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Some stylized facts of returns in the foreign exchange and stock markets in Peru

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Some Stylized Facts of Returns in the Foreign Exchange and Stock Markets in Peru*

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Abstract

Some stylized facts for foreign exchange and stock market returns are explored using statistical methods. Formal statistics for testing presence of autocorrelation, asymmetry, and other deviations from normality is applied to these financial returns. Dynamic correlations and different kernel estimations and approximations of the empirical distributions are also under scrutiny. Furthermore, dynamic analysis of mean, standard deviation, skewness and kurtosis are also performed to evaluate time-varying properties in return distributions. Main results reveal different sources and types of non-normality in the return distributions in both markets. Left fat tails, excess kurtosis, return clustering and unconditional time-varying moments show important deviations from normality. Identifiable volatility cycles in both forex and stock markets are associated to common macro financial uncertainty events.

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1 Introduction

Volatility in the foreign exchange (forex) and stock markets usually rises with macro financial uncertainty. Price dynamics in these markets reveal information on the empirical distribution of financial returns. This paper aims at uncovering some of the stylized facts for these markets in Peru by assessing the statistical features of their returns.

A flexible forex rate with occasional official intervention provided the framework for a 22-billion US dollar spot market in the Peruvian banking system in December 2009. This monthly amount of forex transactions represented about 60 percent of the total stock of credits to the private sector by a 46-percent credit-dollarized financial system. On the other hand, by the end of 2009, the 310-billion market capitalization of the Lima Stock Exchange was about 81 percent of that year nominal GDP. These markets' dimensions are important in Peru but there is certainly enough space for expansion (as compare to other financial markets in the region).

In order to assess the main characteristics of their unconditional return distributions, we explore forex and stock market returns by statistical methods. There are not many previous formal or systematic studies reporting on the stylized facts of the forex and stock markets for Peru.[1] This research is a first approach to a more in-depth modeling of these financial returns and, thus, it is part of a broader research agenda for financial market dynamics.

After initial basic visual inspection of forex and stock market returns, the analysis starts with standard descriptive statistics of nominal series at daily, weekly, and monthly frequencies. Along with the empirical literature, the analysis reveals evidence of different types and sources of non-normality in the return distributions of these financial prices. Formal normality tests, the Bera and Jarque (1982) test and the comparison between the empirical kernel distribution and its corresponding normal density, confirm non-normality of forex and stock market returns in Peru. Search for best-fitting empirical distribution suggests the Student's t and the Logistic distributions

[1] A useful, but rather short, report on stylized facts in the Lima Stock Exchange could be found in Zevallos (2008) for the sample 2000 - 2006.

are appropriate representations of financial returns in Peru.

One deviation from normality is usually due to serial correlation in returns. If a current asset return is related to a previous return then, as Sheikh (2010) argues, this autocorrelation might distort risk analysis on the asset.[2] Indeed, this research finds evidence of serial autocorrelation at all frequencies in the stock market but only at daily data in the forex market if whole samples are considered for the tests. However, statistically significant autocorrelation in returns tend to disappear (at all frequencies) if shorter samples are used.

Dynamic cross-correlations for returns, mean, and standard deviation reveal interesting co-movements between forex and stock returns. In particular, negative cross-correlation between forex and stock returns, a condition for successful portfolio risk diversification breaks down in periods of greater uncertainty. Further results show evidence of fat left tails and significant excess kurtosis in the return distributions in both markets. The feasibility of conditional heteroskedasticity (ARCH/GARCH effects) is signal by return clustering at all frequencies.

Evaluation of financial returns continues with (one-year rolling) dynamic descriptive statistics that provide information on the empirical mean, standard deviation, skewness, and kurtosis of the unconditional return distribution for each asset price (forex and stock quotes). All distribution moments are time-varying, with identifiable volatility cycles in returns associated to common macro financial uncertainty events.

Once the type of non-normality in the return distributions is established, continuing research agenda includes modeling the sources of this non-normality. It involves modeling explicitly those ARCH/GARCH effects and exploring the feasibility of regime shifts (or the alternative of outlier detection). Further extensions might consider adjusting returns to represent the empirical distribution of data in order to assess volatilities under

[2] The efficient market hypothesis (EMH) is linked to returns being independently and identically distributed. Serial autocorrelation might arise for a number of reasons (recent financial crises, for instance) and it might be at odds with market efficiency. However, this paper does not attend to assess formally the EMH.

different specifications (historical, stochastic, implicit, and realized).[3]

The rest of the paper is organized in the following manner. Section 2 presents briefly the theoretical framework. Section 3 describes data in the forex and stock markets. Section 4 provides analysis on descriptive statistics, empirical distributions, serial correlation, return clustering, and dynamic moments. Finally, Section 5 summarizes and concludes.

2 Theoretical Framework

Forex and stock returns are estimated as percentage log-difference.[4] That is, the corresponding return r_t on any particular price or index time series y_t is generated by the expression:

$$r_t = 100 \times [\ln(y_t) - \ln(y_{t-1})]. \tag{1}$$

Thus estimated, the r_t corresponds to the continuously compounded return for period t. It assumes negligible transaction costs or non-significant differences between bid and ask quotes.[5]

Statistical assessment of return dynamics includes analysis on standard descriptive statistics[6], empirical distributions, serial correlation, return clustering, and dynamic moments. This evaluation is conducted on the unconditional distribution of returns for both markets at different data frequencies.

[3] For applications to portfolio management with non-normally adjusted returns, see Sheikh (2010). For a thorough review of volatility modeling see Andersen et al. (2009) and the papers therein.

[4] A major advantage of using log-differences (rather than price changes) is that multi-period returns are easily calculated as the sum of single-period returns (Taylor, 2005).

[5] This might not be the case at high frequencies or over short periods of time. These spreads seem to have followed a general downward trend, possibly due to some market microstructure developments (i.e. increasing banking competition). Nonetheless, bid-ask spreads increase with market volatility, in particular with financial crises.

[6] Sample size might vary between variables and frequencies but once established, it is kept fixed.

2.1 Descriptive Statistics

For any given sample and frequency, we are interested on four moments of the return distribution: mean, standard deviation, skewness and kurtosis. The first two moments, mean and standard deviation, are measured conventionally. In an informationally efficient market, no regular above-average returns should be obtained for a single asset. Nonetheless, non-zero mean returns is not necessarily at odds with market efficiency since our data represents portfolio allocations. Standard deviation measures the distance of returns to their sample mean although it does not necessarily provide an accurate estimate of financial risk.

The third moment or skewness is an indicator of the asymmetry in the return distribution. Its sample estimation is given by:

$$S = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{r_t - \overline{r}}{\hat{\sigma}}\right)^3, \tag{2}$$

where T is the sample size, $\overline{r}$ is the sample mean and $\hat{\sigma}$ is the estimated standard deviation. Over a given sample, it is common to find the number of negative returns being higher than the number of positive returns. This is shown as a fatter left tail in the return distribution.

The fourth moment or kurtosis is a measure of the peakness of the distribution. Its sample estimation is given by:

$$K = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{r_t - \overline{r}}{\hat{\sigma}}\right)^4. \tag{3}$$

2.2 Empirical Distribution

Stylized facts for financial returns usually suggest strong deviations from the normal distribution. The statistic proposed by Bera and Jarque (1982), denoted by JB, provides a formal assessment of how much the skewness and kurtosis deviate from the normality assumptions of symmetry (zero skewness) and a fixed peak of three. The JB test statistics is calculated as:

$$JB = \frac{T}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \tag{4}$$

where S stands for the sample skewness and K for the sample kurtosis.

In order to assess in the forex and stock markets in Peru what alternative distributions best represent returns that deviate from normality, some theoretical distributions (with sample-based parameters) are compared with the empirical distribution of the data. A preliminary benchmark comparison is done between the empirical kernel distribution and the theoretical normal distribution. Then, up to 12 theoretical distributions are ranked in comparison to the empirical distribution of the data using Crystal Ball, a handy spreadsheet-based financial application for portfolio allocation.[7] Three standard goodness-of-fit tests for the theoretical distribution are used: Anderson-Darling, Chi-Square, and Kolmogorov-Smirnov to select the best fitting distribution.[8]

Although it is not much supported in empirical finance, the normal distribution is a usual assumption for theoretical finance. The seminal analysis of standard portfolio allocation proposed by Markowitz (1952), the β-coefficient estimation of an asset's portfolio risk contribution and the asset management techniques suggested by Sharpe (1964) and Lintner (1965), all assume normally distributed financial returns. Increasingly, though, non-normality is considered for asset allocation studies; see, for instance, Graeme (2010), Hu and Kercheval (2008), and Sheikh (2010).[9]

The density function for a normal distribution is given by:

$$f(r_t) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{r_t - \bar{r}}{\sigma}\right)^2\right) \tag{5}$$

Thus, a first assessment of the degree of departure from normality is to

[7] Among others, the theoretical distributions used here are Normal, Lognormal, Student's t, Logistic, Beta, and Gamma.

[8] Which are readily available also in standard time series econometrics software.

[9] Normality comes from the assumption that financial prices are geometric Brownian motions, so that logarithmic returns are normally distributed. See, for instance, Mills and Markellos (2008).

fit a kernel distribution (smoothing the histogram) to the data and compare it with the normal distribution with mean and standard deviation based on the data sample. A kernel density provides an empirical estimation of the density function of a random variable without parameterizing it theoretically. For the forex and stock returns, the kernel density estimate is a function:

$$f(r) = \frac{1}{Th} \sum_{t=1}^{T} W\left(\frac{r - r_t}{h}\right) \tag{6}$$

where T is the number of observations, h is the smoothing parameter or bandwidth and W is a kernel weighting function.[10]

Among the many theoretical distributions that are considered here for comparison to the data, it is particularly important the Student's t distribution, which is frequently found as an efficient fit to financial returns as in Hu and Kercheval (2008). Importantly, combined with a suitable GARCH-type model, as in Graeme (2010), it could accommodate time-varying skewness and kurtosis along with a time-varying variance.

2.3 Serial and Cross Correlation

As Sheikh (2010) argues, serial correlation renders inaccurate forecasts of financial returns as conventional risk estimates would be underestimated. Serial correlation in financial asset returns is a form of non-normality and it appears whenever there is time dependence in the returns. The Ljung-Box Q-statistics is used here to test for a null hypothesis of no serial correlation up to p lags. The Q-statistics is asymptotically distributed as a χ^2 with degrees of freedom equal to the number of autocorrelations being tested. If the corresponding p-value of the test is less than 0.05, the null of no serial correlation is rejected and, therefore, it can be concluded that there might be serial correlation in the returns.

Another type of deviation from normality for joint asset returns is time-varying correlation. In particular, it might be the case that expected correlation between two asset returns breaks down and, for example, shifts from

[10] Usually Gaussian.

negative (beneficial to portfolio diversification) to positive under a period of extreme market volatility. That is, episodes when diversification should prevent overall portfolio return from sliding down are unexpectedly much riskier because asset return correlations become positive. Rather than estimating correlations of asset returns for a number of sample sizes, as in Sheikh (2010), dynamic cross correlation for stock and forex returns are estimated through the entire sample using one-year rolling windows.

2.4 Return Clustering

Time-varying volatility in financial returns is empirically shown as return clustering. That returns agglomerate is a stylized fact in empirical finance by which large changes (both positive and negative) in returns are followed by further large changes. This feature is referred to as the presence of ARCH/GARCH effects.

In the autoregressive conditional heteroskedastic (ARCH) model from Engle (1982), the conditional variance of shocks, h_t, is a linear function of past squared shocks:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2. \tag{7}$$

where $\omega > 0$ and $\alpha_1 > 0$. Therefore, the ARCH model explains volatility clustering as the variance is a increasing function of previous shocks. It does not actually matter the sign of the shock, but if ε_{t-1} is big in absolute value, then ε_t is expected to be big as well.

Bollerslev (1986) suggested adding lags of the conditional variance to allow for high persistence in the empirical autocorrelation function in a generalized ARCH model which is well known as a GARCH model. In its simplest representation, a GARCH(1,1) model, is given by:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}, \tag{8}$$

where, in addition to the ARCH parameter conditions, $\beta_1 \geqslant 0$ to guarantee that $h_t \geqslant 0$. In order to assess for this type of deviation from normality, still with no econometrics, we do visual inspection of the squared returns for both forex and stock markets (at all frequencies).

2.5 Dynamic Moments

Time-varying moments in return distributions are common in financial markets. In order to assess whether there is evidence of any behavioral pattern in mean, standard deviation, skewness or kurtosis, these moments are estimated dynamically. One-year rolling windows are used for sample estimation of these moments.[11]

Dynamic skewness is then estimated using the expression:

$$S_j = \frac{1}{\tau} \sum_{t=j-(\tau-1)}^{j} \left(\frac{r_t - \overline{r}_j}{\hat{\sigma}_j} \right)^3, \tag{9}$$

where $j = \tau, ..., T$, τ is the size of the rolling window, T is the total sample size available, $\overline{r}_j$ and $\hat{\sigma}_j$ are the estimated mean and standard deviation for the corresponding rolling window j.

Similarly, the dynamic kurtosis is calculated as:

$$K_j = \frac{1}{\tau} \sum_{t=j-(\tau-1)}^{j} \left(\frac{r_t - \overline{r}_j}{\hat{\sigma}_j} \right)^4. \tag{10}$$

Plots of $\overline{r}_j$, $\hat{\sigma}_j$, S_j, and K_j might provide hints on any particular pattern for financial return distributions and, therefore, on any macroeconomic or financial event influencing these financial markets.

3 Data Description

This section describes data used in the estimations from forex and stock markets in Peru. It reports on variables, samples, sources of data collection, frequency, date recording (average- or end-of-period), and some additional

[11] These are actually near-one-year rolling windows, since the number of observations for any given year is rather varying. For daily observations in the stock market, for instance, we take 260-day windows ($\tau = 260$), which approximates one calendar year (with 5-day weeks).

methodological details as frequency conversion and error checks. For an overview of the financial context, those markets in Peru are briefly described.

Statistical analysis is conducted for daily, weekly, and monthly nominal returns for the forex and stock markets.[12] Results are reported in detail for the daily frequency. Differences in results with other frequencies are pointed out whenever necessary. Sample size for each variable and frequency is selected according to data availability, but the general starting date for analysis is January 1994.

The Peruvian economy was exposed to a long period of macroeconomic instability during the 1980s and, in particular, during the 1988-1990 hyperinflation period. In the 1990s, stabilization policies were launched and they eventually succeeded in bringing down macroeconomic and financial fluctuations by late 1993. Therefore, the period from 1994 onwards excludes large volatilities due to macroeconomic turmoil. In all cases, data samples end in December 2009.

Daily data points correspond to day-average observations in the forex market and end-of-trading quotes in the stock market. For weekly data, observations on Wednesdays are considered. Whenever data is unavailable for Wednesday, either Tuesday or Thursday is taken to represent weekly data. For monthly data, both end-of-period and average-of-period observations are considered. Results are quantitatively and qualitatively similar for both, though whenever reported they correspond to end-of-period data.

Treatment for public or general holidays has been standardized for both forex and stock markets, so that final database is homogenous as to the non-available (NA) observations. Visual inspection of returns and of forex spreads has allowed detecting a number of clear-cut mistakes in data. Therefore, those observations were corrected based on cross-information sources.

[12] Difficulties to allocate inflation records for daily or weekly returns prevent the use of real returns. Furthermore, widespread practice is to evaluate nominal returns for financial markets.

3.1 Forex Market

In Peru, exchange rates float freely but official intervention usually takes place whenever excessive market fluctuations prompt expectations of balance sheet effects in the economy. By December 2009, total transactions in the spot forex market for the banking system is 22 197 millions of US dollars. From those transactions, US$ 7 807 millions correspond to purchases and US$ 7 594 millions to sales to non-financial counterparts, while that US$ 6 796 millions are interbank transactions. The forward forex market (US$ 6 162 millions) is less than one third the size of the spot market.

Two types of forex rates are selected for analysis: the bank forex for transactions between banks and their non-financial customers (for which results are reported on) and the interbank forex for operations among banks. Both bid and ask quotes are considered in each case. Daily observations correspond to transaction-weighted daily average across banks. No bid-ask average forex rates are generated, since direct market quotes are preferred for estimations.[13] However, bid-ask spreads are estimated to search for risk premium signals of market uncertainty. An informal parallel forex rate is also available but with somewhat less reliable data, so it is not included here.[14]

Daily data sample is from January 1997 onwards, with a total of 3 146 observations. Analysis on weekly data covers the same sample range, with a total of 676 observations. Monthly data is available for a longer period, starting in February 1994, with 191 data points. Both bank and interbank forex rates are taken from the webpage of the Central Reserve Bank of Peru.[15] However, original sources of data are the Superintendence of Banking for the bank rate and Datatec, a subsidiary of the stock exchange (through which actual transactions are negotiated) for the interbank rate. Forex quotes are expressed as units of local currency (Peruvian soles) for a US dollar. Returns are expressed as the percentage log-difference of those

[13] Though they are actually average forex rates rate from all banks in the system.

[14] Nonetheless, preliminary estimations for this parallel forex rates show similar results, quantitatively and qualitatively, than for the bank and interbank forex rates.

[15] At www.bcrp.gob.pe/statistics.

quotes. Public holidays are treated as non-available observations.

3.2 Stock Market

By December 2009, total market capitalization in the Lima Stock Exchange reached 310 thousands of millions of Peruvian Soles (more than 100 billions of US dollars). Two general stock exchange indexes are considered: the General Index and the Selective Index (IGB and ISB, respectively, for their Spanish acronyms from the Lima Stock Exchange). In order to assess industry-specific features, sector indexes for agriculture, banking, industry, mining, and services are also considered. The share of market capitalization for IGB is 65 percent and for ISB is 47 percent. For all sector indexes combined market share is 85 percent (Mining index is the largest with 56 percent of market capitalization). From a total of 226 firms listed in the stock exchange, there are 32 stocks in IGB, 15 in ISB and 121 stocks in sector indexes all together (the Industry index is the largest with 62 stocks).

The stocks included in IGB best represent the average market trend in stock prices. Turnover, trade amounts, and number of transactions are the criteria for stock selection. Although particular stocks could be withdrawn from IGB because of lower market importance, others are add in to keep the number of stocks constant in IGB. Thus, at all times, IGB remains representative of the most market traded stocks. Fewer stocks are included in ISB, but the index is constructed with the same selection criteria. For all cases, daily estimation of the indexes (by the Lima Stock Exchange) involves quote changes and dividend payments alike.

Data sample runs from January 1994 to December 2009. It includes 3 860 daily observations, 834 weekly data points, and 191 monthly observations. For sector indexes, the sample is from November 1998 onwards, with 2 685; 582; and 134 points for day, week and month observations, respectively. These samples are rather shorter, with respect to the general indexes, because in 1998 a methodological change rendered sector indexes non-comparable to previous data.

Data on the general indexes is readily available, at all frequencies, from the Central Reserve Bank of Peru. Original source, though, is the Lima Stock Exchange. The actual base of IGB and of ISB is December 31st 1991 and of sector indexes is October 30th 1998.

4 Stylized Facts in Financial Returns

Non-normality of financial returns is a common stylized fact in the empirical literature.[16] In order to generally assess return dynamics in the forex and stock markets in Peru, this paper searches for various types of non-normality features. In particular, the analysis focuses on four distribution moments (mean, standard deviation, skewness and kurtosis) to identify deviations from normality in returns. Besides, serial autocorrelation and presence of return clustering are also explored in these financial returns. Results are reported primarily for daily bank forex (bid quote) and for IGB returns. Whenever relevant, results on other frequencies and quotes are reported.

4.1 Descriptive Statistics

Visual inspection (Figure 1) of daily, weekly and monthly returns reveals somewhat similar patterns in the dynamics of forex and stock returns but at different levels. Greater volatility seems to cluster around common dates for both markets. For instance, the 2007-2009 international financial crisis effects on mean and volatility of returns for both markets are the largest in the sample.

Descriptive statistics are estimated for bank forex returns on the bid quote (Table 1). The daily mean for forex returns is 0.004 percent (or 1.51 percent in annual terms) but this value is not statistically different from zero. Weekly mean is 0.015 percent (or annual return of 0.81 percent) and monthly mean is 0.152 percent (1.84 percent annually) but neither of them differs from zero significantly either. The median is centered in zero at all frequencies. The maximum daily return in sample is 2.2 percent and the minimum is -2.3 percent. Return distribution shows a small positive

[16] For reports on some stylized facts on financial time series see, for instance, Franses and van Dijk (2000), Mills and Markellos (2008), Sheikh (2010), and Taylor (2005).

skewness, a relative fatter right tail, and very large kurtosis (leptokurtic), clearly peaking above the normal distribution. For monthly data, however, the skewness is rather negative, more in line with stylized facts for financial series.[17]

For stock returns, descriptive statistics are given for IGB (Table 2). Tails of the return distribution spread out longer with a daily maximum of 12.8 percent and a minimum of -11.4 percent, more than five times greater than in the forex market. Both mean and median are statistically different from zero at all frequencies. Along with these larger returns, standard deviation is almost six times larger than in forex returns.[18] There is clear evidence of fat left tails (negative skewness) at all frequencies, more in line with financial return stylized facts.[19] Leptokurtosis is also present.

Descriptive statistics for sector returns in the stock exchange reveal also non-normal features.[20] Daily returns mean varies from 0.0417 percent in the services index to 0.1054 percent in the mining index (from 16.42 to 46.9 percent annually), all of them statistically different from zero. Returns are negatively skewed, at all data frequencies, for the mining index (the most important in terms of market share). Returns are rather positively skewed for the agriculture index, at all data frequencies. Skewness of returns on the other indexes is either positive or negative depending on data frequency. For instance, the industry index presents a negative skewness at all but weekly returns. In all cases, return distributions are leptokurtic.

[17] However, negative skewness is rather relative to the specific measure of the exchange rate (soles per dollar). Should it be measured the other way around (dollar per soles), there would not be any a-priori reason for the skewness to be either positive or negative.

[18] See Franses and van Dijk (2000) for a similar feature in a sample of well developed financial markets. Preliminary estimations for selected Latin American countries show also evidence of a much higher mean (and volatility) for the stock market than for the forex market.

[19] Official intervention in forex markets might prevent extreme negative returns to accumulate in the empirical distribution. Evidence for some Latin American stock exchanges is rather mixed.

[20] Specific results are available from the authors upon request.

4.2 Empirical Distributions

The JB statistic confirms strong rejection of the null hypothesis of normality for both forex and stock returns. Furthermore, in all but one case (weekly banking index) the JB test rejects normality for sector indexes.[21]

In the forex market, as Figure 2 (first column) shows, the empirical kernel distribution confirms strong deviations from normality in returns at all frequencies. In particular, for monthly data, tails are much fatter than from the corresponding theoretical distribution and them even display multiple hump-shaped. The best fitting distribution is Logistic for daily and monthly returns, but it is Student's t for weekly returns (see second column of Figure 2). Importantly, though, only in the case of weekly returns, the empirical distribution captures most of the histogram display. For daily and monthly observations, even the best fitting distribution leaves out quite a significant part of the histogram area.

For daily and weekly data, all other forex returns (apart from the reported bank forex, bid quote) are best represented by the Student's t distribution. Logistic is still the best empirical representation of the monthly returns for all other forex data.

Similarly, kernel distributions largely divert from the theoretical normal distribution at all frequencies for the stock market returns as Figure 3 (first column) reveals. Again, for monthly observations, distribution tails are multiple hump-shaped. However, in the stock market, the best representation of daily data is the Student's t distribution with a close coverage of all observations. It is the Logistic distribution for the case of weekly and monthly returns, but with a less precise representation of the histogram (see second column of Figure 3). Sector index returns follow similar patterns, especially for the two most important indexes, mining and industry.

[21] For robustness, Quantile-Quantile plots confirm clear deviations from normality for all series under analysis.

4.3 Serial and Cross Correlations

The Q test for serial autocorrelation up to 12 lags is implemented for the forex and stock series at all frequencies for the entire samples. Table 3 shows the Q statistics and their corresponding p-value for each series of forex returns. In the forex market, there is evidence of serial autocorrelation in daily data. However, the null of no autocorrelation is not-rejected for weekly and monthly data up to lag 3 (rejected from lags 4 up to 12). Table 4 presents similar information for stock market returns. In this case, however, results show evidence of serial correlation at all frequencies, though only at 10 percent significance for the monthly data.

If a current asset return is related to a previous return then it would be possible for investors to take advantage of this pattern and generate above normal returns. At first impression, this statistical significant serial correlation questions efficiency in both markets. For robustness, the Q test is also conducted for both series at all frequencies for shorter periods of time. Thus, for daily and weekly observations, the test is successively conducted for each year over the sample. In the case of monthly data, the test is applied for three-year subsamples. At daily frequency, mixed results in the stock market show slightly more years in which serial correlation is not rejected than when there is no evidence of autocorrelation. In the forex market, there is slightly more years in which serial correlation is clearly rejected. At week and month frequencies, there is no evidence of serial correlation.

Cross-correlation between forex and stock market returns is negative and it ranges from -0.27 (daily data) to -0.21 (monthly) for the entire sample. If we consider mean returns, these correlations are still negative, ranging from -0.41 (daily) to -0.36 (monthly). Nevertheless, the correlation across assets for the standard deviation is strongly and significantly positive. It varies from 0.73 for daily data to 0.81 for monthly observations. The large correlation between these two financial returns would suggest similar patterns of market uncertainty (as it was discussed above). Most notably, it seems that financial turmoil episodes increase volatility simultaneously in the forex and stock markets in Peru.

In order to assess if these correlations follow a regular pattern or are rather subject to shifts, we estimate them dynamically with one-year rolling windows (see Figure 4). Cross correlation between forex and stock market daily returns is exclusively negative throughout the sample. It gets sporadically positive for weekly data and somewhat more frequently for monthly observations. In the case of volatility, at all frequencies, positive and negative cross correlations alternate. Noticeably, though, most negative (dynamic) cross-correlations between forex and stock volatility cluster around 2001 and 2003-2004, periods of lesser uncertain scenarios in the stock market. In other terms, with higher market volatility, the expected negative correlation between investments in forex and stocks breaks down and turns into a positive correlation reducing the diversification benefits in a portfolio containing these two type of assets.

4.4 Return Clustering

The uncertainty in both forex and stock market returns (see below), is time-varying across the selected sample. It seems to be associated to financial turmoil episodes (usually, international) in the one hand, and to domestic financial unrest (associated to political cycle) in the other hand. There is evidence indeed of clustering in returns as Figure 5 shows. In particular, observations around 1998-1999 and 2007-2009 seem to display large return agglomeration. In the stock market (with a larger sample for daily data) this clustering is also present around 1995.

This evidence would suggest describing return volatility by GARCH-type models. However, as Perron and Qu (2008) argue, it might also be the case that considering structural breaks or outliers in the econometrics specification might fade out the ARCH/GARCH effects present in the return dynamics. Indeed, Bali and Guirguis (2007) show that correcting outliers dramatically reduces the non-normality and bias in estimated parameters and residuals in ARCH and GARCH models (for small samples). These and other related issues are the object of a broad ongoing research agenda based in the data set used in this paper.

4.5 Dynamic Moments

For the forex market, a dynamic representation of the four distribution moments of returns shows clearly time-varying features (Figure 2). The mean return displays its peaks at the starts of 1999 and of 2009. At the beginning of 2006 there is another upsurge tough at a lesser level than those other peaks. Their lowest average run is during the first semester of 2008. A diminishing trend in mean return during most of the sample is canceled off by the effects of the 2007-2009 financial turmoil.

Volatility shifts to more uncertain scenarios during 1999, 2006 and 2008-2009. In these years, there are clear cycles of upsurge in uncertainty with posterior decline in risk. Without testing for further association at this stage, those cycles seem to correspond to the late 1990s international financial crises (Russia and Brazil), domestic political cycle in 2006 and the 2007-2009 global financial crises. The recent international financial turmoil provides the more market uncertain scenario of the sample.

Hump-shaped dynamics in mean coincide temporally with volatility cycles. Indeed, the evidence suggests that periods of increasing average returns occur along greater market volatility. Most definitely, neither the average nor the standard deviation of returns is constant through time. Furthermore, periods of greater market volatility seem to accentuate non-normality of financial returns.

Skewness and kurtosis of forex returns are also clearly time-varying, but with a somewhat different pattern than mean and standard deviation.[22] Asymmetry of the distribution is on average positive (as reported above) but it gets deeply negative for most of 2001 and 2002 and moderately negative for most of 2006 and 2007. It is worth to recall here that negative asymmetry of returns is a stylized fact for financial series; however, it only appears in two specific periods of the entire sample. On the other side, distribution peakness is clearly above normality throughout the entire sample and it gets further above its average peak during 2001 and 2002.

[22] Alternative two-year and sixty-day windows show similar patterns for the distribution moments.

For weekly and monthly frequencies, the dynamic patterns in mean and in standard deviation are qualitatively similar to that of the daily frequency. Nonetheless, the third and fourth moments of the return distribution vary with data frequency in a seemingly irregular manner.

In the stock market, the four moments of the return distribution are also clearly time-varying (Figure 7) though with different dynamics patterns than those from forex returns but with the exception of the standard deviation. Mean return shows a rather upward trend through 2001 - 2006 which is cancel off by the effects of the 2007-2009 international crisis. This large decrease in returns due to the recent crisis is to some extent prevented in the forex market, possibly through volatility-reducing official intervention.[23]

Interestingly, uncertainty in both markets follows similar dynamics (Figure 8). In both cases, there are three clear episodes of upsurge in volatility (1999, 2006 and 2008-2009), although there seems to be differences in the duration of the cycles. They are more prolonged in the forex market. Again, the 2008-2009 cycle in volatility is the largest for the stock market as well. There is negative asymmetry of returns and the kurtosis is well above normality levels for most of the sample in the forex market.

Thus far, the stylized facts found reveal characteristics of non-normal return distribution in both forex and stock markets in Peru. Distribution moments are all time-varying, seemingly associated to market uncertainty. Return clustering also point out at market volatility as a key factor in explaining asset price dynamics. Furthermore, dynamic cross-correlations (for returns, mean, and standard deviation) reveal interesting co-movements between forex and stock returns.

5 Conclusions

In this paper, some stylized facts in the returns of forex and stock markets are explored by statistical methods. Standard descriptive statistics of

[23] Official forex intervention occurs whenever excessive market volatility threatens to activate balance sheet effects in the highly dollarized Peruvian economy. Therefore, the expected forex should be (ex-post) less volatile than otherwise in those episodes in which the central bank intervenes to reduce (ex-ante) volatility.

nominal series at daily, weekly, and monthly frequencies reveal evidence of different types and sources of non-normality in the return distributions of these financial prices, confirmed by formal normality tests. The Student's t and Logistic are the best-fitting distributions for forex and stock market returns in Peru.

At first evidence from the entire sample under study, serial correlation seems to be present in both financial returns. However, statistically significant autocorrelation in returns tend to disappear (at all frequencies) if shorter samples are used. Negative cross correlations for returns (a desirable feature for portfolio diversification) is present at most parts of the entire sample, but it breaks down into positive correlation for return volatility in periods of greater market risk. Further results show evidence of fat left tails, excess kurtosis, and return clustering at all frequencies.

Dynamic descriptive statistics show that all distribution moments for both forex and stock market returns are time-varying, with identifiable volatility cycles in returns associated to macro financial uncertainty events.

Uncovering the main stylized facts in these two financial markets is a necessary condition in order to understand fully their price dynamics. The discussion on the roots of return dynamics is not trivial since non-normality of returns distribution could be explained by a number of different factors: structural breaks, regime shifts, ARCH/GARCH effects or even the presence of outliers. For instance, a Markov switching model with time-varying probabilities could capture both the timing of shifts and the variables inducing them in financial returns. Alternatively, models of regime dependent variance for financial returns would reproduce the type of non-normality found in the data. Thus, research agenda includes modeling the sources of non-normality of returns. It involves modeling explicitly those ARCH/GARCH effects, but also exploring the feasibility of regime shifts of various kinds, while considering alternatively the presence of outliers. Further extensions might consider adjusting returns to represents the empirical distribution of data in order to assess volatilities under different specifications (historical, stochastic, implicit, and realized).

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Table 1. Descriptive Statistics for Returns in Bank Forex, Bid Quote

	Daily	Weekly	Monthly
Mean	0.0041	0.0155	0.1524
Median	0.0000	0.0000	0.0000
Maximun	2.2087	5.0630	6.4737
Minimum	-2.3041	-5.1346	-5.5377
Standard Deviation	0.2484	0.6822	1.5275
Skewness	0.2320	0.4988	-0.1719
Kurtosis	15.1291	16.1837	6.9155
Jarque-Bera (JB)	19312.620	4923.681	122.952
(p-value)	(0.000)	(0.000)	(0.000)
Observations	3146	676	191
Sample	Jan97 - Dec09	Jan97 - Dec09	Feb94 - Dec09

Table 2. Descriptive Statistics for Returns in Stock Markets (IGB)

	Daily	Weekly	Monthly
Mean	0.0589	0.3230	1.3349
Median	0.0384	0.3478	1.1535
Maximun	12.8155	22.8661	32.5409
Minimum	-11.4408	-18.5937	-46.6485
Standard Deviation	1.4547	3.7478	9.1292
Skewness	-0.2245	-0.2791	-0.4903
Kurtosis	12.0012	7.8514	7.9772
Jarque-Bera (JB)	13063.410	828.750	204.800
(p-value)	(0.000)	(0.000)	(0.000)
Observations	3860	834	191
Sample	Jan94 - Dec09	Jan94 - Dec09	Feb94 - Dec09

Table 3. Serial Autocorrelation for Returns in Bank Forex

Lags	Daily		Weekly		Monthly	
	Q-statistic	(p-value)	Q-statistic	(p-value)	Q-statistic	(p-value)
1	160.040	(0.000)	0.004	(0.951)	0.409	(0.522)
2	169.410	(0.000)	0.345	(0.841)	3.980	(0.137)
3	173.950	(0.000)	3.230	(0.357)	6.068	(0.108)
4	174.000	(0.000)	15.708	(0.003)	16.305	(0.003)
5	175.290	(0.000)	16.770	(0.005)	16.992	(0.005)
6	175.630	(0.000)	16.777	(0.010)	18.629	(0.005)
7	176.360	(0.000)	18.245	(0.011)	20.984	(0.004)
8	176.900	(0.000)	27.932	(0.000)	23.005	(0.003)
9	177.570	(0.000)	35.720	(0.000)	23.383	(0.005)
10	177.610	(0.000)	40.975	(0.000)	23.614	(0.009)
11	177.710	(0.000)	40.995	(0.000)	24.643	(0.010)
12	182.350	(0.000)	42.077	(0.000)	24.658	(0.017)

Table 4. Serial Autocorrelation for Returns in Stock Market (IGB)

Lags	Daily		Weekly		Monthly	
	Q-statistic	(p-value)	Q-statistic	(p-value)	Q-statistic	(p-value)
1	152.250	(0.000)	9.661	(0.002)	3.392	(0.066)
2	152.450	(0.000)	18.992	(0.000)	11.009	(0.004)
3	160.760	(0.000)	22.183	(0.000)	11.129	(0.011)
4	173.320	(0.000)	28.251	(0.000)	12.259	(0.016)
5	173.590	(0.000)	28.924	(0.000)	14.627	(0.012)
6	175.540	(0.000)	29.646	(0.000)	14.726	(0.022)
7	175.540	(0.000)	31.657	(0.000)	14.727	(0.040)
8	178.140	(0.000)	34.312	(0.000)	14.809	(0.063)
9	182.220	(0.000)	38.550	(0.000)	15.350	(0.082)
10	183.160	(0.000)	39.368	(0.000)	16.474	(0.087)
11	183.520	(0.000)	54.451	(0.000)	18.757	(0.066)
12	184.050	(0.000)	55.711	(0.000)	18.793	(0.094)

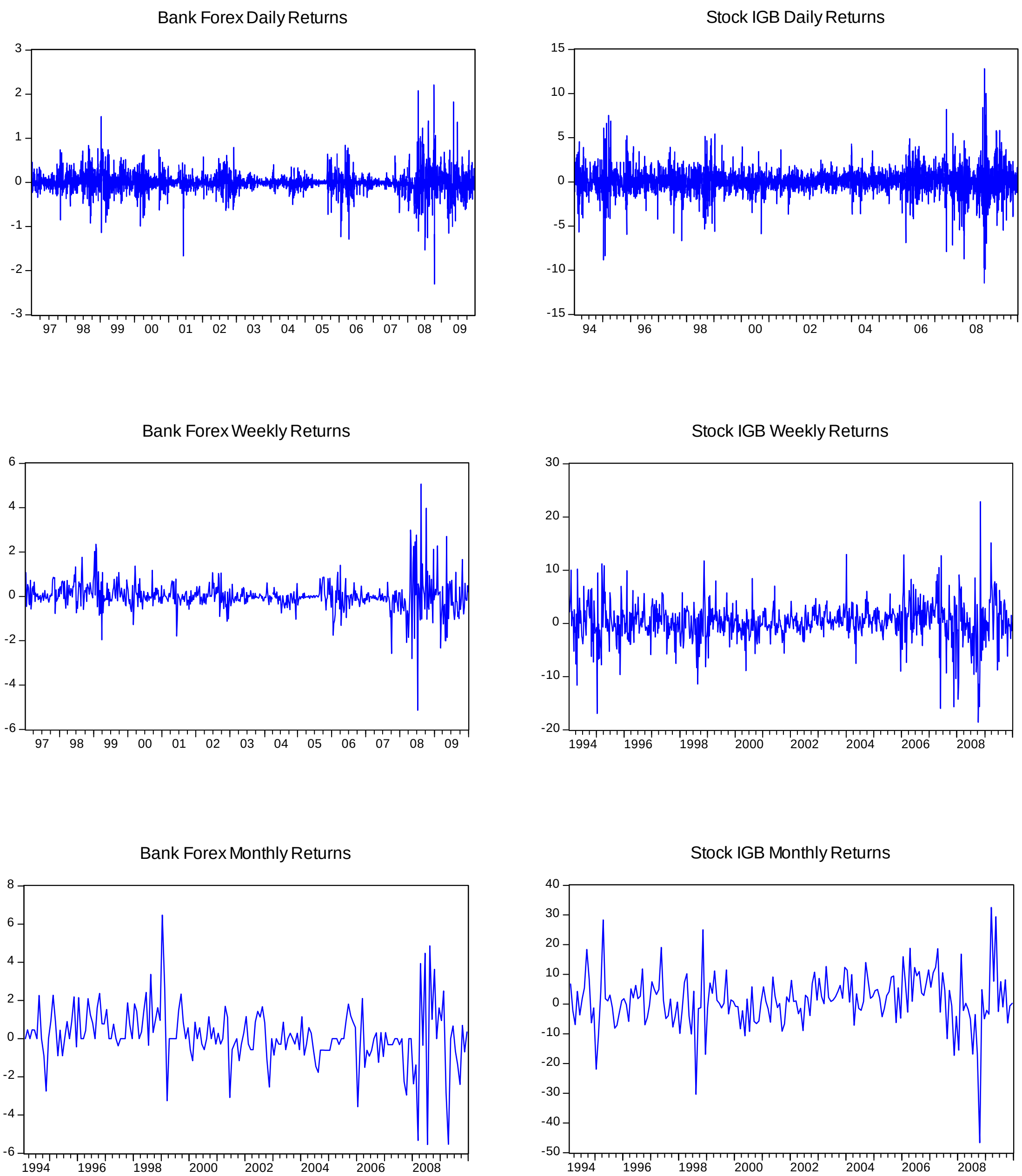

Figure 1. Forex and Stock Returns

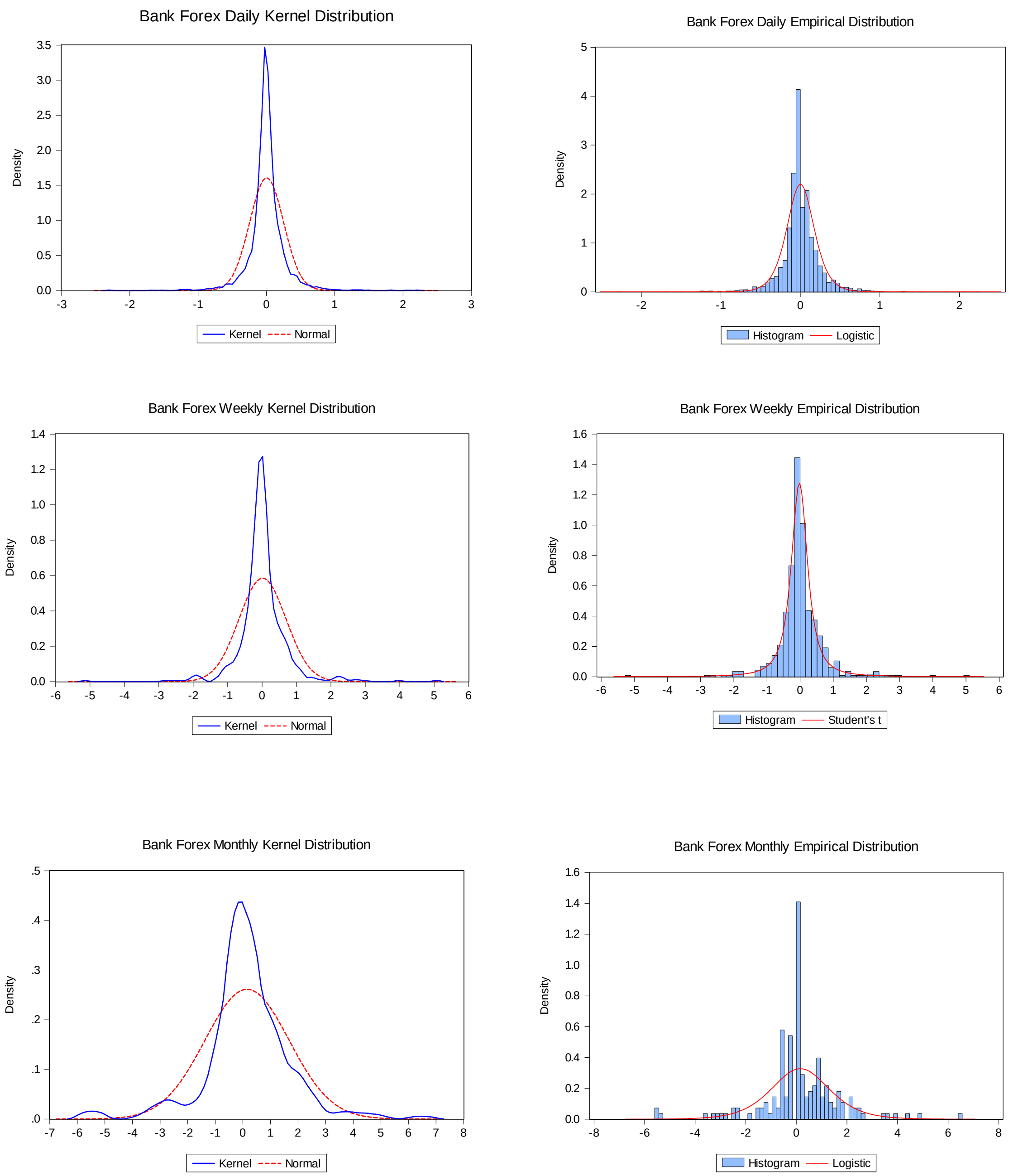

Figure 2. Empirical Distribution of Forex Returns

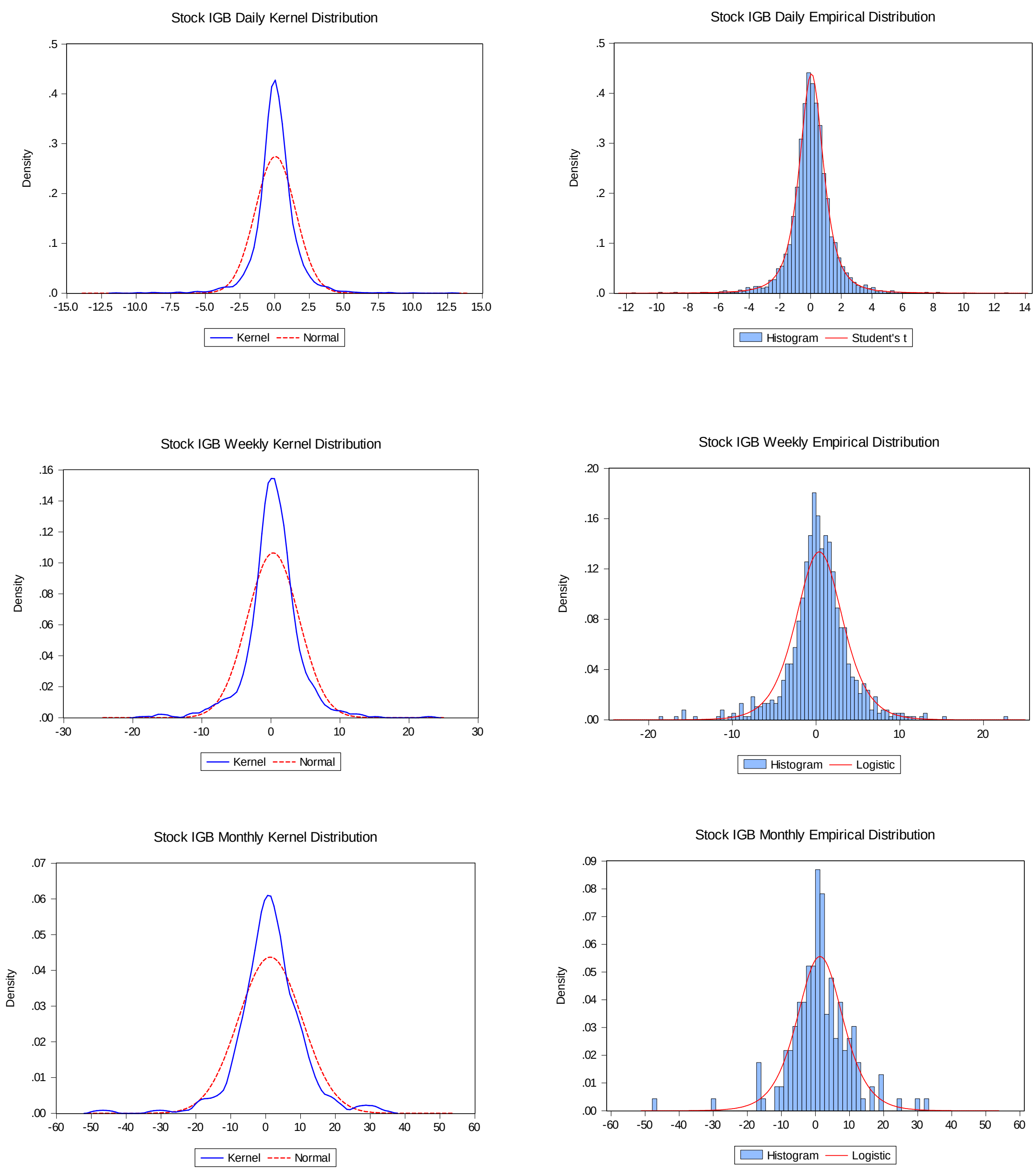

Figure 3. Empirical Distribution of Stock Returns

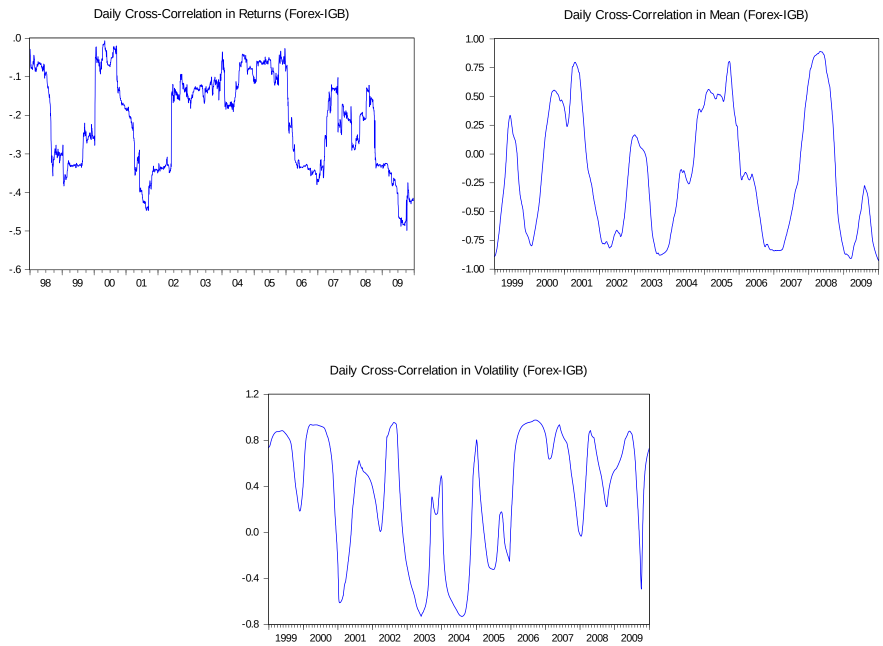

Figure 4. Forex and Stock Cross Correlations

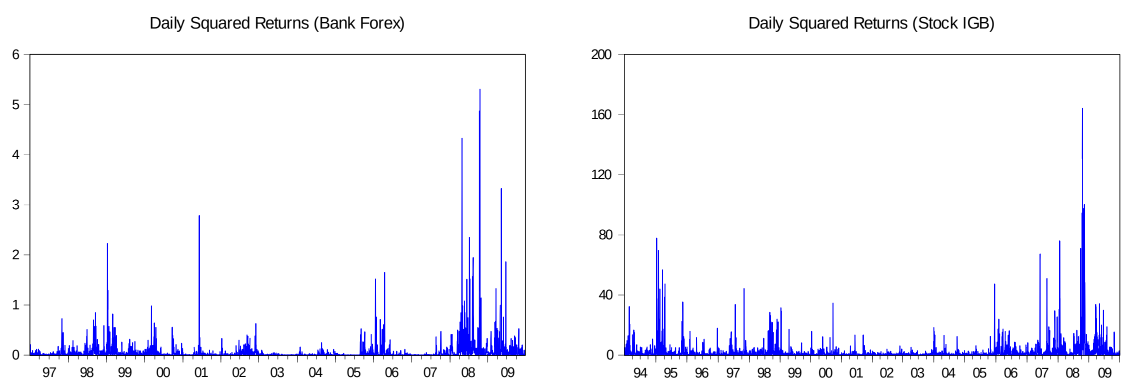

Figure 5. Daily Squared Returns

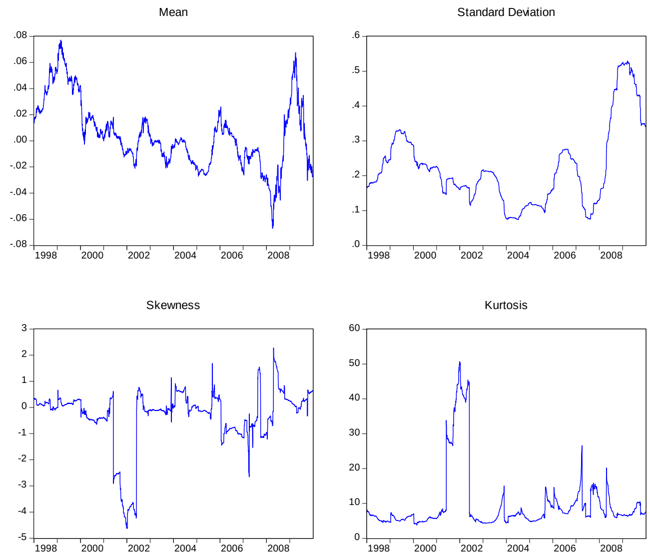

Figure 6. Dynamic Moments of Forex Returns

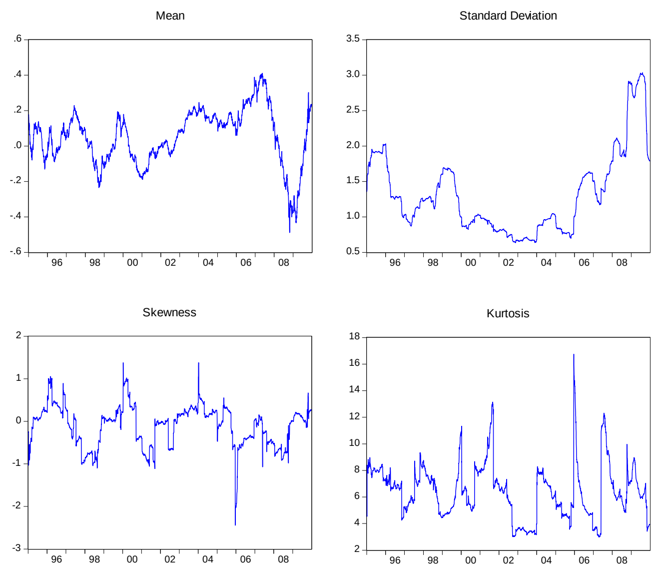

Figure 7. Dynamic Moments of Stock Returns

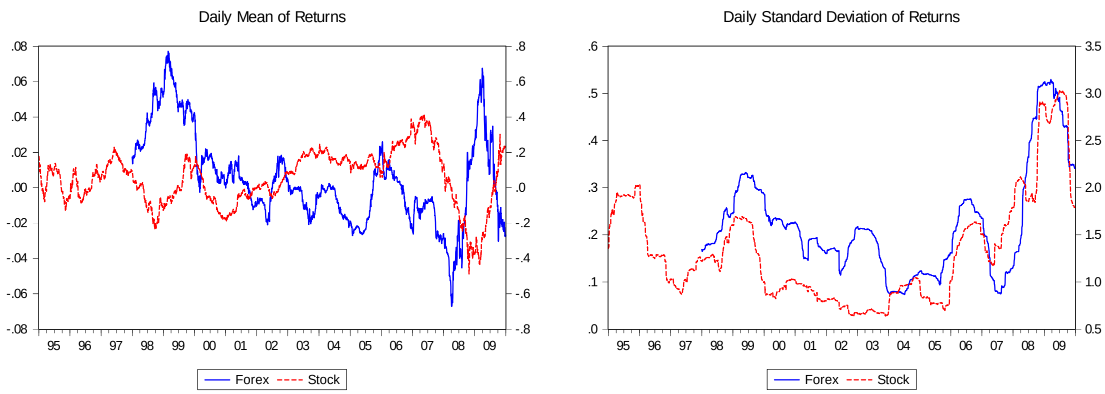

Figure 8 Mean and Standard Deviation of Returns