the model specification in accordance with the issue discussed in earlier paragraphs. Section IV analyzes the most relevant results and some concluding remarks are provided in the last section.

2 The data.

For the first part of this paper, only currencies that switched to the Euro in 1999 are considered. This will permit to model the structural change that took place when those currencies initially quoted against the dollar later switched to a "USD quoted against the EUR structure". The Greek Drachma is excluded from the initial sample because this currency joined the Eurozone in 2001 while most currencies did in January 1999. The Irish Pound is also excluded because the Irish currency was the base currency before and after the Euro, so the structural change did not take place for this one. Finally, the Luxemburg Franc is excluded due to lack of data availability.

This leaves us with 9 Euro currencies for the first part of this document, the ATS (Austria), BEF (Belgium), FIM (Finland), FRF (France), DEM (Ger-

[3] Speculators, in this context, are defined as traders that take uncovered positions or simply those whoses' orders are not motivated by real activity.

many), ITL (Italy), NLG (Netherlands), PTE (Portugal) and ESP (Spain). The entire sample period includes log daily prices from January 1st 1988 to December 30th 2005 for the Euro currencies and the obtained from publicly available data at Pacific Exchange Rate Service at UBC. Missing data was obtained from Economagic and for discontinuities, a simple algorithm was applied. That is, monthly averages were calculated and the monthly series were translated back to high frequency (i.e., daily) by quadratic-match average; then, when there was missing data in the original daily series, the empty cell was replaced with the new data generated from low frequency.

A second sample consists of fairly liquid currencies and some other from emerging economies that float during the entire sampling period (i.e., since January 1st 1988). The same data source and missing data algorithm described for the Euro currencies was applied to the rest of the sample. The third sample consists of the main Latin-American currencies during their respective floating periods. The entire list of currencies under study is provided below.

Euro Currencies		Main sample currencies		Latin-American currencies	
ATS	Austria	CAD	Canada	ARG**	Argentina
BEF	Belgium	JPY	Japan	BRL***	Brazil
FIM	Finland	KRW	Korea	CLP	Chile
FRF	France	SGD	Singapur	COP*	Colombia
DEM	Germany	TWD	Taiwan	MXN*	Mexico
ITL	Italy	ZAR	South Africa	PEN*	Peru
NLG	Netherlands	CHF	Switzerland		
PTE	Portugal	SEK	Sweden		
ESP	Spain	DKK	Denmark		
* Sampling period spans from January 1st 1996 to December 30th 2005					
** Sampling period spans from January 1st 2002 to December 30th 2005					
*** Sampling period spans from November 23rd 1998 to December 30th 2005					
The sampling period spans from January 1st 1988 to December 30th 2005, for the remainder.					

Sample currencies.

From the early studies of Meese and Singleton (1982) to more recent empirical studies such as Belaire-Franch & Opong (2005), a random walk behavior has been widely documented for the log nominal exchange rates[4]. The following table provides some insight on this claim for euro currencies included in the sample.

[4]Logs are computed as a mean to avoid Siegel's (1972) paradox.

Log Currency	R-squared	coefficient	tstat	Q stat
ATS	0.9967	1.0000	24,195.3924	121.3331
BEF	0.9969	1.0000	35,808.4036	73.7673
FIM	0.9981	1.0000	15,524.0045	73.6847
FRF	0.9968	1.0000	18,195.4941	75.4817
DEM	0.9969	0.9999	5,592.6453	79.7316
ITL	0.9985	1.0000	72,741.0889	88.6054
NLG	0.9968	1.0000	6,598.8386	104.9332
PTE	0.9978	1.0000	49,707.6997	170.0062
ESP	0.9986	1.0000	48,268.3285	106.8916

AR(1) estimation (no drift) of log currencies.

It is clearly showed from Q stats and the coefficients themselves on table 2 that shocks are highly persistent or furthermore, that the possibility of a unit root is not ruled out. In order to clear the doubts, Dickey-Fuller [Dickey & Fuller (1979, 1981)] and Kwiatkowski et al. (1992) tests are provided[5] for the Euro currencies. Using Schwartz's criterion, 9 lags are provided in both tests. The following table shows the results.

	ADF	KPSS
Log Currency	Without intercept or trend with 9 lags	9 lags, Eta(mu) values.
ATS	-0.066920	3.922370
BEF	-0.072300	3.929100
FIM	0.314090	3.765890
FRF	-0.118230	3.764320
DEM	-0.377440	3.925940
ITL	0.658940	5.182620
NLG	-0.299440	3.963350
PTE	0.481880	4.022170
ESP	0.470050	4.603760
ADF critical values: 1%= -2.566 5%= -1.939 10%= -1.616		
KPSS critical values: 1%= 0.739 5%= 0.463 10%= 0.347		

Unit root tests.

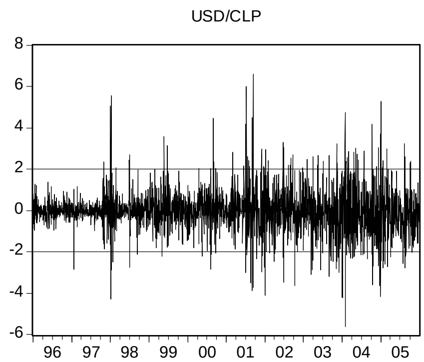
The currency process appears to have a unit root in all cases, so shocks do not fade away and this conclusion is maintained for the rest of the sample.

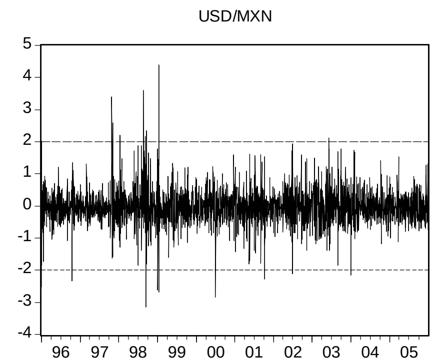
[5] The latter is considered given that we already know that shocks are persistent, so placing stationarity as the null hypothesis will improve the performance of the test.

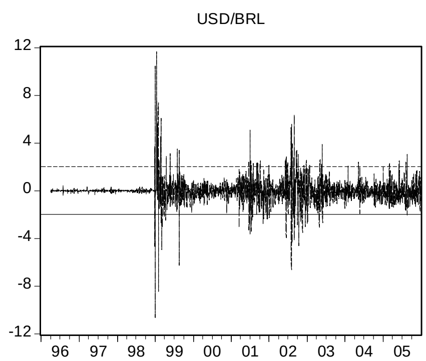
Given those results, USD currency returns are modeled instead of log levels, in order to assure a stationary process[6].

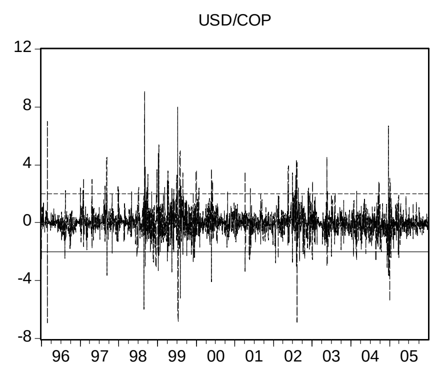
For the second part of this paper, an application to some of the non Euro-zone major currencies and a sample of more exotic currencies is also provided. Furthermore, a sample of Latin-American currencies is also analyzed for the recent free floating period (i.e., from January 1996 to December 2005).

Clustering in the variance is easily observable from the following selected graphs for Latin-American currencies.









Plus-minus one standard deviation is included on each graph, in order to spot unusually high volatility. Volatility appears in bursts which is a visual indication that an ARCH structure is present. But to clear the doubts, Q tests are provided below.

[6] Currency returns are stationary in all cases. Tables are available on request.

Log Currency	qstats6	sig6	qstats12	sig12	qstats18	sig18
ATS	84.4101	0.0000	93.4887	0.0000	103.6955	0.0000
BEF	44.9606	0.0000	51.4915	0.0000	52.8392	0.0000
FIM	41.2138	0.0000	50.9011	0.0000	59.2898	0.0000
FRF	45.4575	0.0000	49.4712	0.0000	51.8382	0.0000
DEM	44.5867	0.0000	48.3130	0.0000	49.7902	0.0001
IEP	48.3619	0.0000	50.2250	0.0000	50.8317	0.0001
ITL	62.8080	0.0000	71.0359	0.0000	78.3908	0.0000
NLG	61.2440	0.0000	68.3372	0.0000	74.9723	0.0000
PTE	111.8982	0.0000	123.1785	0.0000	124.0863	0.0000
ESP	64.5078	0.0000	74.6930	0.0000	88.0728	0.0000

The significant Q stats for up to 18 lags are a solid indication that an ARCH structure is indeed present. The results for the remaining currencies in the sample are similar to those obtained for the Euro currencies. These findings are consistent with the evidence presented in early tests such as Lastrapes (1989)

3 Empirical model specification.

The traditional behavioral approach to include noise traders in a model usually follows the idea that these traders will place orders according to some random distribution where their assessment of the expected return is biased, such as described in De Long, Shleifer, Summers & Waldmann (1990). This bias in their estimate is attributed to heuristics that affect human behavior as initially described by Tversky & Kahneman (1979). For instance, one very important bias that affects financial assets is overconfidence such as described in Barberis, Shleifer and Vishny (1998); Daniel, Hirshleifer and Subrahmanyam (1997) or Hong & Stein (1999), among others. Nevertheless, in this particular study it is necessary to isolate the PIP value effect on the variance of the residuals by assuming that the only channel by which noise traders affect variance is by responding to a changing PIP value.

Let the mean equation be described as:

$$de_t = E_t(de_t) + \mu_t \tag{1}$$

Where e_t is the log nominal exchange rate or $e_t = \log(\epsilon_t)$. and de_t is $\log(e_t) - \log(e_{t-1})$. $E_t(de_t)$ in turn, is the conditional expectation of the mean equation. Hence, it reflects the appropriate ARMA specification for each currency.

And where $\mu_t \tilde{} N(0, \sigma_\mu^2)$

For most currencies, the process is found to be AR(1) with no MA structure[7].

[7] Tables for different ARMA structures are not provided here but are available upon request

Standard Akaike and Bayesian information criterion suggest that such a specification is parsimonious and is preferred to most other ARMA specifications [I tested ARMA(1,0) to ARMA(5,5)].

Let the PIP value be measured as:

$$P_t = \frac{LxF}{\epsilon_t} \tag{2}$$

Where L is a full lot (100,000) or minilot (10,000). In simple terms, it is the notional amount of the base currency considered for calculations, as described in the first section of this document. F is the factor that specifies the number of decimal places in use for the quoted currency (typically 0.0001 for most currencies or 0.01 for some currencies such as the Yen, Chilean Peso or the old Italian Lira). ϵ_t is the level current exchange rate measured in units of the quoted currency (currency against the USD for the sample). To make this even clearer, LxF is a constant and the function $Pt = f(\epsilon)$ turns out to be a negatively sloped hyperbola.

The ARCH specification of Engle (1982) or its generalization [Bollerslev (1986)] is a natural choice for this model, given the results of the previous section. For instance,

$$h_t^2 = \beta_1 + \beta_2 \mu_{t-1}^2 + \beta_3 h_{t-1}^2 + \beta_4 dp_{t-1} \tag{3}$$

Where h_t^2 is the conditional variance, μ is the mean equation's residuals, $p_t = \log(P_t)$ and dp_t is $p_t - p_{t-1}$. Eventually, p_t can be substituted with Dp_t, a dummy variable that takes value 1 when $dp_t > 0$ and 0 otherwise.

Nevertheless, the problem with the above specification is that the β coefficients are not necessarily $\geqslant 0$ (in particular β_4 which is expected to be negative). In the PIPs estimations, this condition is crucial because parameters that accompany the PIP variables can be negative, so we must rule out any theoretical or empirical possibility of having negative conditional variances. An alternative choice that has gained much attention in financial theory has been the Nelson (1991) EGARCH model, so given that the conditional variance is in exponential form, negative parameter values will not cause a negative variance.

Two important and different ingredients from most other studies so far are required. First, the fact that the PIP values affect the conditional variance in an exogenous way, which corresponds to an EGARCH-X specification. Secondly, the model must consider that the mean equation has an effect on the variance rather than the other way around (as it has been the classic approach in the literature). Some simple algebra will help in explaining the reason for both conditions.

Given that equation 2 provides us with the PIP value formula, it is then straightforward to show that $dp_t = -de_t$. This implies that from equation 3, $h_t^2 = g(\mu_{t-1}, h_{t-1}, de_{t-1})$, g is a function of e_{t-1} and the partial derivative of g with respect to de_{t-1} is expected to be positive, given that β_4 is in turn expected to be negative. For the first ingredient, e_{t-1} is indeed exogenous because its value can cause h_t^2 but the opposite is not true because of the lag. For the second ingredient, it has been showed in the previous paragraph that the conditional variance does indeed depend on the mean equation.

Given the analysis above, an appropriate model for the variance equation would be the following:

$$\ln(h_t^2) = \omega + \nu \left[\theta \frac{\mu_{t-1}^2}{\sqrt{h_{t-1}}} + \gamma \left(\frac{|\mu_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right) \right] + \beta_3 \ln(h_{t-1}^2) + \beta_4 PIPterm1 + \beta_5 PIPterm2 \tag{4a}$$

But equation 4a can equivalently be expressed as:

$$\ln(h_t^2) = \omega + \beta_1 \left[\frac{\mu_{t-1}^2}{\sqrt{h_{t-1}}} \right] + \beta_2 \left[\frac{|\mu_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right] + \beta_3 \ln(h_{t-1}^2) + \beta_4 PIPterm1 + \beta_5 PIPterm2 \tag{4b}$$

Where $\beta_1 = \nu\theta$ and $\beta_2 = \nu\gamma$.

The PIPterm added to equation 4b will correspond to the following (depending on the subsample used). For the Euro currencies (left side of table 2), $PIPterm1 = Dp_t$ and $PIPterm2 = D_t^1$ where D_t^1 i is given by the following formula:

$D_t^1 = D_t^0 * Dp_t$. D_t^0 , in turn, is an indicative variable that takes value 1 for the period before 1999/01/01 or where the EUR took place and 0 afterwards.

For the other two subsamples described in table 2, $PIPterm1 = Dp_t$ and $PIPterm2 = dp_t$, described earlier.

In order to maximize the log likelihood function for the above specification and avoid the risk of obtaining a local maximum as a resulting outcome, it is important to determine appropriate initial values for the parameters. A value of zero, an alternative model or an educated guess are the common alternatives. In this case, we will estimate the initial parameters by assuming an alternative model where we will consider the squared residuals rather than the conditional variance as the dependent variable and dropping the exponential function. In this case, equation 4b reduces to:

$$\mu_t^2 = \Sigma + \beta_1 \mu_{t-1}^{3/2} + \beta_2 \mu_{t-1}^{1/2} + \beta_3 \mu_{t-1}^2 + \beta_4 PIPterm1 + \beta_5 PIPterm2 + \tau_t \tag{5}$$

Where $\Sigma = \omega - \beta_2 \sqrt{\frac{2}{\pi}}$

Equation 5 will provide us with appropriate initial values for $\omega, \beta_1, \beta_2, \beta_3, \beta_4$ and β_5 in order to estimate equation 4a. It has been found that a model truncating $\beta_3 = 0$ permits convergence for the likelihood function, otherwise, several currencies do not attain a solution.

4 Analysis of the results.

The first subsample (i.e., the Euro currencies), will provide a first approach to determine just how sensible noise traders are to PIP value by assuming that any increase in the order flow from these investors will be translated into additional volatility of exchange rates. Table 1 provides the results for this first subsample.

Figure 1: Euro sample results (standard error in parenthesis).

$$\ln(h_t^2) = \omega + \nu\left[\theta \frac{\mu_{t-1}^2}{\sqrt{h_{t-1}}} + \gamma\left(\frac{|\mu_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}}\right)\right] + \beta_4 D_{t-1}^1 + \beta_5 Dp_{t-1}$$

Variable	ATS	BEF	FIM	FRF	DEM	ITL	NLG	PTE	ESP
AR(1)	-0.0865 *	-0.0584 *	-0.1201 *	-0.0613 *	-0.0628 *	-0.0761 *	-0.0869 *	-0.1104 *	-0.0778 *
	(0.0154)	(0.0154)	(0.0121)	(0.0156)	(0.0155)	(0.0155)	(0.0153)	(0.0158)	(0.0157)
Variance Constant	-10.0914 *	-10.2009 *	-10.0782 *	-10.2402 *	-10.1988 *	-10.2288 *	-10.1758 *	-10.1503 *	-10.1482 *
	(0.0215)	(0.0273)	(0.0209)	(0.0272)	(0.0270)	(0.0261)	(0.0268)	(0.0261)	(0.0230)
Lagged Sqr.Residual	0.2608 *	0.2871 *	0.3207 *	0.2743 *	0.2755 *	0.3093 *	0.2967 *	0.2938 *	0.2848 *
	(0.0179)	(0.0221)	(0.0150)	(0.0214)	(0.0206)	(0.0143)	(0.0234)	(0.0228)	(0.0190)
Dummy (D{t-1}¹)	0.1426 *	0.1099 *	0.0685	-0.0043	0.1262 *	0.1582 *	0.0424	0.1486 *	0.1113 *
	(0.0484)	(0.0502)	(0.0476)	(0.0499)	(0.0508)	(0.0453)	(0.0491)	(0.0490)	(0.0467)
Dummy (Dp{t-1})	-0.1825 *	-0.1067 *	-0.2290 *	-0.0463	-0.1031 *	-0.0982 *	-0.0530	-0.1504 *	-0.1577 *
	(0.0448)	(0.0465)	(0.0447)	(0.0461)	(0.0466)	(0.0465)	(0.0447)	(0.0461)	(0.0452)

* Significant at 5% level.

The AR(1) coefficient corresponds to the mean equation and is significant for all the currencies in the sample. The same is also true for the ARCH structure in the conditional variance. But the most important aspect to focus on are the dummy variables introduced to control for the PIP value effect. D_t^1 accounts for the switch to the Euro currency while Dp_t focuses exclusively on the log change in PIP value. The latter is negative for all currencies in the subsample and is significant for all currencies with the sole exception of the FRF and the NLG. This is exactly what was expected from the initial hypothesis given that a rise in PIP value discourages noise traders from placing orders [because of the higher perceived stake at risk] and reduces the conditional variance.

The former dummy, with the EUR change, reverses the PIP effect and is significant for 6 out of 9 currencies. It is important not to rule out other Euro effects not discussed here that may be contaminating these results but it appears as an interesting conclusion that the higher PIP value effect diminishes when one considers the pre-Euro period. The pre-Euro time frame appears as one of higher volatility but the PIP value effect is still important for most currencies. Another explanation is that many traders are located in the UK (as indicated in the first section of this document), so it is an indication that many of them may be using the EUR or the GBP as their base and placing the USD in their currency basket, reversing the PIP interpretation.

Nevertheless, we can reasonably consider that the PIP effect is present for the first subsample, this will permit to test the PIP effect for the main sample by using Dp_t just as in the first subsample and adding the log variation of PIP value in the variance equation.

Figure 2: Main sample results (Standard error in parenthesis).

$$\ln(h_t^2) = \omega + v\left[\theta \frac{u_{t-1}^2}{\sqrt{h_{t-1}}} + \gamma\left(\frac{|u_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}}\right)\right] + \beta_3 \ln(h_{t-1}^2) + \beta_4 Dp_{t-1} + \beta_5 dp_{t-1}$$

	CAD	JPY	KRW	SGD	TWD	ZAR	CHF	SEK	DKK
AR(1)	-0.0300 *	-0.0737 *	0.3194 *	-0.0980 *	-0.1322 *	-0.1427 *	-0.0669 *	-0.0543 *	-0.0778 *
	(0.0146)	(0.0144)	(0.0038)	(0.0104)	(0.0081)	(0.0097)	(0.0155)	(0.0153)	(0.0156)
Variance Constant	-11.4822 *	-10.1677 *	-10.2999 *	-11.7220 *	-12.0141 *	-10.1394 *	-10.0426 *	-10.1958 *	-10.2527 *
	(0.0254)	(0.0261)	(0.0079)	(0.0140)	(0.0088)	(0.0195)	(0.0324)	(0.0295)	(0.0298)
Lagged Sqr.Residual	0.3620 *	0.3220 *	0.3061 *	0.4612 *	0.5503 *	0.5749 *	0.2252 *	0.3102 *	0.2684 *
	(0.0205)	(0.0158)	(0.0034)	(0.0129)	(0.0134)	(0.0143)	(0.0214)	(0.0210)	(0.0224)
Dummy (Dp{t-1})	0.0112	0.0160	-0.1280 *	0.0447 *	-0.3361 *	0.1033 *	0.0791	-0.0626	0.0739
	(0.0390)	(0.0366)	(0.0113)	(0.0224)	(0.0158)	(0.0276)	(0.0466)	(0.0418)	(0.0444)
dP{t-1}	-18.1075 *	7.8928 *	2.3151 *	-9.1958 *	23.6070 *	-3.5094 *	-4.1108	-4.7447	-6.2834 *
	(4.8259)	(1.9150)	(0.1752)	(1.8095)	(2.6966)	(1.1908)	(2.7635)	(3.0297)	(3.0544)

* Significant at 5% level.

Table 2 provides the results for the main subsample that includes Asian currencies, the Canadian dollar, the South-African Rand and selected non EUR European highly traded currencies. As in the Euro sample, the AR mean equation and the ARCH structure is significant. The log variation in PIP value has a negative effect (as expected) for 6 out of 9 currencies but statistically significant for only 4 of them. It appears very clear that the Asian currencies have reversed the PIP coefficient sign with the sole exception of the Singapore dollar. One reason for this is that noise traders that trade in Asian currencies (with the apparent exception of the SGD) have one of those as their local currency and rather than having their own currency in their portfolio, they include the USD. The other currencies behave as expected, indeed, they appear to be included in a US based noise trader's portfolio. As in the previous case, the dummy PIP variable tends to reverse the log PIP variation effect.

Table 3 presents the same specification as table 2 but is focused on the last subsample of fairly traded Latin-American currencies.

Again, most of the coefficients are significant for this subsample, the dummy tends to reverse the log PIP value variation effect and the signs are reversed for

Figure 3: Latin-American sample results (Standard error in parenthesis).

$$\ln(h_t^2) = \omega + v\left[\theta \frac{\mu_{t-1}^2}{\sqrt{h_{t-1}}} + \gamma\left(\frac{|\mu_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}}\right)\right] + \beta_3 \ln(h_{t-1}^2) + \beta_4 Dp_{t-1} + \beta_5 dp_{t-1}$$

	ARG	BRL	CLP	COP	MXN	PEN
AR(1)	-0.1768 *	-0.0592 *	0.1094 *	-0.0424 *	-0.0888 *	0.0101
	(0.0035)	(0.0132)	(0.0070)	(0.0139)	(0.0182)	(0.0151)
Variance Constant	-7.8590 *	-8.9166 *	-11.2723 *	-10.7562 *	-10.7712 *	-12.4916 *
	(0.0066)	(0.0138)	(0.0107)	(0.0189)	(0.0353)	(0.0272)
Lagged Sqr.Residual	1.0604 *	0.4607 *	0.5446 *	0.4241 *	0.4154 *	0.5209 *
	(0.0242)	(0.0214)	(0.0203)	(0.0208)	(0.0277)	(0.0230)
Dummy (Dp{t-1})	-1.3764 *	-0.5557 *	0.1417 *	0.0163	-0.1069 *	-0.0953 *
	(0.0240)	(0.0293)	(0.0212)	(0.0281)	(0.0515)	(0.0376)
dP{t-1}	11.8238 *	14.1460 *	-28.5823 *	4.2021 *	-11.8915 *	5.2967
	(0.2368)	(1.1340)	(2.6089)	(2.1312)	(4.0841)	(7.8197)

* Significant at 5% level.

most of them, with the exception of the CLP and MXN. It is apparent from these results that with the exception of the Chilean and Mexican Peso, noise traders would not incorporate most Latin-American currencies in their portfolios but rather the other way around, that is, noise traders located in Argentina, Brazil or Colombia would hold USD in their portfolios and reverse their interpretation of the PIP value. It is important to recall that the ARG and BRL were tested on a narrower time line, when they each started to float after their respective currency crises.

The Chilean Peso is an interesting case in this subsample. It is the only Latin-American currency that reasonably floats since 1988 (similar to other currencies in the previous subsamples). "Reasonably" here is used to emphasize that Central Bank interventions are made within bands as it is the case for Chile during a significant part of the nineties or sporadically, in which case, CB intervention can be treated in similar terms as to an informed trader that does not intervene the market in any dramatic way. Following with this argument, the CLP mimics the behavior of non-Asian currencies in the main subsample and an acceptable conjecture for this behavior would be that noise traders would tend to incorporate in their portfolio currencies that float during large periods of time. The Mexican Peso, in turn, has a long story of CB intervention, yet, the MXN is the most highly traded Latin-American currency. From these two examples, it would be reasonable to conjecture that long time floating currencies such as the Chilean Peso or fairly traded currencies such as the Mexican Peso are good candidates for a US based noise trader and that the PIP value argument should potentially affect their conditional variance.

5 Concluding remarks.

This study's main objective is to provide some initial tests on the PIP value effect on the conditional variance of exchange rates. According to the author's knowledge, this approach has never been addressed in the past. The sample currencies under scope have been divided in three subsamples. The first one corresponded to currencies that switched to the EUR in 1999. This first sample permitted to assess the effect of a quoted currency that turned into the base and its impact on noise trading and furthermore, on the variance equation. The PIP effect was correctly signed and significant for most of the EUR currencies, providing new evidence that the PIP value affected the conditional variance of exchange rates returns. The Euro effect was inversely signed and diminished the PIP effect which can be explained by noise traders having the EUR or GBP as local currency instead of the USD, reversing their interpretation of the PIP value. Another possibility is that the Euro dummy was contaminated with additional effects not covered in this document.

The results for the other two subsamples were also interesting. The model was slightly modified to directly assess the PIP value effect. Non EUR European currencies, the Canadian Dollar, the South African Rand, the Singapore Dollar, the Chilean Peso and the Mexican Peso evidenced the correct sign and magnitude for the PIP value effect, indicating that a rise in PIP value diminishes the conditional variance and that US based noise traders do potentially have these currencies in their portfolios.

The major share of the Asian currencies and the Argentinean and Brazilian currencies reverted their signs and magnitude. One explanation conjectured here for the fact that noise traders interpret the PIP value in the opposite direction, is that for these currencies, their counterpart, the USD, is the currency included in the portfolio, so the interpretation of the PIPs is reversed.

This research is based on the notion that noise traders are affected by a variable PIP value and that their order flow should be a function of the PIP value and not just the currency prices. This idea has strong empirical considerations, given that practitioners calculate their gains and losses in terms of PIPs before they translate those results to their local currency. This issue opens a new branch of research in the solution to the excess volatility puzzle [or the fact that currencies fluctuate more than the macro variables that should affect them in the long and short run].

6 Appendix

The expected variance equation depends on the lagged term of the mean equation (i.e., a mean-in-GARCH rather than the more familiar GARCH-in-mean model) and in order to rule out the possible non-zero correlation between the residuals and the lagged term of the mean equation, the following demonstration is included. Indeed, If eventually the lagged term is correlated with the residuals, we would have a serious specification problem but fortunately it is not the case. Using some simple statistical manipulations and under a plausible condition, I will demonstrate that the covariance between the residuals and the squared residuals is zero. The latter is a sufficient condition to rule out any linear relation between the lagged term in the mean equation and the residuals.

First, let's specify the model in a simple setting.

Let the mean equation be:

$$X_{t+1} = \beta X_t + \varepsilon_{t+1} \tag{6}$$

Where ε_{t+1} is a zero expected value and finite variance disturbance term.

Let the variance equation be expressed as:

$$\varepsilon_{t+1}^2 = f(X_t) + \eta_{t+1} \tag{7}$$

Where η_{t+1} is a pure random white noise process.

Proposition 1 *Given a model specified by equations 6 and 7 and assuming that* $E_t(\eta_{t+1}) = 0$ *and* $cov(X_{t+1}, \eta_{t+1}) = 0$,*then* $cov(\varepsilon_{t+1}\varepsilon_{t+1}^2) = 0$ *so there is no linear relation between* X_t *and* ε_{t+1}.

Proof. We can express the covariance between the residuals and their squared version as: $cov(\varepsilon_{t+1}\varepsilon_{t+1}^2) = E_t(\varepsilon_{t+1}\varepsilon_{t+1}^2) - E_t(\varepsilon_{t+1})E_t(\varepsilon_{t+1}^2) = E_t(\varepsilon_{t+1}\varepsilon_{t+1}^2)$, given that $E_t(\varepsilon_{t+1}) = 0$. Given equations 6 and 7, the residuals can be expressed as $\varepsilon_{t+1} = X_{t+1} - \beta X_t$ and $\varepsilon_{t+1}^2 = f(X_t) + \eta_{t+1}$,respectively. So, the covariance is determined by $cov(\varepsilon_{t+1}\varepsilon_{t+1}^2) = E_t[(X_{t+1} - \beta X_t)(f(X_t) + \eta_{t+1})]$ The latter result can be expressed as $cov(\varepsilon_{t+1}\varepsilon_{t+1}^2) = f(X_t)E_t(X_{t+1}) + E_t(X_{t+1}\eta_{t+1}) - \beta X_t f(X_t) - \beta X_t E_t(\eta_{t+1}) = f(X_t)E_t(X_{t+1}) + E_t(X_{t+1})E_t(\eta_{t+1}) + cov(X_{t+1}, \eta_{t+1}) - \beta X_t f(X_t) - \beta X_t E_t(\eta_{t+1})$ But given that $E_t(\eta_{t+1}) = 0$ and $cov(X_{t+1}, \eta_{t+1}) = 0$, the latter expression reduces to $cov(\varepsilon_{t+1}\varepsilon_{t+1}^2) = f(X_t)E_t(X_{t+1}) - \beta X_t f(X_t)$. Furthermore, $E_t(X_{t+1}) = \beta X_t$, so $cov(\varepsilon_{t+1}\varepsilon_{t+1}^2) = 0$. ■

According to this proposition, there are no flaws in the specified equations that may lead to a biased estimation.

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