

# LUND UNIVERSITY

## THE EFFECT OF EXCHANGE RATE AND MONETARY POLICY CHANGES ON STOCK RETURNS IN MEXICO AFTER THE TEQUILA CRISIS

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## PREFACE

This Master Thesis was written during the course "Degree Project in Finance - Master Level" at Lund University. This course is the final element of the one year Master program in Finance (M.Sc. Finance - Autumn 2011).

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## ABSTRACT

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- Advisor: Jens Forssbaeck.
- **Key words:** Mexico, Stock Returns, Fixed Exchange Rate Regime, Monetary Tightness, Vector Auto-Regression, Impulse Response, Variance Decomposition, Monetary Aggregates, Difference in Difference Approach.
- **Purpose:** To address any effect in Mexico's stock returns due to changes in exchange rate and monetary policy after an economic shock (crisis).
- Methodology: We used a framework based on the Vector Auto-Regression approach. Additionally, the Difference-in-Difference regression approach was employed in order to briefly generalize our results.
- **Empirical foundation:** The empirical data employed comes from the historical financial information of the selected macroeconomic variables. This information was collected from Thomson-Reuters Data-stream database which was available at the Finance Society of Lund University.
- **Findings:** We found that the selected exchange rate and monetary policy variables significantly affected Mexico's stock returns after the Tequila crisis. In addition we also confirmed the presence of a structural break-point in stock returns (which was our hypothesis).

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## **SECTION I**

### **1 INTRODUCTION**

#### 1.1 Background

During the late 1980s and the early 1990s, the Mexican government's efforts for recovery from the previous debt-based crisis were focused on promoting market openness, quasi-pegged exchange rates regimes and financial liberalisation policies. The main aim of these reforms was to improve external perception of the country's short and long-term investment opportunity prospects and as well as meet the U.S. government's economic policy requirements which were necessary to successfully reach the long desired North America Free Trade Agreement (*NAFTA*).

As a result, Mexico's economy was rapidly favoured by an unexpected increase of foreign private capital investment. These capital inflows were mainly due to the country's newly and rapidly developing financial liberalisation policies which implied attractive investment opportunities for foreign investors compared to those offered in industrialised countries (specially in the context of low U.S interest rates). It is worth noting that in this setting of high liquidity, foreign inflows were allocated in a large extent to domestic portfolio investments (speculative) rather than to domestic direct investments.

Furthermore, this liberalisation process under which lending rates (despite high) began moving freely, led to a lending boom. This created an economic bubble in Mexico. Companies' easy access to funds, as a result of the privatization of banks, launched the undertaking of private investment opportunities. As a result, this improved the performance of the private sector and by consequence, the stock market as well.

The benefits of a sudden market openness and financial liberalisation did not come without dangerous economic imbalances. Most of the excessive foreign capital inflows were allocated in short term securities (speculative). This made them subject to withdrawals even in the slightest case of unfavourable market conditions. The dramatically increased current account deficit threatened the quasi-pegged exchange rate regime despite the high levels of international reserves to support it. The gradual increase seen in the interest rates deteriorated the loan portfolio of the newly established private banks. Furthermore the absence of major direct investment (real investment) to support the long term domestic economic growth lowered investors' confidence.

These facts plus an uncertain political environment were strong enough threats to quickly collapse the developing Mexican economy. As exhibited in 1994, the political instability and an increase in the U.S. interest rates triggered investors' capital to outflow from the country. These were the main factors that sparked off the well known *Tequila Crisis/Peso crisis*.

As a response to try to soothe the effects of the ongoing crisis, the government and national policymakers agreed on re-stating its national exchange and monetary policies and finally decided to adopt the one that is suited for the prevailing economic environment. These policy changes were believed to have an impact on the stock market performance.

#### 1.2 Problem discussion

According to most of the existing literature, the effect of changes in monetary policy can have a significant positive or negative impact in stock performance. Whereas exchange rates effects on stock returns can vary according to the country specific economic conditions. Therefore one would expect a significant structural break in stock returns when changes in monetary policy take place and that exchange rate policy changes can impact stock returns in different magnitudes (this will serve as our hypothesis).

In the case of Mexico, both monetary and exchange rate shocks were exhibited in the *Tequila Crisis* where the local currency (*Peso*) was devalued due to current account pressures. In addition, the interest rates experienced sharp increases to avoid massive capital outflows. In this respect we did not find any major empirical research that intended to measure the significance of a structural break in stock returns (if any) between the pre and post crisis periods in Mexico.

It is already well known from economic literature that stock prices are equivalent to the expected present value of future net cash flows generated by companies. In this regard, *Thorbecke* (1997) employs the evidence that positive monetary shocks increase stock returns to posit that expansionary monetary policy exerts real effects on stock returns by increasing future cash flows or by decreasing the discount factors at which those cash flows are capitalized from.

Similarly, *Crowder* (2006) states that the financial sector is one sector that is believed to be influenced by the monetary policy whether by altering discount rates or by influencing market participant's expectations of future economic activity. Thus it plays an important role in determining equity returns.

Regarding the exchange rate policy, *Ma* and *Wenchi* (1990) state that the economic effect of exchange rate changes suggests that, for an export dominant country, the currency appreciation reduces the competitiveness of export markets and has negative effects on domestic stock market. Conversely, they also suggest that for an import-dominated country, the currency appreciation will lower import costs and generate a positive impact on the stock market. *Soenen* and *Aggarwal* (1989) ascertained combined effects amidst industrial countries. *Morely* and *Pentescot* (2000) argue that the reason for the lack of strong relationship may be due to exchange controls that were in effect in some countries during the past decades. Overall, we conclude that the relation between stock market and exchange rates can vary depending on the economic and financial features of the countries examined.

#### 1.3 Purpose

With regards to the above discussion, this master thesis is focused on discussing changes in Mexico's monetary and exchange rate policies after the *Tequila Crisis* and test for its impact in domestic stock returns through the *Vector Auto-Regression* framework which includes *impulse responses*, *Granger causality* test, *variance decompositions* and the *Chow test*. This will enable us to document any significant structural break present in stock returns derived from the policy changes that were previously commented upon. Additionally, macroeconomic data for emerging Asian countries which experienced a collapse of the same nature will be used to jointly test for the impact of changes in exchange and monetary policy on stock returns relative to a *control group* (a group of countries that did not undergo any sort of crisis) through the use of the "*difference-in-difference*" approach.

As stated previously, there is no empirical research yet on this subject which has been applied to the case of Mexico. Thus, we hope this thesis will be an important starting point for future national economic research given the increasing worldwide importance of Mexico's capital markets among other emerging markets for international capital allocation.

#### 1.4 Outline

This document is organized as follows: After the introduction (*Section I*) we present *Section II* which talks about the features of the empirical methodologies employed including data collection, analysis of empirical material, trustworthiness of the chosen methods and the criticisms to it. *Section III* presents the theoretical background, the theoretical framework and the literature that relates monetary policy variables with the performance of stock returns. In this section we also include a brief description of the *Tequila Crisis* and its main triggers and as well as a brief description of the exchange rate and monetary policy changes that took place in the post crisis period. *Section IV* focuses on explaining the applied methodology and the processes that we followed to measure and test our hypotheses. *Section V* posits the analyses of the tests applied. Finally, *Section VI* contains our conclusions.

## **SECTION II**

## 2 METHODOLOGY

#### 2.1 Research Type

This document embodies a quantitative research intended to describe and explain the effects of monetary variables on Mexico's stock returns around an economic event (*The Tequila crisis*) in a given time span. Further, this thesis also includes a panoptic approach (*The Difference-in-Difference*) to describe the effect of monetary variables on stock returns in general for countries that underwent a currency crisis. This will help us generalise our conclusions from the case of Mexcio.

*Cohen* (1980) refers to quantitative research as the social science that uses empirical methods and empirical statements. In this regard *Creswell* (1994) defines quantitative research as a type of research that explicates processes by gathering numerical data that is examined using methods founded on mathematics, statistics and econometrics.

*Cormack* (1991) posits that quantitative methodologies test theory analytically from existing knowledge, by building hypothesized relationships and purported outcomes used for analyses and study.

#### 2.2 Data collection

The data used in our analysis consists of the short term interest rate (government treasury bills with 3 months maturity), exchange rate, gross domestic product (GDP/output<sup>1</sup>), consumer price index, monetary aggregates (M1<sup>2</sup>) and a national stock index. These data were collected for Mexico, Malaysia, Thailand, Indonesia, South Korea, Switzerland, Netherlands, Canada, Singapore and Taiwan from the *Thomson-Reuters Data-stream* database available in the *Finance Society* of *Lund University*. The sample period comprises 18 years of monthly (except for output which was quarterly) observations beginning from January 1986 to December 2003 (in the case of México) and from August 1988 to July 2006 (for other foreign countries). The data sample consists of 8,640 observations (216 time periods \* 4 variables \* 10 countries). The sample periods were constructed by choosing a time span in such a way that both the *Tequila Crisis* and the *Asian Crisis* starting dates (December 1994 and July 1997 respectively) coincide at a single data point in the very middle of the sample periods.

<sup>&</sup>lt;sup>1</sup> Later on we use short term interest rates, output and consumer price index (inflation) in a Taylor-type rule to calculate the tightness of monetary policy.

<sup>&</sup>lt;sup>2</sup> It is defined as the total amount of money available in an economy at a specific time. There are several ways to define money but standard measures usually include currency in circulation and demand deposits. M1 is a measure of money supply that includes currency in circulation plus demand deposits, traveler checks or checking account balances.

This implies 9 years of sample data for the pre-crisis period and 9 years of sample data for the post crisis period. (The figure below shows a snippet of the above idea. Here the highlighted blocks are the dates in which the crisis took place.)

Mexico	1986/01	1986/02	1986/03	•		1994/09	1994/10	1994/11	1994/12	1995/01	1995/02	1995/03		2003/10	2003/11	2003/12
Foreign Countries	1988/08	1988/09	1988/10			1997/04	1997/05	1997/06	1997/07	1997/08	1997/09	1997/10		2006/05	2006/06	2006/07

Regarding output (GDP) observations, it is well known that this macroeconomic variable is presented only in a quarterly basis mainly due to its estimation complexity (for governments, central banks and monetary authorities). Since observations are required to be expressed in monthly terms (for our testing purposes), we subjected the quarterly output data series to a *linear interpolation* in order to obtain monthly observations.

All time series were converted to log differences. According to *Chris Brooks* (2008), log returns have the property that they can be interpreted as continuously compounded returns so that the frequency of compounding of the return does not matter. Thus returns across assets can be more easily compared. By converting to log differences we no longer have to worry about the units in which the variables are measured and in addition, log differences have the unique property of *additivity* which comes in handy at times.

It must be noted that the time series data of short-interest rates, consumer price index and output (GDP) was used to compute a monetary tightness variable through the application of a *Taylor rule* type method. This rule requires the creation of two additional variables (namely inflation target and potential output) for each of the countries that compose the sample. Detailed information regarding this is presented later in this document.

#### 2.3 Analysis of Empirical Data

The VAR models which we will employ in our analyses can be viewed as a modification of the *CLRM (Classical Linear Regression Model)*. Here we describe the assumptions of the models we employ. The empirical check of these assumptions is presented later on in the *results section*.

#### **Model Assumptions**

We make a few basic important assumptions for the models that we will be employing later.

We would like our residuals to be normally distributed for easy inference and to conduct tests. However in reality, macroeconomic data is hardly normally distributed. The

*central limit theorem* comes in handy here, which states that normality can be assumed asymptotically provided that the sample size is sufficiently large.

*OLS*'s first assumption is that the average value of the errors is zero. This implies we always should desire to have a constant term in our regression which helps us with the non-violation of this assumption. The *R*-squared might become meaningless when the intercept (constant) term is absent (*Chris Brooks, 2008*).

Under the *OLS* framework it is assumed that the covariance among the error terms over time and/or cross-sectionally is zero. This assumption implies that the errors are uncorrelated with each other (*Chris Brooks, 2008*). He also mentions that the aftermaths of neglecting autocorrelation when it is present could be that the coefficient estimates derived using *OLS* are still unbiased, but they are inefficient. This leads to incorrect standard errors and hence wrong illations could be made about whether a variable is or not an important determinant that explains variations in the dependent variable.

Likewise under the *OLS* framework it is also assumed that the variance of the errors is constant (*homoscedastic*). If the errors do not have a constant variance they are said to be *heteroscedastic*. According to *Chris Brooks* (2008), if *OLS* is still used in the presence of heteroscedasticity, *OLS* may return unbiased co-efficient estimates but they will be inefficient. Standard errors could be incorrect and thus any illations made could be deceptive. Typically the standard errors will be too huge for the intercept.

Further we assume that the regressors are non-stochastic. That is, they are uncorrelated with the error terms. This, if not violated will give us consistent and unbiased estimators.

Another basic assumption under the *OLS* framework is that the independent variables are uncorrelated with each other within a system. When the variables are found to be correlated with each other, they are said to be multicollinear. According to *Chris Brooks* (2008), when variables are multicollinear, removing a variable from the system will cause the coefficient of the other to change. When the variables are not correlated they are said to be *orthogonal*. When multicollinearity is observed in the variables, the *OLS* regression will be spurious. In other words the R-squared will be high and according to *Chris Brooks* (2008), the coefficients will have high standard errors and most probably be insignificant.

We also assume there is no specification error. That is, the functional form of the model is correctly specified.

Later on, we check these assumptions by performing empirical residual diagnostic tests. It is explained later in this document and will be presented along with their respective results.

We assume all variables under the VAR model are stationary. We test this assumption below and make the necessary changes if violated. In case we are required to

stationarise the data, many proponents of the VAR model say that the process of stationarising the data throws away long term relationship in the model (*Chris Brooks,* 2008). Furthermore, we expect residuals are zero and the error terms are not autocorrelated.

Later when employing the *Difference-in-Difference* model, we assume that the difference between the control group and treatment group solely arises because of the treatment received by the treatment group.

#### **Test for Stationarity**

The first and foremost step before conducting a *VAR* estimation is to check for the stationarity of the variables employed. This is a very crucial step, as working with a non-stationary time series leads to a number of undesirable effects like as follows:

- a. The persistence of shocks will be infinite in the presence of non-stationary time series data. The effect of a shock to one variable will have effects on other variables not only during the time period "t", but also in time periods "t+1", "t+2", etc. In case of a stationary time series, these shocks will gradually die out as the time period increases.
- b. Employing non-stationary time series data often lead to nonsensical and *spurious regressions*.
- c. The standard "t" and "F" ratios will not follow "t" and "F" distributions respectively.
- d. A non-stationary process often has means, variances and co-variances that keep changing over time. Therefore it is really inconvenient to work with them as they cannot be forecasted or predicted with such properties.

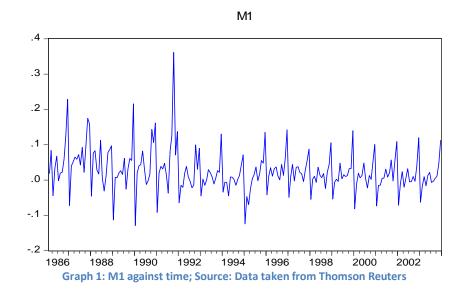
To check for stationarity of the time series data (which we are intending to employ in the *VAR*), we run the *Phillips-Peron* (PP) test and as well as the *Kwiatkowski-Phillips-Schmidt-Shin* (KPSS) test on them. We conduct the PP test rather than the much popular *Augmented Dickey-Fuller* (ADF) test. The PP tests are similar to the ADF tests which tests for a unit root and both often give the same conclusions. We employ the PP test here mainly because it includes an automatic correction to the *Dickey-Fuller* procedure to allow for auto-correlated residuals and secondly because it is based on a much more comprehensive theory of unit root stationarity. However the PP tests suffer from most of the same important limitations as that of the ADF tests. (*Chris Brooks*, 2008). The null hypothesis under the PP test states that the time series data of the variable under scrutiny is non-stationary. The ADF and the PP tests are subject to criticism. According to *Chris Brooks* (2008), the main criticism stems from the low power of these unit root tests, especially in cases where the process is stationary but with a root close to unity (non-stationary boundary). This is exacerbated when dealing with small sample sizes. To overcome this problem *Chris Brooks* (2008) suggests that one

should compare the results of the unit root tests (ADF or PP) with that of stationarity tests (KPSS) where the time series data is stationary under the null hypothesis. This type of joint use of unit root and stationarity tests is known as '*confirmatory data analyses*'. Thus we use the KPSS test as an additional test of stationarity to make robust decisions.

The results of both the PP and KPSS tests that we conducted in EViews are displayed in *Table 1* and *Table 2* respectively which are presented in *Annexure 1*.

We can clearly see from the test results that all time series data except  $M1^3$  (Monetary base/Money supply) have robust results when subjected to PP and KPSS tests. They give the same conclusion that the time series data are stationary and do not contain a unit root. However we get conflicting results for M1. According to the unit root test (PP) we reject the null of unit root (non-stationarity) but according to the stationarity test (KPSS) we reject the null of stationarity. These results are conflicting and must be corrected and made sure that it is stationary before we employ them in our *VAR* analyses.

If we encounter a non-stationary time series we must first refine them to make it stationary. Non-stationarity is either caused by a deterministic time trend or by a random walk or by both. Depending on the type of non-stationary process encountered, we hope to convert them into a stationary process either by differencing or de-trending or by both. Usually if the non-stationary process is a random walk we go for differencing. If it exhibits a deterministic trend then we go for de-trending. If the non-stationary process exhibits both a stochastic and deterministic trend then we apply both differencing and de-trending to stationarize the data.



We look at how M1 is graphed against time. EViews returned the following graph:

<sup>&</sup>lt;sup>3</sup> By M1 we implicitly imply the log differences of M1. We work with logarithmic data as mentioned before.

By looking at the graph superficially we might find a plausible deterministic time trend. We try to bolster this evidence further by running the following regression in EViews:

$$M1_t = c + \beta(t) + e_t$$

Where *t* denotes the time period (1986 to 2003), c is a constant,  $e_t$  is the disturbance term and  $M1_t$  is the monetary base at time *t*.

EViews returned the results as shown in *Table 3* which is presented in *Annexure 1*.

The coefficient of the time period ( $\beta$ ) is significant, enabling us to confirm that there is in fact a deterministic time trend present in the time series data of M1 which causes non-stationarity. However we must note that the R-squared is very low (probably due to the wide dispersion of the data).

After confirming the presence of a deterministic time trend, we now check for the presence of a random walk that might also be present in the M1 data series. This can also cause M1 to be non-stationary. We run the following regression in EViews:

$$M1_t = \mu + M1_{t-1} + e_t$$

This model is a typical random walk model with drift. The constant term  $\mu$  is the drift term. The above regression can be rewritten as:

$$M1_t - M1_{t-1} = \mu + e_t$$

Now the dependent variable is simply the first difference of M1. Thus,

$$d(M1_t) = \mu + e_t$$

This can be easily run in EViews. The results obtained are displayed in *Table 4* which is presented in *Annexure 1*.

We see that the drift term (C) is insignificant. This implies that there is no random walk with drift. Moreover the R-squared of this regression is zero implying there is no relationship at all.

In order to bolster this result we perform the *Variance Ratio test* on the M1 time series data in EViews. The obtained results are shown in *Table 5* which is presented in *Annexure 1*.

The Random Walk hypotheses assert that the increments are uncorrelated over all lags. This means that the Variance Ratio should be equal to one for all time periods in

order for M1 to be a Random Walk. We can see that for period 2 from Table 5, the Variance Ratio = 1 is rejected implying M1 does not follow a random walk.

#### De-Trending:

Therefore, we confidently conclude that the non-stationarity in M1 is caused by a deterministic time trend. Thus, we need to de-trend it before using it in a *VAR* framework. We run the unit root (PP) test and the stationarity (KPSS) test again in EViews for M1 by including a trend and an intercept. We obtained robust results as shown in *Table 6* and *Table 7* which are presented in *Annexure 1*.

Now, by '*confirmatory data analyses*' we have robust results, meaning that we arrive at the same conclusions regarding the stationarity of the de-trended M1. Thus we have stationarized M1 by de-trending it and is ready to be used in a *VAR* framework.

The time trend in M1 is as follows:

M1= 4.72509493996531 - [(6.451986272052591e-06)\*(time period)]

The de-trended M1 is thus,

De-trended (M1) = M1 - 4.72509493996531 + ((6.451986272052591e-06)\*(t))

We see that the de-trended M1 is stationary from the above tests whose results are presented in *Table 6* and *Table 7* (*Annexure 1*).

#### 2.4 Trustworthiness and advantages of the chosen method

In this section we highlight the benefits of the different econometric approaches that we have applied in order to test for our hypotheses. In theory, before conducting any empirical research one should be aware of the statistical advantages and drawbacks of the chosen econometric approach. Knowledge regarding this will enable the researchers to interpret the outcomes in a more comprehensive manner.

#### VAR

This model shows a number of advantages relative to other univariate time series models. *Chris Brooks* (2008) identify the following advantages of *VAR* models:

 One does not need to define which variables are endogenous or exogenous, all of them are considered endogenous. This gives the researcher a high degree of discretion on how to classify the variables.

- 2. VAR models permit the value of a variable to be described by more than just its own lags.
- 3. It is possible to use *OLS* separately on each equation due to the fact that there are no contemporaneous terms in the equation.

According to *Bjornland* (2000, p.5), *"The VAR Models have the advantage over traditional large scale macroeconomic models in that the results are not hidden by a large and complicated structure, but are easily interpreted and available."* 

#### Granger Causality Test

This Causality test helps to identify a relationship between variables within a given system. In economics, one usually wants to know the relationship or the causality relation between macroeconomic variables in order to address the implications of any policy change or structural break. It is said that a variable X *Granger Causes* variable Y if past values of X contain information that helps to forecast or predict Y.

In practice the *Granger Causality* test is easy to apply and the results are quite straight forward to interpret.

#### Impulse Responses and Variance Decomposition Functions

In contrast to the traditional *F-test*, the impulse response and variance decomposition functions will reveal whether the changes in the value of a given variable have a positive or negative effect on other variables within the system. Likewise the impulse responses show how long it will take for the changes in a variable to impact the other variables through the system along a time period. Additionally, it is easy to infer the relationships between variables within a system by merely looking at the impulse response graphs.

Furthermore, a variance decomposition function measures the proportion of the movements in the dependent variable that are due to their own shocks versus shocks to other variables.

#### Chow Test

Under the *OLS* framework it is assumed that the estimated coefficients of the independent variables are constant over time. However, researchers can intuitively presume that these coefficients vary at a certain point in time due to specific events that can be of different nature and magnitude. *Chris Brooks* (2008) suggests that this hypothesis can be tested by measuring the stability of the parameters through the Chow Test. Thus, the Chow Test allows us to estimate the significance of any change in the parameters given a structural break (specific point in time). This parameter stability test is very simple to implement in practice.

#### Taylor Rule

In this Master thesis the Taylor rule was applied in order to construct a broader monetary variable that reflected the historical behavior of Central Bank's monetary policy of the countries that compose our sample. In this respect, the variable of interest is the "Monetary Tightness". Monetary Tightness will be used along with other macroeconomic variables to tests our hypothesis.

According to *Kohn* (2007) the *Taylor* rule exhibits benefits inherent to simplistic monetary rules:

- 1. It is useful for comparison purposes to policy makers because it uses simplistic inputs that produce on average reasonable outcomes.
- 2. It helps economic agents to generate reasonable monetary policy expectations even in the case where policymakers use more sophisticated models to lead monetary policy.
- 3. Gives the market agents a clearer idea of how the monetary policy is conducted through the analysis of simplistic macroeconomic variables (inflation, target inflation, output and potential output)

#### Difference in Differences (DID) Approach

According to Bertrand, Duflo and Mullainathan (2004), the DID estimation consists "of identifying a specific intervention or treatment. One then compares the difference in outcomes after and before the intervention for groups affected by the intervention to the same difference for unaffected groups".

Wooldridge (2007) suggests that some benefits of DID approach are as follows:

- 1. The method eliminates biases between the treatment and the control group that lead to permanent differences between those groups.
- 2. Inference from the outcomes of this approach is straightforward.
- 3. The approach is easy to implement in panel data through econometric software.

#### 2.5 Criticisms of the chosen method

On the order hand, as usual, most of the econometric methods used for empirical research suffer from certain limitations that should be balanced with its identified benefits in order for the researcher to be able to make adequate inferences of the results. Knowing the inherent drawbacks of the applied model enables the researcher to get a more comprehensive understanding about potential deviations of model's results from the theoretical framework. In this section we intend to describe the most important limitations of the main approaches applied in our empirical research.

#### VAR

*Chris Brooks* (2008) suggests that the *VAR* models have drawbacks and limitations relative to other model classes. These limitations have to do with the following:

- 1. VAR models use no or few theoretical information regarding the relationships between the variables.
- 2. It is not clear how the *VAR* coefficient estimates should be interpreted thus researchers must use theoretical knowledge to make inferences.
- 3. For small sized samples, standard errors will be large and hence it causes confidence intervals to be wide for the regression coefficients. This is mainly because of the fact that the degrees of freedom are rapidly used up.

Stock and Watson (2001) state "that VAR methods have some limitations, one is that the standard methods of statistical inference may give misleading results if some of the variables are highly persistent".

Similarly, *Bjornland* (2010) suggests that any misspecification or omitted variables within the system could end up in unexplained information being reflected in the disturbance terms. This fact will make the impulse responses and variance decomposition even more difficult to interpret.

#### Granger Causality Test

The most evident limitation of this test is the fact that it tests for a potential correlation between the current value of a variable and the past values of others without stating the sign and size of the effect through the time span. Macroeconomic variables are usually well defined to be correlated to each other.

On the other hand, *Stern* (2011) posits that data subjected to logarithmic transformation exhibits no sign of causality meanwhile untransformed data shows significant results. This is because logarithmic transformation are usually said to reduce heteroscedasticity and increase the stationarity of the variables of interest. This biases the Granger Causality test.

#### Impulse Responses and Variance Decomposition Functions

Since the responses of one variable to other can vary according to the ordering of the variables it is not clear what ordering the variables should take. Thus variance decomposition and impulse responses are in a large extent subject to the researcher's theoretical knowledge regarding the variables relationship.

Another important limitation inherent to these functions is the fact that shocks can only be generated in one variable at the time. This is not a realistic assumption since in real life all macroeconomic variables exhibits significant correlation to a certain extent. Thus assuming no correlation between the variable within the system could lead to a misinterpretation of the dynamics of the system.

#### **Chow Test**

According to *Chris Brooks* (2008) an important issue with *Chow Test* is that it is mandatory to have enough data to perform the regression on both sub-samples. In this respect it could be the case where one will like to test the impact of dividing the sample period at some point just near to the start or just close to the end of the sample in which case *Chow test* is not useful. Moreover if the *Chow test* rejects the null of no breakpoint, we would still not know which among the parameters changed significantly. This is because it is a joint test and thus is silent about the stability of the individual parameters.

For the purposes of our empirical research, the sample period was constructed in such a way that the data available before and after the structural break point (*Tequila Crisis*) is of the same length.

#### Taylor Rule

Kohn (2007) posits the following limitations to the rule.

- 1. Since the inputs to the model usually can take different forms (eg. inflation, consumer price index, output deflator, etc) the rule prescriptions can vary according to the nature of the chosen proxy.
- 2. The rule contains unobservable variables whose values can vary according to the different models used in its estimation.
- 3. The rule includes simple variables that might not be sufficient to capture the monetary dynamics of complex economies.

#### Difference in Differences (DID) Approach

According to Bertrand, Duflo and Mullainathan (2004), some identified limitations of the *DID* approach are as follows:

- 1. DID relies on a fairly long time series.
- 2. It is subject to serial correlation issues.
- 3. It is believed that the model underestimates the standard deviation of the coefficient Beta.

#### 2.6 VAR model in detail

We employ the Vector Auto Regressive (*VAR*) model to a large extent in order to aid us in our thesis. Therefore we give a detailed description of it below.

The *VAR* model is a generalization from the univariate autoregressive models. It is also a system of simultaneous equations. Hence it can be seen as a hybrid mix of univariate time series models and a system of simultaneous equations (*Chris Brooks, 2008*). It helps us capture the linear interdependent relationships between multiple time series.

*VAR* models have been used in macroeconomics primarily for two functions. As a device to deduce "*stylized facts*" of impacts of certain shocks, mainly policy shocks, on relevant economic variables. Second, it is used as a process to analyse models of economic theory (*Escanciano, Lobato* and *Zhu*, 2010). They also mention that *VAR* models have often been used for structural, causal and policy analyses. Therefore *Granger-causality* tests, impulse responses functions and forecast error variance decompositions are nowadays standard tools of macroeconomists.

These models give us a thorough understanding of the relationships between macroeconomic variables and financial variables. It looks into the relationships between many variables and explores how lagged values of different variables including the lagged values of the variables of interest affect the variables of interest.

The VAR model estimation does not require the specification or differentiation between exogenous and endogenous variables. All variables are treated as endogenous. Often theory gives a vague idea about this differentiation. Therefore this comes in really handy for researchers. VAR models are really flexible and can be easily generalized. Another nice feature of these VAR models is that an extensive VAR model can be compactly expressed which is easy to understand. In most cases simple OLS can be employed separately on each equation. Moreover forecasts generated by the VAR models are generally better than that generated by traditional structural models (*Chris Brooks, 2008*).

Some of the shortcomings as explained before is that they are a-theoretical, appropriate lag length decisions are unclear, too many variables eat up too many valuable degrees of freedom and stationarised variables throw away valuable long run information in the model (because *VAR* can be used only on stationary data) (*Chris Brooks, 2008*).

Regarding assumptions of the *VAR* model, we don't have many assumptions. This is because there is often no theoretical background available for these models. It lets the data to determine the model. It employs minimal assumptions about the fundamental structure of the economy.

There are two main assumptions about the error terms.

- 1. The expected residuals are zero.
- 2. The error terms are not autocorrelated

Another assumption could be that all the variables used in the VAR model should be stationary in order to avoid spurious relationships and other undesirable effects. The

correlations between the variables used in the *VAR* model are assumed to hold in the forecast period as well.

Moreover, the ordering of the variables is really important because the changing the ordering can lead to different relationships. Ordering is established using theory, evidence and experience. Similarly selecting an appropriate lag length plays an important role and it is done with the help of information criteria.

The main point of *VAR* is that the data employed is usually auto- and cross- correlated over time. Whereas, each of the *VAR* equations are estimated by OLS separately. So, one can say that the diagnostics/underlying assumptions are equivalent. We therefore use the assumptions for *OLS* with the justification that they are similar to the assumptions made on *VAR* models. However, this is not always the case, we do not assume absence of autocorrelation among data in a *VAR* model (We assume absence of autocorrelation in the residuals but not in the data).

For the purposes of our thesis, we ran 3 VAR models, namely,

- 1. VAR for the whole data sample
- 2. *VAR* for data before the crisis
- 3. *VAR* for data after the crisis

By running these *VAR* models (which are presented later in the document), we are able to clearly see the relationships between the variables in play and how the relationship changes before and after the crisis.

We are able to intelligibly see the dynamics of these relationships through *Granger* causality, impulse responses and variance decompositions. All of which is presented later on in the document.

The estimation of the VAR model can be broken down as follows:

- 1. Determine the endogenous variable with the help of economic theory, empirical evidence and experience
- 2. Transform the data using logarithms
- 3. Stationarise the data.
- 4. Run the VAR.

This concludes the detailed description of the *VAR* model. The *VAR* models employed in our thesis are presented and explained further below in the document.

## SECTION III

## **3 THEORY**

In this section we will present literature and studies concerning the economic relationship between exchange rate and monetary policy variables, and stock returns. By consequence, this will facilitate our understanding of the theoretical impact of these variables on the performance of stock markets. Thus, the following theoretical section will help us build our analysis and construct our conclusions.

#### 3.1 Theoretical background

#### The Central Bank's main tools for the procurement of monetary stability:

The Central Bank uses monetary policies to procure monetary stability in the economy. By monetary policy we mean exchange rate regimes, money supply decisions, interest rate announcements and inflation controlling policies. In this section, we present and exhibit past empirical research on how monetary policy and exchange rates affect the performance of stock returns. Especially, for Central Banks, it is important to have a deep understanding on how monetary policy can influence stock market prices. These previous empirical studies will help and guide us in constructing the intuition which will be required to base and conclude our empirical findings regarding this issue.

#### Central Bank and Money Supply policies:

According to the basic *IS-LM-BP* framework put forth by *Mundell* (1963) and *Fleming* (1962), it can be stated that under fixed exchange rate regimes, monetary policies (money supply decisions) are ineffective in altering domestic output and by consequence no effects on stock prices are expected. On the other hand, monetary policies can be effective when the Central Banks follow a flexible exchange rate regime in altering the domestic output in the economy. In general terms, the *Mundell and Fleming* framework uses basic macroeconomic concepts like investments-savings (IS), liquidity preferences-money supply (LM) and balance of payments (BP) curves to explain the way domestic output can or cannot be affected by changes in money supply (assuming both, fixed and flexible exchange rate regimes when capital mobility exists).

The intuition behind the Mundell (1963) and Fleming (1962) framework is that in a fixed exchange rate regime (assuming partial capital mobility) a contractionary or expansionary monetary policy, where both alters the amount of money supply in the economy negatively and positively respectively, causes movements in interest rate levels by altering the IS and LM equilibrium. In this regard, when interest rates get lower (when an increase in money supply takes place) it induces huge amounts of capital outflows and creates a deficit in BP. This stimulates a pressure on the exchange rate to depreciate due to many unwanted domestic currency (*Pesos*) on the foreign exchange market. Since the Central Bank is maintaining a fixed exchange rate policy it decides to buy back the unwanted *Pesos* by selling foreign currency. As a result, money supply is

reduced to initial levels. The economy is restored back indicating no change in money supply or interest rates. Therefore we can conclude that monetary policy is ineffective in changing the domestic level of output under a fixed exchange rate regime when there is partial capital mobility and thus, no changes in stock market prices are expected. The exact opposite effect is observed when a decrease in money supply takes place due to a contractionary monetary policy.

In case of flexible exchange rate regimes, an increase in money supply will induce a decrease in interest rates which will further cause capital outflows and domestic currency depreciation. Due to the existence of a flexible exchange rate regime, the Central Bank will allow the currency to float freely. This depreciation will cause domestic goods to be more competitive with regards to international prices and will cause fuel exports to rise. This has two consequences. Firstly the *IS* curve shifts to the right. Secondly the current account improves and causes the *BP* curve to shift right as well. Therefore the new and final equilibrium is where IS, LM and BP meet (more to the right). The economy is now at *a point where* the output increased. Therefore we can conclude that monetary policy is in fact effective in changing the domestic level of output under a flexible exchange rate regime when there is partial capital mobility. The exact opposite can be observed when money supply decreases in an economy with flexible exchange rate regimes.

This framework gives us a clear picture about how this macroeconomic variable works in altering the domestic output. It is worth noting that Mexico was following a quasi fixed exchange rate policy before the Peso crisis in December 1994 and after the crisis it started to follow a floating exchange rate regime. Furthermore, in the late 1980's and the early 1990's Mexico started promoting market openness and policies of financial liberalisation which implied an environment of partial capital mobility.

#### Central Bank and Interest rate policies:

Until now we have focused on expansionary and contractionary monetary policies which alter money supply. However, there are monetary policies which focus on interest rates. By changing interest rates, the Central Bank can control inflation. Inflation is primarily caused by an increase in the velocity of circulation of money in the economy. This happens when there is too much money in the economy tracking too few goods and services. Thus, by altering interest rates they can control the level of money in the economy as well as the velocity of its circulation and hence curb inflation. Basically the Central Bank increases the interest rate to lower money supply. This makes it more expensive for banks, businesses and individuals to borrow money. Since it is now more expensive for banks to borrow money from the Central Bank, they charge a higher interest rate to their customers. Individuals will start spending money more carefully and will limit their spending. This will affect businesses' revenues and profits. Businesses will also be affected directly as they now face a higher cost of capital. They will cut down on spending and expansion which will affect their growth, resulting in a decrease of profits. We know that stock prices are valued by summing up the discounted future cash flows and dividing it by the total number of outstanding shares. With an increased

discount rate set by the Central Bank and with decreased cash flows from the business as a result of reduced profits (as explained before), we have strong reasons to believe that the price of the stock will go down. When stock prices of enough firms go down, the stock market/stock index starts to decline. In addition, investors will require a risk premium for them to be induced to invest in stocks. With the facts mentioned above investors are not satisfied with the risk premium offered by the stocks and with the Central Bank offering a higher interest rate (risk free rate), investors will perceive stocks as risky investments and will look elsewhere to invest their money. From this chain reaction we can say that if the Central Bank tries to curb inflation by increasing interest rates, it might actually have a negative effect on the stock market. We will later see in our thesis if this was actually true, i.e. if interest rates (monetary policy) did help explain stock price movements before and after the *Peso crisis*.

#### 3.2 How changes in exchange rates and monetary policies are expected to affect stock prices? Empirical evidence :

#### Exchange rate and stock price:

We believe exchange rates and monetary policies to play an important role in shaping up stock returns. In the case of exchange rates, stock returns are affected by currency management strategies in financial markets that are highly integrated and also by the implications of fluctuations of company profits derived from exchange rate movements (*Bodart and Reding*, 2001). Firms (e.g. Multinational Corporations) which have overseas operations, overseas markets, foreign customers, foreign suppliers and so forth will be adversely affected by exchange rate movements as their costs and revenues maybe denominated in foreign currency. This will affect their performance and hence their value of their equities.

Basic economic theory suggests that exchange rates are influenced by macroeconomic factors such as inflation, GDP, interest rates and etcetera, while financial journalists believe that there is a relationship between stock prices and exchange rates. Financial liberalisation has become a common phenomenon on a global level. Most countries have now open economies with increased international capital mobility. *Hau and Rey* (2006) suggest that an increasing proportion of these capital in/out flows consists of equity flows compared with public bonds and bank loans. This gives us reason to analyse how exchange rates can affect stock indices.

#### Empirical Evidence:

Dornbusch and Fischer (1980) in their goods market approach propose that when the domestic currency appreciates, there are less favourable terms of trade. This leads to a diminution in domestic stock prices. With this approach, one can conclude that when the value of home currency appreciates, domestic stock prices should fall. We can see here that there is a negative relationship between stock prices and exchange rates with causation running from exchange rate movements to stock prices. Whereas the *Portfolio Balance Model* asserts there is a positive relationship between stock prices

and exchange rates with causation running from stock prices to exchange rates. An increase in domestic stock prices leads to increased wealth and demand for domestic currency. With higher domestic interest rates there will be a high demand for local currency and the domestic economy will start attracting foreign currency. This causes exchange rates to appreciate. Krylova, Capiello and De Santis (2005) believe that there is a trade-off relationship between exchange rate and stock prices. For example, if expected stock returns are higher in one country, then the exchange rate of that country depreciates and vice versa. Here we can perceive an arbitrage relationship between stock returns and exchange rate. This is very similar to the concept of uncovered interest parity where the exchange rate neutralises returns arising from differences in interest rates between two countries. For example let us assume a domestic investor realises huge profits from his foreign equity investments abroad. When he extradites his profits back to his domestic currency it will be neutralised with an appreciation of the local currency. Therefore differences in stock returns between countries influence the exchange rates. Recently Georgios Katechos (2011) concludes that exchange rates are linked to global stock market returns. According to him the value of higher yielding currencies is positively related to global stock market returns whereas the value of lower yielding currencies is negatively related to global stock market returns. He also finds that the relationship between them is strong when interest differentials are relatively wide and the relationship is weak when interest differentials are relatively narrow.

#### Monetary policy and stock price:

In the case of monetary policies, researchers have been analyzing for a long time on how it affects stock returns and whether holding equity is a good hedge against inflation. We will refer to existing literature and discuss what has actually been going on. Monetary policy changes affect macroeconomic variables in addition to inflation. Most of the early literature has focused on how the monetary policy shocks are transmitted to the economy through money and interest rates (bond markets) channels. A change in monetary policy eventually shifts the interest rates from equilibrium and in turn affects real activities in the economy and inflation as well. However we should not forget that stock markets also act as an important channel to transmit monetary policy effects onto the economy. As of late many Central Banks around the world have now become interested on how the stock market transmits monetary policy shocks onto the economy. A change in monetary policy (for example a change in money supply) causes investors and capitalists to revalue the stock market. This is because a stock is simply valued by the sum of discounted future cash flows (dividends). Therefore a tight or lax monetary policy affects the stock index through expected future earnings. In addition it can also be affected by the discount rate used to discount the expected future cash flows. The re-valued stock market will change the investors' wealth assuming certain proportion of the investors' wealth were held in equities. This change in investors' wealth will cause an alteration in consumption expenditure. Similarly firms' cost of capital will also change and will affect real investment spending. These modifications in real activities will finally have a huge say in inflation. Central Banks are thus concerned

about the inflationary implications of highly valued stock markets and this is one of our main reasons in assessing how monetary policy affects the stock markets when trying to keep inflation under control.

#### Empirical Evidence:

A change in the stock price should only have a small effect on the aggregate demand and output in the economy (*Boone, Giorno* and *Richardson*, 1998) but we should never underestimate this effect in the case when stock prices plunge. If we find that changes in monetary policy have only a minimal effect on stock indices we can confidently conclude that the stock market is not the prevalent source nor channel to transmit monetary policy shocks into the economy.

According to *Chami, Cosimano* and *Fullerkamp* (1999), there exists stock markets alongside interest rates and credit markets to channel monetary policy shocks onto the economy. They suggest inflation caused by a monetary expansion decreases the real value of firms' assets. This is an implicit tax on capital stock. Therefore, they believe that an expansionary monetary policy negatively affects stock prices and causes a decrease in stock returns. As a consequence, stock and bonds are differentiated and we can see that stock markets are a channel for monetary transmission.

However, a contractionary shock in monetary policy usually has a negative but temporary effect on the stock index. *Cooley* and *Quadrini* (1999) employ a more mathematically sophisticated approach. They formulate a dynamic stochastic general equilibrium model in which they give more importance to financial factors when studying about the firms' decisions and the monetary policy transmission mechanism. They fabricate a value weighted stock market index as the firms they worked with were heterogeneous with regards to its equity size. With this index, they asses its reactions to monetary policy shocks. A contractionary monetary policy shock of magnitude 1% decreases the constructed stock market index by 0.2% on impact.

Money can be viewed as an asset among a portfolio of other assets held by an investor. When there is a shock in money supply, investors reconcile and readjust their portfolios by substituting between money and other assets (stocks). Usually this happens with a time lag unlike financial markets where reaction to the release of new information is instantaneous. Thus, it seems like past money supply data can actually predict stock returns (*Sprinkel*, 1964; *Keran*, 1971; *Homa* and *Jaffee*, 1971; *Hamburger* and *Kochin*, 1972). These empirical studies contradict the model and theory on efficient markets developed by *Fama* (1970) which states that stock prices already incorporate all past, present and available information. Studies conducted later also disproved it. However, we can notice the presence of a reverse causality where we use stock market data to predict changes in money supply (*Cooper*, 1974; *Pesando*, 1974; *Rozeff*, 1974; *Rogalski* and *Vinso*, 1977). Given that financial markets react immediately to new information we can use financial data to help identify a more direct and instantaneous

changes in monetary policy and enhance our understanding of the transmission mechanism (channels) of shocks to the economy.

*Berkman* (1978) and *Lynge* (1981) have detected that stock prices show a negative reaction on monetary policy (money supply) announcements. *Lynge* (1981) did not differentiate between anticipated and unanticipated announcements, while *Berkman* (1978) did differentiate.

Different hypotheses give different reactions of stock markets to monetary policy announcements. The *Keynesian hypothesis* is based on a sticky price model. In a sticky price model the prices do not accommodate shocks in the short run as they stay constant whereas interest rate changes to bring the economy back to equilibrium. An announcement of money supply will affect the stock prices positively. A positive shock will signal a tightening monetary policy to investors. Therefore, investors will try to hoard funds driving up interest rates. Therefore, we can say that increasing money supply will reduce stock prices because of high discount rates and lower expectations of future cash flows as a result of slower economic activity in the future.

The *real activity hypothesis* claims that when a big money supply move is announced, it provides information about money demand in the future. This causes expected output to increase leading to higher expected cash flows in the future which finally drives up stock prices.

The *risk premium hypothesis* which was proposed by *Cornell* (1983) emphasizes on the precautionary motive for holding real money balances. An increase in money supply simply suggests that the aggregate risk level in the economy has gone up and thus the risk aversion of investors. Therefore investors will now require a higher risk premium which will cause stock prices to drop. This can be explicitly seen to contradict the *real activity hypothesis*.

Finally none of the hypotheses were consistent with the data *Cornell* (1983) used, but he proposed that a combination of these will be consistent in the end. *McQueen* and *Roley* (1993) found out that in an economy which is in a slump, unanticipated positive shocks are good news for the stock market. Whereas, in an overheated economy, unanticipated positive shocks are bad news for the stock market.

Sellin (2001) in his panoptic survey refers to a wide range of literature most of which have been referenced above and concludes that monetary easing leads to higher equity prices. According to him, pro-cyclical monetary policy causes a positive inflation-stock returns relationship and a counter-cyclical monetary policy causes a negative inflation-stock returns relationship. He also presents empirical evidence that equity is not a good hedge against inflation in the short run whereas it might be a good hedge in the long run.

## **SECTION IV**

## **4 EMPIRICAL DATA ANALYSIS**

According to *Thorbecke* (1997), a variety of empirical techniques are used such as *VAR*, impulse responses functions and variance decompositions in order to scrutinise the relationship between monetary policy and stock returns.

In this section we will present a description of how we conducted our empirical research. Primarily we look and test for a structural break in stock returns and study the change in impact of exchange rates and monetary policy (in terms of a Taylor Rule) on Mexico's stock returns (if any) around the *Tequila crisis*.

VAR, Chow test, Granger Causality tests, Lag exclusion test, Impulses Responses, Variance Decomposition and finally a more generalized regression (*difference-in-difference* approach) were performed to extend our analysis. The results and conclusions of these methods and tests are to be presented in the forthcoming sections. It is worth noting that each these tests were performed for the whole data sample, the pre-crisis period and as well as the post crisis period. The *Chow test* was conducted, aiming to find a significant structural break (December 1994) in stocks returns caused by changes in monetary tightness, exchange rates and monetary aggregates after the crisis. Finally we perform a *difference-in-difference* regression which helps us generalize the significance of these structural breaks in crisis stricken countries.

#### <u>4.1 Monetary policy (Tightness of monetary policy) through the Taylor</u> <u>Rule</u>

In this essay, the monetary policy variables were measured through the use of the *Taylor Rule* approach. This approach in general terms consists of an optimal monetary policy model which uses the inflation and gross domestic product performance relative to a target as its main economic input. This aids us to set an appropriate (optimal) federal funds interest rate that enables the government to pursue long run economic stability.

The *Taylor Rule* was developed in 1993, in a period where Central Bank's reliance on monetary aggregates as tools to maintain price stability and economic growth vanished. This was mainly because of unfruitful economic results in the past. Additionally, the previous years were defined as high inflationary periods which led most of the Central Bankers to rebalance their monetary policy objectives in order to achieve a setting oriented to price stability.

In this respect *John Taylor* (1993) developed a simplistic monetary model that enables policymakers to react in response to potential deviations of inflation and output from its respective target. The model is defined as follows:

$$i_t^* = r^* + \pi_t + \alpha (\pi_t - \pi^*) + \beta (y_t - y_t^*)$$

Where:

*i*<sup>\*</sup>= prescribed federal funds rate *r*<sup>\*</sup>= real federal funds rate  $\pi_t$ = inflation rate  $\pi^*$ = target inflation rate *y*<sub>t</sub>= logarithm of real output *y*<sup>\*</sup><sub>t</sub>= logarithm of potential output.

*Woodford* (2001) posits that the response the *Taylor* Rule dictates to variations in inflation or the output gap inclines to stabilize those variables. This stabilization of both the variables is an appropriate goal, at least when the output gap is properly set.

Furthermore, *Taylor's* model coefficients were empirically found both to be 50%. This suggests that the deviation of inflation rate and output from its respective targets should equally affect movements in the optimal federal funds interest rate.

In this context, the *Taylor rule* states that Central Banks must increase interest rates when the observed output climbs higher than the potential output and reduce the interest rates otherwise. Along similar lines, the rule states that policymakers must increase interest rates when the inflation rate is higher than its long-term target and must reduce it otherwise.

*Taylor* (1993) stated that, the rule should not be used as a mechanical approach to set federal interest rates but as a guide for implementing monetary policy. In this respect, it is possible to say that the prescribed federal funds interest rate is subject to policymaker's discretion by a large extent. This may reflect expansionary or contractionary policies embedded in the observed federal funds rates.

Having said so, both positive and negative deviations of the observed federal funds interest rates, defined by  $i_t$ , relative to the *Taylor's* prescribed  $i_t^*$  can be seen as deliberate monetary measures intended to expand or contract the economy in any given country.

Therefore, we used the difference between i and  $i^*$  as the monetary policy variable in our research methods, tests and data analyses. This reflects, just as mentioned before, the extent to which the Central Banks are committed to an expansionary or contractionary monetary policy. This monetary policy variable is defined as follows:

#### $\textit{Monetary Tightness} = i_t - i_t^*$

Firstly, in order to be able to estimate  $i_t^*$  we use the time series data collected for all sample countries. This data includes, as we have already mentioned, the real output (GDP), inflation rate (constructed using Consumer Price Index) and the government short term interest rate (3 month treasury bills). All of them were expressed as monthly observations. However, as we can see in the *Taylor Rule* specification, there are three unobserved parameters, namely the real federal funds interest rate, the inflation target and as well as the output target. All of them are required in order to determine  $i_t^*$ .

In the case of the real federal funds interest rate, *Judd* and *Rudebusch* (1998), *Kozicki* (1999) and *Clarida*, *Gali* and *Gertler* (2000) state that it can be shown as the difference between the average federal funds interest rate and the average inflation rate. Therefore, by deducting the annual average of the monthly inflation observations from the annual average of the monthly short term federal interest rate observations for the eighteen year period for each of the countries within the sample we obtain  $r^*$ . In other words, we obtained eighteen different  $r^*$  values (one per year) for each of the different countries that compose the sample.

#### <u>4.2 The "Hodrick-Prescott Filter" to estimate Inflation Target and Potential</u> <u>Output</u>

Secondly, we estimated target inflation and potential output by using a "*Hodrick–Prescott Filter*<sup>4</sup>" (*HP Filter*). According to economic literature the potential output is the amount of goods and services that an economy can supply without putting pressure on the rate of inflation. Therefore, the deviation of real output relative to the potential output implies a measure of inflationary pressure in a given economy. On the other hand, the primary element of inflation targeting is a public commitment to price stability in the form of a medium-term numerical inflation target.

*Conway and Hunt* (1997) states that since potential output cannot be directly observed, economists have constructed techniques that infer the level of potential output from information locked in observable macroeconomic data. They state, that the most common class of techniques extradite a trend measure from the actual output series. Trend output is later taken as a measure of the potential output level in the economy. Furthermore, they state that these techniques break down the output into its supply

<sup>&</sup>lt;sup>4</sup> According to Razzak and Richard Dennis (1999, p.3) four considerations were taken into account during the construction of the *HP Filter*. 'First, the trend approximates the curve that business cycle researchers would build through a time plot of the series. Second, the trend is a linear transformation of the original series. Third, lengthening the sample should not significantly change the trend, except at the sample ends. Finally, the detrending method should be well defined and easily reproducible.'

(trend) and demand (cyclical) components which are entirely based upon the information comprised in the actual output series.

Specifically, the *HP Filter* disintegrates the time series into growth and cyclical components  $Y_t = Y_t^g - Y_t^c$  where  $Y_t$  is the natural log of output and  $Y_t^g$  and  $Y_t^c$  are the growth and cyclical components respectively. This decomposition asserts that the series being de-trended does not contain any seasonality/diurnality and, because the cycle is derived residually, it does not disunite the cycle from any irregular movement (Razzak and Richard Dennis, 1999). The *HP Filter* is given by the following specification according to them:

$$min_{Y_t^g} = \sum_{t=1}^T (Y_t - Y_t^g)^2 + \lambda \sum_{t=1}^T [(Y_{t+1}^g - Y_t^g) - (Y_t^g - Y_{t-1}^g)]^2$$

Where:

 $\lambda$ = Parameter that controls for  $Y_t^g$  smoothness.

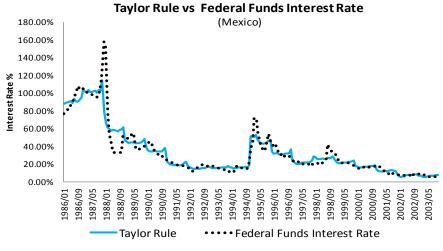
The minimization of this specification supplies a mapping from  $Y_t$  to  $Y_t^g$  with  $Y_t^c$ , ascertained residually. Thus, the estimate of potential output using the *HP Filter* depends on the selected  $\lambda$ . According to *Conway* and *Hunt* (1997) the parameter  $\lambda$  is a *smoothness constraint* that influences how closely trend output follows the actual output series.

Regarding estimation of inflation targets, *Bernanke* and *Woodford* (2005) state that inflation targets can be estimated using a *HP filter* as well because they are not always available for all the time periods subject to research.

Taking into account the above stated facts, we estimate the monthly data series for inflation targets and potential output using a *HP Filter* through EViews. In doing so we applied a  $\lambda of 14,400$  and  $\lambda of 100$  for potential output and target inflation respectively. We employed these  $\lambda s$  due to the fact that in the long run, the behaviour of potential output is smoother compared to that exhibited in inflation. Also, due to the higher volatility exhibited in the monthly inflation rate time series we decided to fit the inflation target as close as possible to the inflation rate by decreasing the level of  $\lambda$ . The graphs depicting the *HP Filter*ed trend for each of the variables of interest for the different country samples are presented in the *Annexure 2*. The monthly time series data for inflation target and potential output generated by this process are available to the reader upon request.

#### 4.3 Taylor Rule estimation and Monetary Tightness

Once we have obtained the real federal funds interest rate, the inflation target and the potential output, it is possible to estimate Taylor's  $i_t^*$  on a monthly basis and as well as the *Monetary Tightness* measure for each of the countries in the sample. The following graph shows the estimated relation between  $i_t$  and  $i_t^*$  in the case of Mexico during the period 1986-2003:



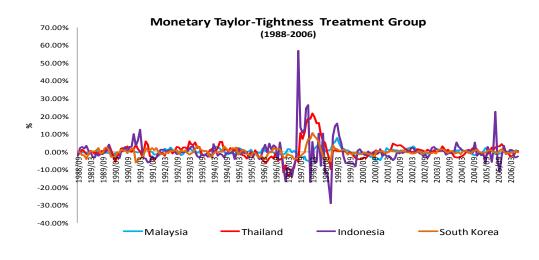
Graph 11; Source: Data taken from Thomson Reuters

We can clearly note from the above graph that the Taylor Rule describes the movements of Mexico's federal funds interest rate in a significant way. The policymakers should take into account the performance of the inflation and gross domestic product relative to its targets as the main drivers to determine interest rates. In *Annexure 3* of this document we present this relation for the remaining countries that are under our radar.

Additionally, from the graph above it is possible to observe that in the late 1994, federal interest rates in Mexico were much higher than *Taylor's* prescribed optimal interest rate implying a contractionary policy which at that time was attractive for foreign investors in a context of low interest rates in industrialized countries. This coincides with the theoretical background exposed previously in relation to the fact that high interest rates were the main drivers of capital inflows into the country.

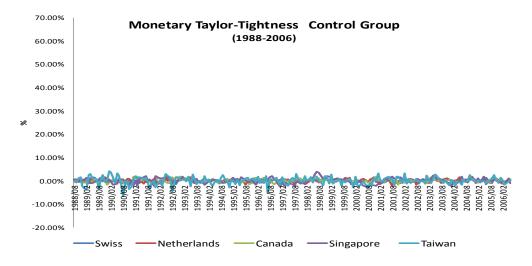
The following graphs depict the *Monetary Tightness* of the countries that compose our sample for periods before and after the *Asian Crisis*. It is possible to say that the main disruptions in monetary policy were observed in the Treatment Group in late 1997 where the crisis took place (July-1997) meanwhile the periods around this event exhibit relative monetary calmness in terms of interest rates. According to the graph below, the Asian Central Banks took restrictive monetary policies (increase of interest rates)

during the period 1997-1999. The intuition behind this is that by increasing the domestic interest rates, the Central Banks tried to help diminish flight of capital. This makes lending more attractive to investors in a context of exchange rate pressures just as in the case of Mexico. High domestic interest rates in a fragile economy could worsen the economic environment by slowing down industrial and commercial activity.



Graph 12; Source: Data taken from Thomson Reuters

On the other hand and as expected the Control Group depict monetary steadyness along the sample period which includes both the period of the *Tequila Crisis* (December 1994) and as well as the *Asian Crisis* (July 1997). This in fact will allow us to make much better inferences regarding the effects of monetary policy in stock returns by comparing the Treatment Group to an unaffected benchmark (Control Group).





#### 4.4 Vector Auto-Regression

We start off our main empirical investigation with the help of Vector Auto Regression (*VAR*). The *VAR* model gives us a deeper understanding of the relationships between macroeconomic variables (such as monetary policy tightness, money supply and exchange rates) and financial variables (such as stock returns). It investigates the relationships between many variables and explores how lagged values of different variables affect other variables of interest. According to *Chris Brooks* (2008), *VAR* forecasts are generally better than the forecasts generated from traditional structural models.

#### 4.5 Estimating the VAR for the whole data sample

Based from the data we collected for Mexico (1986 to 2003), we ran an unrestricted *VAR* model with the stock returns from the Mexican national stock exchange, tightness of the Mexican monetary policy as given by a *Taylor* rule which measures the deviation of the actual policy interest rate in the economy from the optimal prescribed policy interest rate, exchange rate with the U.S. dollar and the de-trended money supply in the Mexican economy as endogenous variables with the help of EViews. We employed 2 lag intervals for these endogenous variables and a constant for the exogenous variable. The obtained results are presented in *Table 8* of *Annexure 4*.

**Note:** '*Stock*' denotes stock returns from the Mexican national stock exchange, '*Tight*' denotes the tightness of the monetary policy in Mexico, '*FX*' denotes the exchange rate between the Mexican Peso and the U.S. Dollar, and '*DETM1*' denotes the de-trended monetary base (money supply) in Mexico.

After running the above mentioned *VAR* we decide on the appropriate lag length. We use the '*lag length criteria*' command under '*lag structure*' in EViews to decide the appropriate lag length. The lag length selection will depend on the size of the information criteria used. For the purposes of our thesis we will use the *Schwarz information criterion* (*SC*) and *Hannan-Quinn information criterion* (*HQ*) to decide for the appropriate lag length that is to be employed. We tested with 8 lags and 20 lags. In both cases *SC* and *HQ* suggest 2 lags as the appropriate lag length. It is very important to choose the correct number of lags when constructing a VAR model, as the inference of the model depends on the correct model specification.

Selecting a very small lag order may lead to ignoring interesting dynamics of the economic variables. Selecting a very lag large order leads to inefficiency in estimation, which translates into large coefficients standard errors and large confidence bands for the impulse response functions (*Escanciano, Lobato* and *Zhu*, 2010).

#### Ordering of the variables

When running a VAR model, the ordering of the variables is important. Different orderings will change the output results of the impulse response and variance

decomposition estimations which are to follow. Hence the results of the relationships between the variables may be different with different ordering. This problem arises due to the fact that when a unit shock is applied to the error of one equation, it affects other errors in other equations. This also happens due to the fact that the errors are somewhat correlated. In other words, all of them contain a so called "common component of variability", which cannot be attributed to any single variable's error. Thus a shock to one variable will be accompanied by a shock in the other variable. The movements in some variables are likely to follow rather than precede others. Therefore the dynamics of the system depend crucially on the ordering of the variables. This dependency will be highlighted if the residuals are highly correlated. Thus the ordering of the variables can be trivial only if the residuals are almost uncorrelated. Ideally, financial theory should suggest the ordering (Chris Brooks, 2008). Given that the objective of this thesis is to look at the relationship between developments in financial markets and key macroeconomic data, we believe the first variable should be the stock price index. The second variable should be the tightness of monetary policy as it has a direct effect on the discount rate, which is used to discount the cash flow of a stock and thus calculate its present value. The third variable should be the exchange rate and finally de-trended monetary base (M1).

The *VAR* estimation output is presented in *Table 8* of *Annexure 4* and *Table 9* in *Annexure 4* presents the coefficients that are significant in the *VAR* model.

#### VAR Model Inference

By looking at the R-squareds in the *VAR* estimation output for the whole data sample exhibited in *Table 8* of *Annexure 4*, we see that only 24.42% of movements in stock returns can be explained by the other variables. One must take note that 71.25% of the tightness of monetary policy can be explained by the remaining variables. However we are not interested in explaining monetary tightness. If we take a closer look at the coefficients of the independent variables which explain movements in stock returns we find that all variables are significant at the 10% level except for de-trended monetary base and one period lagged exchange rate. From these results we therefore think of dropping out monetary base from explaining stock returns completely. Monetary tightness with a single period lag seems to have a positive impact on stock returns but as the information gets old by two periods it seems to have a negative impact. Alternatively, exchange rates with a single period lag are insignificant in explaining movements in stock returns probably because it is too soon for the information to be incorporated in stock prices. However exchange rates with a double period lag have a positive impact on stock returns.

#### **Granger Causality Tests**

As mentioned by *Chris Brooks* (2008), causal tests are used as a tool to determine whether changes in variable X are related to changes in variable Y. Therefore, if X

causes Y, the lags of X should be significant as well. In addition, it should also be noted that *Granger Causality* more accurately implies correlation between the current value and past values, rather than a change in a variable as a direct result of a change in another variable. We were able to run the *Granger Causality* tests in EViews. The results are displayed in *Table 10* of *Annexure 4*.

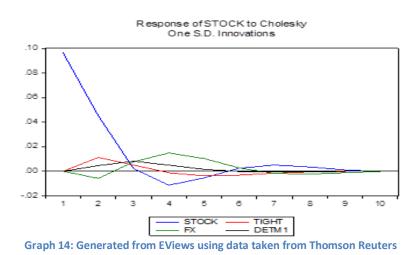
#### Lag Exclusion Tests

We conduct the *VAR* lag exclusion *Wald* test in EViews to confirm that no information was lost by incorrectly restricting the lag length. The test results are presented in *Table 11* of *Annexure 4*. We can see from the results that both lags are jointly significant from their extremely low p-values. This ensures the fact that *VAR* was indeed appropriately estimated by employing 2 lags.

#### Impulse Responses

The VAR's impulse responses and variance decompositions are used to discern the nature of the effect (positive/negative impact) of changes in the value of a particular variable on the other variables present in the system. As well as to perceive the time it takes for the effect of the particular variable to work through the system. Such information will not be emitted by the conclusion of *F-tests* such as the *Granger Causality* tests.

It can be seen that the 16 graphs (given 4 variables) presented in **Box 1** of **Annexure 4** are the VAR's impulse responses. These graphs were easily generated using EViews. We use *Cholesky* – degrees of freedom adjusted decomposition method with the initial ordering of the variables maintained. We present the impulse responses in multiple graphs with analytic response standard errors (**Box 1** of **Annexure 4**). The shocks gradually die out for all the variables after 10 periods. This implies that the VAR system is stable.

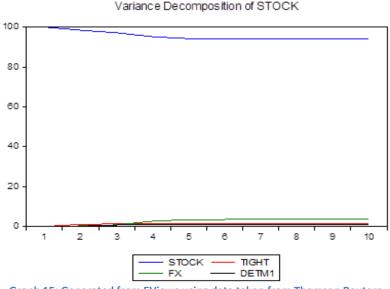


We will concentrate only on the effects on stock returns as picturised below:

#### Variance decomposition

Variance decomposition signals the amount of information each variable contributes to the other variables in a VAR model. Variance decomposition determines how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables (Chris Brooks, 2008). Thus they offer a slightly different method for examining VAR system dynamics. They imply the proportion of the movements in the dependent variables that are due to their 'own' shocks, versus shocks to other variables. A shock to one variable will not only affect that variable but also other variables through the dynamics of the VAR system. The innovations to each explanatory variable explain the s-step-ahead (where s=1, 2, 3...) forecast error variance. Variance decomposition gives us the extent to which these innovations explain the forecast error variance (Chris Brooks, 2008). For both impulse responses and variance decompositions, the ordering of the variables is important. We can easily depict variance decompositions in the form of multiple graphs by using EViews. From the information exhibited in **Box2 of Annexure 4**, it is possible to view the nature of the effects of a given variable on other variables in the VAR system. This gives us a clearer picture on the dynamics of the VAR system.

We will concentrate on the percentage of stock variation due to the 4 variables under the limelight. From the graphs, we are able to see that the behavior of variation settles down quickly to a steady state.



Graph 15: Generated from EViews using data taken from Thomson Reuters

Graphical illustrations of variance decompositions, give us a great deal of information about how much of the variance of one variable can be explained by other variables. *Runkle* (1987) argues that both impulse responses and variance decomposition are outstandingly difficult to interpret accurately. He advises the construction of confidence

bands around them. However, even then the confidence intervals are generally so wide that sharp inferences are impossible (*Chris Brooks*, 2008). Nevertheless impulse responses and variance decompositions offer us information that other tools such as conventional *F-tests* fail to provide. Therefore they are good instruments to study the dynamics of the *VAR* system.

From the section above on Granger Causality, we just know that a certain variable Granger causes the other. But it is the impulse responses and the variance decomposition that gives us a detailed insight as to in which direction that certain variable causes the other. Our results from both the (Granger Causality test & impulse responses and variance decomposition) seem to be in the same line with the latter giving more information.

## 4.6 Before Crisis (February-1986 to December-1994) VAR

We still employ the same de-trended M1 data series as it is, because we found out the pre-crisis and post-crisis time series data for M1 to be non-stationary individually. Of course, this non-stationarity arises from a deterministic time trend.

Using the data we collected for Mexico from 1986 to 1994 (Pre-crisis data), we ran again an unrestricted *VAR* model. The results are shown in *Table 12 of Annexure 4*.

After running the above *VAR*, we decide on the appropriate lag length. In both cases *SC* and *HQ* information criteria suggest 2 lags as the appropriate lag length. It is very important to choose the correct number of lags when constructing a *VAR* model, as the inference of the model depends on the correct model specification.

### Ordering of the variables

As done previously with the whole data sample, we use the same variable ordering to run the pre-crisis *VAR* model using Eviews. The *VAR* estimation output is presented in *Table 12* of *Annexure 4*, and *Table 13* in *Annexure 4* presents the coefficients that are significant in the estimated *VAR* model.

### **Granger Causality Tests**

We were able to run the *Granger Causality* tests in EViews and we obtained the results as shown in *Table 14* of *Annexure 4*.

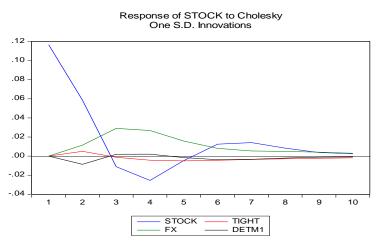
## Lag Exclusion Tests

We can see from the results in *Table 15* of *Annexure 4* that both lags are jointly significant from their extremely low p-values. This ensures the fact that *VAR* was indeed appropriately estimated by employing 2 lags.

#### Impulse Responses

**Box 3** of **Annexure 4** presents the impulse responses in multiple graphs with analytic response standard errors. The shocks gradually die out for all the variables after 10 periods. This implies that the VAR system is stable.

We will concentrate only on the effects on stock returns as presented in *Graph 16* below:

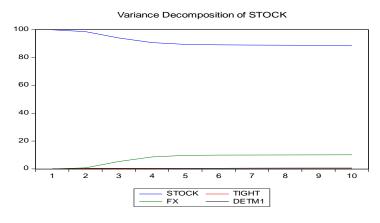


Graph 16: Generated from EViews using data taken from Thomson Reuters

#### Variance Decomposition

From the information exhibited in **Box 4** of **Annexure 4**, it is possible to view the nature of the effects of a given variable on other variables in the VAR system. This gives us a clearer picture on the dynamics of the VAR system.

We will concentrate only on the percentage of stock variation due to the 4 variables under the limelight. From the graphs, we are able to see that the behavior of variation settles down quickly to a steady state.





### 4.7 After Crisis (January-1995 to December-2003) VAR

We still employ the same de-trended M1 data series as it is, because we found out the pre-crisis and post-crisis time series data for M1 to be non-stationary individually. Of course, this non-stationarity arises from a deterministic time trend.

Using the data we collected for Mexico from 1995 to 2003 (Post-crisis data), we ran again an unrestricted *VAR* model. We obtained the results as shown in *Table 16* of *Annexure 4*.

Both *SC* and *HQ* information criteria for lag length suggests 1 lag as the appropriate lag length. It is very important to choose the correct number of lags when constructing a *VAR* model, as the inference of the model depends on the correct model specification.

#### Ordering of the variables

As done before, we use the same variable ordering to run the post-crisis *VAR* model using Eviews. The *VAR* estimation output is presented in *Table 16* of *Annexure 4* and *Table 17* in *Annexure 4* presents the coefficients that are significant in the estimated *VAR* model.

#### VAR Model Inferences (Comparision between pre and post crisis VAR)

By looking at the R-squareds in the *VAR* estimation for the pre-crisis (*Table 12* of *Annexure 4*) and post crisis (*Table 16* of *Annexure 4*) period we can see that 32.90% and 20.25% of the movements in stock returns can be explained by the other variables, respectively. It is also possible to see within the *VAR* estimations that in the case of the tightness of the monetary policy, 81.54% of it in the pre-crisis and 54.79% of it in the post crisis period can be explained by the remaining variables. This suggests a better fit to the model when it comes to explaining monetary tightness using the other macroeconomic variables.

Further, if we take a closer look at the coefficients of the independent variables which explain movements in stock returns, it is possible to note that for the pre-crisis period all variables are insignificant except lagged autoregressive terms of stock returns. This, in contrast to the post-crisis period where one period lagged monetary tightness and one period lagged exchange rate are in fact significant at the 5% significance level.

From these results we can see that none of the macroeconomic variables that we picked help explain stock price movements before the *Tequila Crisis* in 1994, whereas in the period after crisis, both the monetary tightness and exchange rate help to explain stock price movements. Monetary policy tightness has a positive impact on stock returns while exchange rates have a negative impact on stock returns.

The positive impact of the monetary policy tightness on stock returns can be explained by the *Mundell-Fleming* framework which had been already discussed previously. The framework states that under a flexible exchange rate regime (as in Mexico after the crisis), the monetary policy is effective in altering output levels in the economy and thereby influences stock prices. The negative impact of exchange rate on stock returns after the *Tequila Crisis* is contrary to what we expected. According *Dornbusch* and *Fischer* (1980), currency devaluation should increase domestic stock prices. The explanation to this contradictory result could be the fact that a large amount of Mexican public and non-public companies held a large amount foreign-currency linked debt in the beginning of the *Tequila Crisis* which deteriorated its balances once the peso was devaluated against the U.S. dollar.

### **Granger Causality Tests**

We were able to run the *Granger Causality* tests in EViews and we obtained the results as shown in *Table 18 of Annexure 4*.

### Granger Causality Tests' Inferences (Full, pre and post crisis VAR samples)

Regarding the *Granger Causality* test conducted for whole of Mexico's data sample we can see that that none of the variables *Granger Cause* stock returns even at the 10% level as opposed to what we were looking for. Instead stock returns and exchange rates *Granger cause* monetary tightness.

In addition we can see from the results of the Granger Causality tests that exchange rate *Granger Causes* stock returns before the *Peso crisis* (at the 10% significance level). On the other hand, in the period after the crisis, it was found that monetary tightness *Granger Causes* stock returns (at the 10% significance level). Both are worthy points to be noted and we shall see later on how these affect stock returns with the help of impulse responses and variance decompositions. (Refer **Tables 10**, **14** and **18** in **Annexure 4**)

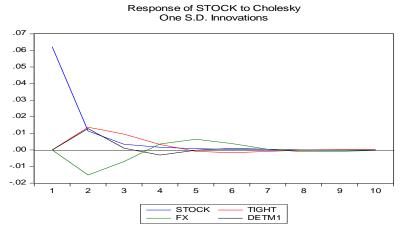
### Lag Exclusion Tests

We conduct the VAR lag exclusion Wald test in EViews to confirm that no information was lost by incorrectly restricting the lag length. We can see from the results **Table 19** of **Annexure 4** that both lags are jointly significant from their extremely low p-values. This ensures the fact that indeed VAR was appropriately estimated by employing 2 lags. Earlier we saw that SC and HQ recommended 1 lag which is contradictory to this test finding. Akaike Information Criterion (AIC) however suggested 2 lags as the appropriate lag length. The most common information criteria are the Akaike and SC. SC will in most cases deliver the correct model order, while the Akaike will, on average suggest too large of a model. However, the Akaike is usually more efficient, because the selected order model variation will be lower. Overall, no model is superior to the others and should be chosen to suit the needs of the researchers (Chris Brooks, 2008).

#### Impulse Responses

We present the impulse responses in multiple graphs with analytic response standard errors in **Box 5** of **Annexure 4**. The shocks gradually die out for all the variables after 10 periods. This implies that the VAR system is stable.

We will concentrate only on the effects on stock returns as presented in *Graph 18* below:



Graph 18: Generated from EViews using data taken from Thomson Reuters

### Impulse Responses' Inferences (Full, pre and post crisis VAR samples) (Refer Boxes 1, 3 and 5 in Annexure 4 for the results)

The main point to take away from observing the impulse response graphs generated for the whole data sample is that the innovations to unexpected shocks in monetary tightness have a positive impact on stock returns before having a small negative impact and then gradually dies out. Whereas innovations to unexpected shocks in exchange rates have a small negative impact on stock returns before having a greater positive impact and finally gradually dies out. Shocks in monetary base generally don't affect the stock returns too much. We can infer that this *VAR* system is stable because the shocks are never persistent and they gradually die out. (Refer back to *Graph 14*)

During the period before crisis, innovations to unexpected monetary tightness have a very small positive impact on stock returns before having a small negative impact and then gradually dies out. This is in contrast to the innovations to unexpected shocks in exchange rates that have large positive impact on stock returns before gradually dying out. Whereas innovations to unexpected shocks in exchange rates in the period after the crisis have a large negative impact on stock returns before gradually dying out. On the other hand, monetary tightness in the period after crisis has a large positive impact on stock returns and then gradually dies out. (Refer back to **Graph 16** and **Graph 18**)

Regarding the monetary base, it generally does not affect the stock returns too much but it can be seen that in the pre-crisis period they start with a small negative impact

and then keep alternating until they eventually die out. In the after-crisis period, shocks in monetary base generally don't affect the stock returns too much but it can be seen that they start with a positive impact and then have a small negative impact until they eventually die out. (Refer back to *Graph 14*, *Graph 16* and *Graph 18*)

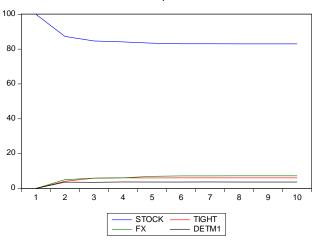
Overall, among the three macroeconomic factors, it can be seen from the impulse response graphs that the exchange rates have a large positive impact on stock returns before the *Tequila crisis* while both monetary tightness and exchange rates have the highest impact on stock returns after the referred crisis (positive and negative impact, respectively). This supports our hypothesis regarding the degree in which monetary and exchange rate policy affects stock returns after the *Tequila Crisis*.

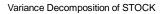
The large positive impact of exchange rates on stock returns during the period before crisis is contrary to what economic literature suggests. According to the literature, an overvalued domestic currency is less competitive in foreign currency markets. This decreases the value of exports. Therefore this is very much relevant to the case of countries like Mexico where a large extent of economic growth is driven by the amount of exports.

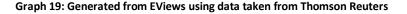
#### Variance Decomposition

From the information exhibited in **Box 6** of **Annexure 4**, it is possible to view the nature of the effects of a given variable on other variables in the VAR system. This gives us a clearer picture on the dynamics of the VAR system.

We will concentrate on the percentage of stock variation due to the 4 variables under the limelight. From the **Graph 19** below, we are able to see that the behavior of variation settles down quickly to a steady state.







#### Variance Decomposition Inferences (Full, pre and post crisis VAR samples) (Refer Boxes 2, 4 and 6 in Annexure 4 for the results)

When we ran the variance decomposition function for the whole data sample, the percentage of errors in stock returns that is attributable to its own shocks is almost 100%, whereas to the others shocks it is a meager single digit (1% for monetary tightness and 4% for exchange rate). From the variance decomposition graphs generated for the period before the crisis, we are able to see that they exhibit a behavior of variation to settle down quickly to a steady state. The percentage of errors in stock returns that is attributable to its own shocks is almost 100% before reducing down to somewhere around 90% where it reaches its steady state. While that to the shocks of monetary tightness and monetary base is a meager one percent. However we are able to see that the percentage of errors in stock returns that is attributable to its own shocks returns that is attributable to the shocks of monetary tightness and monetary base is a meager one percent. However we are able to see that the percentage of errors in stock returns that is attributable to the shocks in exchange rates is a notable 10 percent when it reaches a steady state.

Furthermore, from the variance decomposition graphs for the period after the crisis we are able to see that they exhibit a behavior of variation to settle down quickly to a steady state. The percentage of errors in stock returns that is attributable to its own shocks is almost 100% before reducing down to somewhere around 83% where it reaches its steady state. While that to the shocks of monetary base, monetary tightness and exchange rate are meager single digits (4% for monetary base, 6% for monetary tightness and 7% for exchange rate).

With regards to the facts observed above it is possible to say that the proportion of errors in stock returns explained by monetary tightness and exchange rates suffered a structural break after the *Tequila Crisis*. Overall, the proportion of stock return errors explained by the exchange rate changed from 10% to 6% while the proportion of stock return errors explained by the monetary tightness changed from 1% to 4%.

### 4.8 Multiple regression framework using OLS

Apart from the conducting the traditional *VAR* analyses, we also ran a multiple linear regression with the help EViews. In this multiple linear regression, we regressed the stock returns from the Mexican national stock exchange on the tightness of the monetary policy in Mexico as given by a *Taylor* rule which measures the deviation of the actual policy interest rate in the economy from the optimal prescribed policy interest rate, exchange rate with the U.S. dollar and the money supply in the Mexican economy just as done in the *VAR* framework presented before. The results returned by EViews are presented in *Table 20 of Annexure 5*.

**Note:** '*Stock*' denotes stock returns from the Mexican national stock exchange, '*Tight*' denotes the tightness of the monetary policy in Mexico, '*FX*' denotes the exchange rate between the Mexican Peso and the U.S. Dollar, and '*M1*' denotes the monetary base (money supply) in Mexico. The data employed was from February 1994 to December 2003.

#### Multiple Regression Framework Inferences (Table 23 in Annexure 5)

With regards to the multiregression model conducted for the whole sample period we can see that only monetary tightness is significant in explaining movements in stock returns at the 10% significance level. However we must take note that these macroeconomic variables explain only 6.46% of the stock returns as suggested by the R-squared of the regression. This is understandable because stock returns do not really depend on anything during a crisis (they fluctuate so much that it is difficult to capture their movements using these macroeconomic variables). Stock returns seem to be positively affected by monetary tightness. It increases by 0.1687 units for every unit increase in monetary tightness.

In contrast to the VAR framework, the exchange rate is not significant in explaining stock returns in the multiple regression model. This was probably due to Mexico's quasi-fixed exchange rate regime that did not allow the exchange rate to explain stock prices movements.

#### **Chow Test**

We know that the *Tequila crisis* took place in December 1994. This will act as our break date giving us 9 years of data before and after the crisis. We hope to find that this break date during which the crisis took place, will act as our structural break. We believe that the explanatory variables employed above in our multiple linear regression model affects stock returns in a different way before and after the crisis. Mainly because after the crisis, exchange rate policies drastically changed from a quasi-fixed regime to a freely floating one, in addition to significant changes in money supply, interest rate levels, inflation and much more.

To investigate our belief, we planned to conduct a parameter stability test (namely the *Chow test*). The *Chow test* is extremely useful in this case as we already know the exact period where the structural break takes place. This was easily accomplished in EViews by running the *Chow breakpoint test*. The results of the *Chow test* that we ran in EViews are presented in **Table 25 of Annexure 5**.

We must note that the *Chow test* is not a general test and it cannot say which parameter coefficient of the regressors changed significantly after the structural break as it is a joint test. It is way too simple to implement and does not give us any meaningful insight or result which can be generalized. In search of a more ambitious result which can be generalized for countries that underwent a crisis, we decided to run a *Difference-in-Difference* regression which is presented later.

In addition, we ran two separate sub regressions before and after the crisis. Here again, we have accounted for heteroscedasticity and auto-correlated residuals which were found in the data before the crisis. However we had to account only for heteroscedasticity in the data sample after the crisis because serial correlation among the residuals was found to be absent. We found no multicollinearity to be present and there was no functional misspecification according to *Ramsey RESET* tests in either sub samples. The estimation

outputs which EViews returned are presented in *Table 26* and *Table 27 of Annexure 5* for the pre-crisis and post-crisis sample respectively.

#### Chow Test Inferences (Table 25 in Annexure 5)

From the *Chow* tests results, we reject the null hypothesis of no structural break in the data at the 5% significance level. This confirms our belief that some structural change in the relationship between stock returns and monetary tightness, exchange rates and monetary base took place after the crisis. However the *Chow* test does not reveal the impact of the structural break and does not reveal how the loadings of the independent variables changed.

# Two sub-sample regressions (before and after the crisis) (*Tables 26* and 27 in *Annexure 5*)

By comparing these results, we note that the exchange rates had a more profound negative effect on stock returns after the crisis. Before the crisis only the monetary tightness was significant in explaining stock returns. Before the crisis, we can see that the stock returns increased by 0.19788 units for every unit increase in monetary tightness. Exchange rates were ineffective in explaining movements in stock returns probably because of Mexico's quasi-fixed exchange rate regime before the crisis which did not allow the exchange rates to fluctuate much. This is highlighted after the crisis where the exchange rate policy was switched to a floating regime from a quasi-fixed regime. As it can be seen, for every unit increase in the exchange rate after the crisis the stock returns decreased by 0.4415 units. In fact, monetary tightness is insignificant in explaining movements in stock returns after the crisis. This helps us see how the switch in the exchange rate regime helps us understand stock returns and that monetary tightness is ineffective in explaining movements in stock returns after the crisis.

### 4.9 The Difference-in-Difference (DID) approach

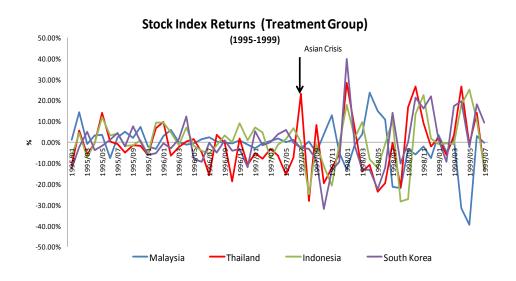
In order to give a broader perspective to our findings from the case of Mexico, we run a *difference in difference* regression. With the *DID* approach we are able to identify the impact of a specific treatment (the effect of a crisis) on stock returns. This will enable us to generalise the effect of the Tequila crisis on stock returns in Mexico to any country that underwent a similar crisis around the same period.

In order to run the *DID* regression, we first need to observe the outcomes for two groups over two time periods. One group should have undergone the crisis at the beginning of the second time period. We call this group as the treatment group. Whereas the other group should not have undergone any sort of crisis during either period. We call this group as the control group. The main assumption in the *DID* approach is that the observed differences between the treatment and control groups are same over time (i.e. it assumes that the trend in both the control and treatment groups are the same in the absence of a crisis).

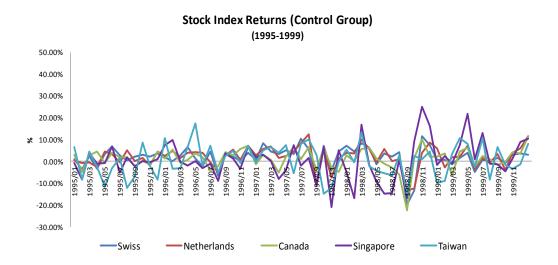
For the treatment group, we considered 4 other countries (Malaysia, Thailand, Indonesia and South Korea) which were severely affected by the Asian crisis in July 1997 (not so far from the Tequila crisis - December 1994) apart from Mexico. All these countries were emerging markets just like Mexico and thus they make a very good treatment group to be employed in the DID regression. According to Eshan Karunatilleka (1999) even before the summer of 1997, there had been doubts about the sustainability of certain economic policies followed by the South East Asian countries, especially the policy of unofficially fixing their exchange rates to the U.S. dollar. Moreover, this researcher notes that the appreciation of the U.S. dollar, in particular against the Japanese yen, caused the South East Asian currencies to also appreciate against third-party currencies. This resulted in a loss of competitiveness in export markets that in turn worsened current account deficits. Things turned unsustainable when the exchange rate was forced to float, causing Asian currencies to be devalued. This is very much similar to that of the Tequila crisis. After this episode the Asian countries present in our Treatment Group experienced a collapse in the level of their economic activity. Due to data availability constraints we were able to gather only 9 years of information prior to the Asian crisis and 9 years of information after the Asian crisis for the treatment group (August 1998 to July 2006). This gives us 18 years of monthly data.

For the control group, we considered 5 countries (Switzerland, Netherlands, Canada, Singapore and Taiwan). In contrast to the treatment group these countries exhibited a relative economic and financial calmness in the same sample period (*August 1998 to July 2006*). We chose the same time period as that of the treatment group so as to make our time frame congruent. This helps us avoid any unwanted biases that might arise due to information spaced at different time intervals. However, the time span for the information collected on Mexico is a little different (*January 1986 to December 2003*). This could be ignored as it not much different. Moreover we need to allow for minor deviations such as this because in reality it is impossible to find data that fits our needs exactly. There were no other countries that underwent a similar crisis at the same time as Mexico. This was our closest match.

From the graphs below we are able to see the above mentioned constructs much clearly. We notice a high volatility in stock returns for the treatment group especially around the *Asian crisis* whereas the volatilities of stock returns are relatively calm for the control group.



**Graph 20: Data obtained from Thomson Reuters** 



Graph 21: Data obtained from Thomson Reuters

As in the case of Mexico, we have collected data on stock returns (*stock*), tightness of the monetary policy as given by a *Taylor rule* which measures the deviation of the actual policy interest rate in the economy from the optimal prescribed policy interest rate (*tight*), exchange rate with the U.S. dollar (*FX*) and the monetary base (*M1*) for the all the other 9 countries. Along with the data on Mexico we arranged the collected information into a dated panel cross sectioned by different countries. In total we have data on 10 countries for 18 years (216 months). We have 4 variables under the limelight (*Stock, Tight, FX* and *M1*). This gives us a total of 8640 observations which is good enough to run a panel regression.

To run our *DID* regression on the assembled panel data we have to employ two important dummy variables namely *D1S* and *D2T*. *D1S* takes the value of 1 if the given country underwent a crisis (i.e. a country in the treatment group). It measures the general differences between crisis and non-crisis countries in affecting stock returns. *D2S* takes the value of 1 if the given observation is after the crisis date (i.e. after December 1994 in the case of Mexico and July 1997 in the case of other countries). It measures the general time period effects on stock returns. The different structural breaks do not matter as long as the dated panel is arranged in such a way that the structural breaks (crisis dates) are exactly matched. We have taken this into account in our dated panel of data. The figure below gives a snippet of how we arranged our data.

Mexico	1986/01	1986/02	1986/03		1994/09	1994/10	1994/11	1994/12	1995/01	1995/02	1995/03		2003/10	2003/11	2003/12
Foreign Countries	1988/08	1988/09	1988/10		1997/04	1997/05	1997/06	1997/07	1997/08	1997/09	1997/10		2006/05	2006/06	2006/07

The stand alone variables that we employ in our *DID* regression are *Tight, FX, M1, D1S, D2T* and a constant. The different interaction terms are *D1S\*D2T, Tight\*D1S\*D2T, FX\*D1S\*D2T, Tight\*D1S\*D2T, Tight\*D1S, FX\*D1S, M1\*D1S, Tight\*D2T, FX\*D2T* and *M1\*D2T*. These will be our entire set of explanatory variables. Thus we run the following regression in EViews:

 $\begin{aligned} Stock &= Constant + Tight + FX + M1 + D1S + D2T + (D1S * D2T) + (Tight * D1S * D2T) \\ &+ (FX * D1S * D2T) + (M1 * D1S * D2T) + (Tight * D1S) + (FX * D1S) \\ &+ (M1 * D1S) + (Tight * D2T) + (FX * D2T) + (M1 * D2T) + u \end{aligned}$ 

We must take note that all the regressors and the regressand has an implicit time subscript which denotes the time period of the observation and u is the residual (disturbance) term.

After running the regression we tested it for possible serial correlation in the residuals using the *Breusch-Godfrey test*. We obtained a high *Chi-squared* test statistic (59.6290) which was way beyond the critical value (15.086) at the 1% significance level. This led to the rejection of the null hypothesis which states that there is zero auto-correlation among the residuals. This is not a surprising result as we had employed time series data whose residuals are generally auto-correlated.

We also checked for heteroscedasticity among the residuals. We did this by running the *Breusch-Pagan test*. We saved the residuals for the original panel regression and regressed its square on the same independent variables employed above. The test statistic is obtained as the product of the R-squared of this auxiliary regression and the sample size, which was 326.3318. This test statistic too is way beyond the critical value (30.578) at the 1% significance level. Hence we rejected the null hypothesis of homoscedasticity.

Therefore we reran the panel *DID* regression in EViews, but this time we included *White* cross-section in the co-efficient covariance method to account for serial correlation in the residuals and used period weights as *GLS* (Generalised Least Squares) weights to account for heteroscedasticity (which probably arises from period variations) in the residuals.

The results of this *DID* regression as returned by EViews is presented in *Table 28* of *Annexure 6.* 

### DID Inferences (Table 28 in Annexure 6)

As highlighted in the results depicted earlier, we can see that only the constant, *M1*, *Tight\*D2T*, *Tight\*D1S\*D2T* and *FX\*D1S\*D2T* are significant at the 5%, 1%, 10%, 5% and 1% significance levels respectively.

The co-efficient of M1 measures the general effects of the monetary base on stock returns regardless of the country and time period. A co-efficient of 0.2852 for M1 implies that for every 1% increase in the monetary base, the stock returns are increased by 0.2852% regardless of which among the 10 countries it is and regardless of the time period.

The co-efficient of *Tight\*D2T* measures the general effects of the monetary tightness (as measured by *Taylor* rule) on stock returns post crisis regardless of the country. A co-efficient of 0.7494 for *Tight\*D2T* implies that for every 1% increase in the tightness of monetary policy after the crisis, the stock returns are increased by a notable 0.7494% regardless of which among the 10 countries it is. This depicts a significant positive relationship between stock returns and monetary policy after a crisis.

The co-efficient of *Tight\*D1S\*D2T* measures the differences in effect of the tightness of monetary policy (as measured by *Taylor* rule) on stock returns after the crisis took place (2<sup>nd</sup> period) in countries that underwent a crisis (treatment group). A co-efficient of -0.9946 for *Tight\*D1S\*D2T* implies that for every 1% increase in the tightness of the monetary policy after the crisis took place (2<sup>nd</sup> period) in the countries that underwent a crisis (treatment group), the stock returns of that country after the crisis decreased by a notable 0.9946%. The combined effects of *Tight\*D2T* and *Tight\*D1S\*D2T* on countries that underwent a crisis causes the stock returns to down by only 0.2452% (=0.7494-0.9946) for every 1% increase in the exchange rate (to the U.S. dollar) after the crisis. This has a kind of cancelling effect on crisis countries after the crisis and reduces the negative impact of monetary tightness on stock returns.

The following is the most significant among all our results. The co-efficient of  $FX^*D1S^*D2T$  measures the differences in effect of the exchange rate (to the U.S. dollar) on stock returns after the crisis took place (2<sup>nd</sup> period) in countries that underwent a crisis (treatment group). A co-efficient of -1.2219 for  $FX^*D1S^*D2T$  implies that for every 1% increase in the exchange rate after the crisis took place (2<sup>nd</sup> period) in the countries that underwent a crisis decreased by a whopping 1.2219%. This is a significant negative relationship for which the stock returns decreases by an amount more than the increase in the exchange rates for

crisis countries after the crisis. This gives us an insight into the exchange rate policies adopted after a crisis in countries that underwent a crisis and how it affects stock returns.

We notice that the R-squared of our panel DID regression is very low. However this is not a surprise given that the stock returns is the dependent variable in our analysis and that we were working around a period of crisis where distortions in the stock market could not really be explained by anything. Moreover we are looking at a pooled time series data for 10 different countries (some which underwent a crisis and some not) and thus the low R-squared is completely understandable. While pooling cross sections with a time series, the data noise arising from the differences in country specific factors result in a low R-squared (*Jui-Chi Huang*, 2010).

The above mentioned findings and results further broaden our understanding on the relationship between stock returns and macroeconomic variables (monetary tightness, exchange rates and monetary base) on a more diverse level which could especially be generalized for countries that underwent a currency crisis.

## 4.10 <u>Residual Diagnostic Testing</u>

According to *Kuan* (2008) performing several diverse diagnostic tests is a crucial stride in time series modeling. In this respect, we conducted a series of diagnostic tests to reveal the most important features of the time series that are about to be modeled.

This section talks about the different diagnostic tests that we conducted. Here we check for and address any violations of the assumptions under which the *classical linear regression model* (*CLRM*) is based upon.

### Normality Test

This test was conducted using the most commonly applied test for normality, the *Jarque-Bera Test*. According to *Chris Brooks* (2008), the *Jarque-Bera* test employs the attribute of a normally distributed random variable that the full distribution is characterized by the first two moments, namely the *mean* and the *variance*. The third moment, the *skewness*, measures the extent to which the distribution of the residuals is asymmetric about its mean and variance. A normal distribution is not a skewed distribution and is defined to have a *kurtosis* coefficient of 3.

In this regard, we ran the above mentioned test for the residual time series from an *ordinary least squares* regression using the dependent and independent variables of interest for Mexico's data. As expected, the series exhibits a kurtosis coefficient of 19.50914 with a *Jarque-Bera* t-statistic equal to 2,469.64 which according to the bell shape presented corresponds to a *leptokurtic* distribution.

Additionally, the results of the normality tests applied to the residual time series from the ordinary least squares regression using the variables of interest for the remaining

countries that compose the sample, exhibited *leptokurtic* features just as in the case of Mexico. These results were expected as well since in real life, macroeconomic data is far from satisfying the normality criteria. The results of these tests are not presented in this document but are of course available to the reader upon request.

According to *Chris Brooks* (2008), any infringement of the assumption of normality is virtually inconsequential for sufficiently large sample sizes. He also states that 'appealing to a central limit theorem, the test statistics will asymptotically follow the appropriate distributions even in the absence of error normality' (*Chris Brooks*, 2008, p. 164) which we think is the case of our data sample.

# • Tests for Autocorrelation, Heteroscedasticity, Multicollinearity and Specification Error

Under the *OLS* framework it is assumed that the covariance among the error terms over time and/or cross-sectionally is zero. This assumption implies that the errors are uncorrelated with each other (*Chris Brooks, 2008*). Before testing for autocorrelation, it is essential to inquire if there is any relationship among the current value of the residuals and any of its previous values. We have employed the *Durbin-Watson* test and *Breusch-Godfrey* test to test for autocorrelation in our research data. The *Durbin-Watson statistic* suggests that the residuals are positively auto-correlated.

Likewise under the OLS framework it is also assumed that the variance of the errors is constant (*homoscedastic*). If the errors do not have a constant variance they are said to be *heteroscedastic*. We have employed the *White* test and *Breusch-Pagan* test to test for heteroscedasticity in our research data. When we ran the *White test* to check for heteroscedasticity, the null of homoscedasticity was rejected. The results of the *White test* are presented in **Table 21 of Annexure 5** 

Another basic assumption under the *OLS* framework is that the independent variables are uncorrelated with each other within a system. When the variables are found to be correlated with each other, they are said to be multicollinear. We check for multicollinearity by inferring t-statistics that are calculated for the correlation among the independent variables. We find that our regressors are free from multicollinearity. The results presented in *Table 22 of Annexure 5* clearly show that none of our regressors were significantly correlated with the other.

After accounting for heteroscedasticity and serial correlation among residuals, we reran the regression in EViews. The results obtained are presented in *Table 23 of Annexure 5*.

We assume that there is no specification error in our model. Therefore we ran the *Ramsey RESET* test in EViews to check if we had adopted the wrong functional form in our regression. From the test results (presented in *Table 24 of Annexure 5*) we could conclude that in fact we had adopted the correct functional form.

## **SECTION V**

## **5 CONCLUSIONS**

## 5.1 Conclusion

The main purpose of this Master thesis was to test the hypothesis of a structural break in stock returns as a consequence of exchange rate and monetary policy changes in Mexico exhibited after the Tequila crisis.

To test this hypothesis we used the *VAR* approach including causality tests, impulse responses, variance decomposition functions and as well as multiple linear regressions to identify any significant relation between the stock returns (dependent variable) and monetary tightness, exchange rates and monetary aggregates before and after the Tequila Crisis. Further, a parameter stabilization test (*Chow* Test) was performed in order explicitly check for this hypothesis and a difference in difference method was applied to generalize and compare Mexico's crisis experience with that suffered by emerging Asian markets in the late 1990s.

Our main findings indeed confirmed our suspicions of a structural break in stock returns due to exchange and monetary policy changes after the crisis. As our *VAR* models show that the monetary tightness and the exchange rates explain the performance of stock returns in the post-crisis period better than in the pre-crisis period. Monetary policy has a positive impact while the exchange rates have a negative impact. This is in contrast to the pre-crisis period under which none of the macroeconomic variables that we picked help explain our dependent variable. Additionally, we rejected the null hypothesis of no structural break under the *Chow* test which strengthens our previous findings.

Further, as a result of the multiple linear regressions applied to both samples (the precrisis sample and the post-crisis sample), we found that the exchange rate negatively affects performance of stock returns just as in the case of the *VAR* models. In contrast to our *VAR* findings, the multiple linear regression found no significant relation between monetary tightness and stock returns.

Finally, the difference in difference approach found a significant negative relation between exchange rates and stock returns for all the emerging Asian countries after controlling for other factors.

*Note:* These findings have been smartly summarized in *Tables 29, 30 and 31* of *Annexure VII*. From these tables we can clearly compare and analyse our findings from the different methods. '+' denotes that the given variable positively affects stock returns and '-' denotes the opposite.

## 5.2 Recommendations for future research

We hope this thesis will be an important starting point for future national economic research given the increasing worldwide importance of Mexico's capital markets among other emerging markets for international capital allocation.

We also recommend aspiring financial researchers to generalize the effects of macroeconomic variables on stock returns both at a time of crisis and financial calmness. We advocate them to delve deeper into other emerging markets in order to understand in what different ways the macroeconomic variables can affect stock price movements. One should also endeavor to analyze the reverse causality between the above relationship in order to fully understand how these variables interact with each other.

## **SECTION VI**

## 6 REFERENCES

## 6.1 Bibliography

- Ben S. Bernanke and Michael Woodford (2005): "The Inflation- Targeting Debate", National Bureau of Economic Research
- Berkman, N. (1978), On the Significance of Weekly Changes in MI, New England Economic Review.
- Boone, L., Giorno C. and P. Richardson (1998), "Stock Market Fluctuation and Consumption Behaviour: Some Recent Evidence", OECD Economics Department working paper, No. 208.
- Brooks, C. (2008): Introductory Econometrics for Finance, 2nd edition. Cambridge University Press.
- Chami R., Cosimano T., F. and C. Fullerkamp (1999a), "The Stock Market Channel of Monetary Policy", IMF working paper, No. 22.
- Charles T. Carlstrom and Timothy S. Fuerst (2003): "The Taylor Rule: A Guidepost for Monetary Policy?", Federal Reserve Bank of Cleveland.
- Christopher K. Ma and G. Wenchi Kao (1990): "On exchange rate changes and stock price reactions", Journal of Business, Finance and Accounting.
- Chung Ming Kuan (2008): "Time series diagnostic tests", Institute of Economics Academia Sinica.
- Cohen, L. And Manion, L. (1980): "Research methods in Education", Groom Helm Ltd.
- Cooley, T. F and V. Quadrini (1999a), "Monetary Policy and the Financial Decisions of Firms", Mimeo.
- Cooper, Richard V. L. (1974) "Efficient Capital Markets and the Quantity Theory of Money." *Journal of Finance*, 29:3, 889.
- Cormack, D.S. (1991): "The research process". Black scientific. Oxford.
- Cornell, B. (1983). The Money Supply Puzzle: Review and Interpretation, American Economic Review.
- Creswell, J.W (1994): "Research design: Qualitative and Quantitative Approaches. London.
- Donald, L. Kohn (2007), 'The role of simple rules in monetary policy making', Federal Reserve Bank of Dallas
- Dornbusch Rudiger and Werner Alejandro (1994): "Mexico: Stabilization, Reform and No Growth", Brookings Papers on Economic Activity, No.1, 253-315.
- Dornbusch, R. and S. Fisher, 1980. Exchange rates and the current account. Am. Econ. Rev.
- E. Han Kim and Vijay Singal (2000): "Stock Market Openings: Experience of Emerging Economies", The University of Chicago Press.
- Elizaveta Krylova & Lorenzo Cappiello & Roberto A. De Santis, 2005. "Explaining exchange rate dynamics - the uncovered equity return parity condition," Working Paper Series 529, European Central Bank.
- Eshan Karunatilleka (1999), The Asian Economic Crisis, House of Commons Library.
- Eugene Fama (1970) Efficient Capital Markets: A Review of Theory and Empirical Work". *Journal of Finance.*
- Frederic S. Mishkin (1999): "Lessons from the Tequila Crisis", Journal of Banking and Finance.
- Garriga, Ana Carolina (2010): "Objective, instruments and Monetary Policy Results, México 1980-2010", Research and Economic Development Centre.

- Georgios Katechos, 2011. "On the relationship between exchange rates and equity returns: A new approach". Journal of International Financial Markets, Institutions and Money, Volume 21, Issue 4, October 2011.
- Hamburger, M.J. and L.A.Kochin (1972), 'Money and Stock Prices: The Channels of Influence', Journal of Finance, Vol. 27 (May).
- Hau, H., Rey, H., 2006. Exchange rates, equity prices, and capital flows. Review of Financial Studies (Spring) 19 (1).
- Heyman T. (1998): "Mexico for the Global Investor", Milenio Editorial, Mexico.
- Homa, K.E. and D.M. Jaffee (1971), 'The Supply of Money and Stock Prices', Journal of Finance, Vol. 26 (December).
- Hurtado, Miguel de la Madrid, Mexico's President (1983): National Development Plan 1983-1988.
- International Monetary Fund website: www.imf.org
- James H. Stock and Mark W. Watson (2001): "Vector Auto-Regressions", National Bureau of Economic Research. Cambridge, Massachusetts.
- John Clark, Elizabeth Berko (1997): "Foreign Investment Fluctuations and Emerging Market Stock Returns: The Case of Mexico", Federal Reserve Bank of New York.
- Joseph A. Whitt, Jr. (1996): "The Mexican Peso Crisis", Federal Reserve Bank of Atlanta.
- Jui-Chi Huang (2010), Hedging On U.S. Export Pricing: An Exchange Rate Pass-Through Analysis.
- Kenneth Silber (2011): "Mexico's Resilient Market", Research Magazine.
- Keran, M.W. (1971), 'Expectations, Money and the Stock Market', Review (Federal Reserve Bank of St. Louis, January).
- Lynge, M. (1981), Money Supply Announcements and Stock Prices, Journal of Portfolio Management.
- Marianne Bertrand, Esther Duflo and Sendhil Mullainathan (2004), 'How much should we trust Differences-in-Differences estimates?', The Quarterly Journal of Economics.
- Martinez, Lorenza, Sanchez Oscar and Werner Alejandro (2000), "Considerations on Monetary Policy Conduction and the Transmission Mechanisms in Mexico", Central Bank of Mexico.
- McQueen, G., and V. V. Roley (1993): Stock Prices, News, and Business Conditions," Review of Financial Studies.
- Mexican Bank Association website: http://www.abm.org.mx/banca\_mexico/historia.htm
- Mexican Stock Exchange website: www.bmv.com.mx
- Michael Woodford (2001): "The Taylor Rule and Optimal Monetary Policy", Princeton Univesity.
- Morley B. and Pentescot E.J. (2000): "Common trends and Cycles in G-7 Countries Exchange Rates and Stock Prices", Applied Economic Letters, Vol. 7, pp 7-10.
- Paul Conway and Bent Hunt (1997): "Estimating Potential Output: A semi-structural approach", Reserve Bank of New Zeland.
- Pesando, James E. (1974) "The Supply of Money and Common Stock Prices: Further Observations on the Econometric Evidence." *Journal of Finance*, 29:3, 909–21.
- Peter Sellin (2001): Monetary Policy and the Stock Market: Theory and Empirical Evidence, *Journal of Economic Surveys*, 2001, vol. 15, issue 4.
- Pierre L. Siklos and Mark E. Wohar, 2005, Estimating Taylor-Type Rules: An Unbalanced Regression, Emerald Group Publishing Limited.

- Rogalski, Richard J., and Joseph D. Vinso. (1977) "Stock Returns, Money Supply and the Direction of Causality." *Journal of Finance*, 32:4.
- Rozeff, Michael S. (1974) "Money and Stock Prices: Market Efficiency and the Lag in Effect of Monetary Policy." *Journal of Financial Economics*, 1:3, 245–302.
- Runkle, D. E. (1987) Vector Autoregressions and Reality, Journal of Business and Economic Statistics
- Soenen and Aggarwal R. (1989): "Financial Prices as Determinants of Changes in currency values", Paper presented at the 25<sup>th</sup> Annual Meetings of Eastern Finance Association, Philadelphia.
- Sprinkel, B.W. (1964) Money and Stock Prices (Homewood, Ill.: Richard D. Irwin, Inc.).
- Statistic and Geography National Institute of Mexico website: www.inegi.gob.mx
- Stephany Griffith-Jones (1997): "Causes and Lessons of the Mexican Peso Crisis", The United Nations University, World Institute for Development Economics and Research.
- Taylor, John B. (1993), "Discretion versus Policy Rules in Practice," *Carnegie-Rochester Conference Series on Public Policy*.
- Tobin James (1978), "Monetary Policy and the Economy: The transmission mechanisms", Southern Economic Journal.
- Tobin James (1988), Comments on Greenwald and Stiglitz, Brooking Papers on Economic Activity.
- Turrent Díaz, Eduardo (2001): "Monetary Policy Perspectives in México: Stabilization after Uncertainty". Economic Analysis XVII (034):257-81
- Vincent Bodart and Paul Reding (2001) DO FOREIGN EXCHANGE MARKETS MATTER FOR INDUSTRY STOCK RETURNS? An empirical investigation. Discussion Papers (IRES - Institut de Recherches Economiques et Sociales) 2001016, Université catholique de Louvain, Institut de Recherches Economiques et Sociales (IRES), Department of Economics, University of Namur, Rempart de la Vierge 8, 5000 Namur, Belgium.
- W. A Razzak and Richard Dennis (1999): "The Output Gap using the Hodrick-Prescott filter with a non-constant smoothing parameter: An application to New Zeland", Reserve Bank of New Zeland and Australian National University.

## **SECTION VII**

## 7 APPENDIX

## ANNEXURE – I (Analysis of Empirical Data):

	TABLE 1								
	Phillips-Peron Test								
	Null Hypothesis: Time series data is Non-Stationary								
	Alternative Hypothesis: Time series data is Stationary								
Country	Time series variable	t-statistic	Probability	Decision					
Mexico	Tight	-4.98	0	Reject Null*					
	ERI	-11.89	0	Reject Null*					
	FX	-8.43	0	Reject Null*					
	M1	-13.28	0	Reject Null*					
	Stock	-9.32	0	Reject Null*					

Spectral estimation method used: Barlett Kernel Bandwidth used: Newey-West Bandwidth

- \* 1% significance level
- \*\* 5% significance level
- \*\*\* 10% significance level

	TABLE 2 Kwiatkowski-Phillips-Schmidt-Shin Test							
	Null Hypothesis: Time series data is Stationary							
	Alternative Hypothesis: Time series data is Non-Stationary							
Country	Time series variable	LM Test Statistic	Decision					
Mexico	Tight	0.02	Do not reject Null***					
	ERI	0.09	Do not reject Null***					
	FX	0.63	Reject Null** but Do not reject*					
	M1	0.90	Reject Null*					
	Stock	0.65	Reject Null** but Do not reject*					

Spectral estimation method used: Barlett Kernel Bandwidth used: Newey-West Bandwidth

- \* 1% significance level
- \*\* 5% significance level
- \*\*\* 10% significance level

#### TABLE 3

Dependent Variable: M1 Method: Least Squares Date: 05/20/12 Time: 11:03 Sample: 1986M02 2003M12 Included observations: 215

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PERIOD_MEX C	-6.45E-06 4.73	2.08E-06 1.52	-3.10 3.11	0.00 0.00
R-squared	0.04	Mean depende	nt var	0.03
Adjusted R-squared	0.04	S.D. dependen		0.06
S.E. of regression	0.06	Akaike info crite		-2.86
Sum squared resid	0.71	Schwarz criteri	on	-2.83
Log likelihood 309.09		Hannan-Quinn criter.		-2.84
F-statistic	9.58	Durbin-Watson	stat	1.90
Prob(F-statistic)	0.00			

#### TABLE 4

Dependent Variable: D(M1) Method: Least Squares Date: 05/20/12 Time: 11:21 Sample (adjusted): 1986M03 2003M12 Included observations: 214 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
С	0.00	0.01	0.08	0.93
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	0.00 0.00 1.35 238.41 2.95	Mean dependent S.D. dependent v Akaike info criteri Schwarz criterion Hannan-Quinn cr	var on	0.00 0.08 -2.22 -2.20 -2.21

#### TABLE 5

Null Hypothesis: Log M1 is a random walk Date: 05/20/12 Time: 12:31 Sample: 1986M02 2003M12 Included observations: 115 (after adjustments) Standard error estimates assume no heteroskedasticity Use biased variance estimates User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max  z  (at period 2)*	2.34	115	0.08
Wald (Chi-Square)	13.77	4	0.01
Wald (Chi-Square)	13.77	4	(

Individu	ual Tests			
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.78	0.09	-2.34	0.02
4	0.79	0.17	-1.20	0.23
8	0.81	0.28	-0.68	0.50
16	1.31	0.41	0.75	0.46

\*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 0.360647754844)

Period	Variance	Var. Ratio	Obs.	
1	1.54		115	
2	1.20	0.78	107	
4	1.21	0.79	104	
8	1.25	0.81	103	
16	2.01	1.31	98	

	TABLE 6								
	Phillips-Peron Test								
	Null Hypothesis: Time series data is Non-Stationary								
	Alternative Hypothe	esis: Time series data is S	Stationary						
Country	Time series variable	t-statistic	Probability	Decision					
Mexico	M1 (After de-trending)	-13.80	0	Reject Null*					

Spectral estimation method used: Barlett Kernel Bandwith used: Newey-West Bandwith

- \* 1% significance level
- \*\* 5% significance level
- \*\*\* 10% significance level

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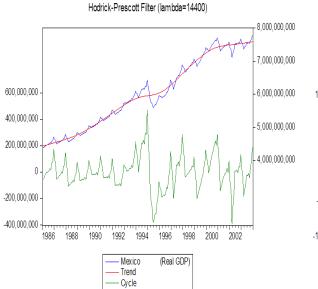
TABLE 7								
	Kwiatkowski-Phillips-Schmidt-Shin Test							
	Null Hypothesis: Time series data is Stationary							
	Alternative Hypothesi	<b>s:</b> Time series data is No	on-Stationary					
Country	Time series variable	LM Test Statistic	Decision					
Mexico	M1 (After de-trending)	0.11	Do not reject Null***					

Spectral estimation method used: Barlett Kernel

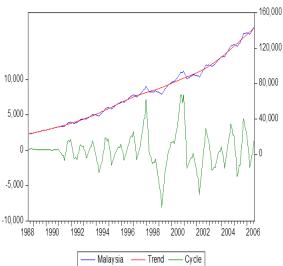
Bandwith used: Newey-West Bandwith

- \* 1% significance level
- \*\* 5% significance level
- \*\*\* 10% significance level

## ANNEXURE – II (Hodrick-Prescott Filter):

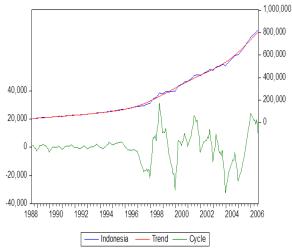


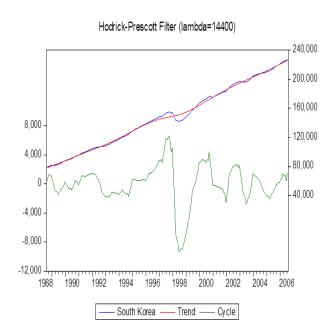
HODRICK - PRESCOTT FILTER PROCESS TO TREND FOR POTENTIAL GDP



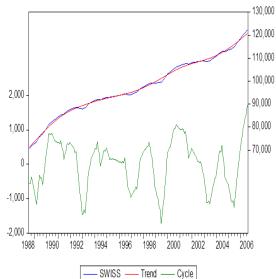
Hodrick-Prescott Filter (lambda=14400)

Hodrick-Prescott Filter (lambda=14400) Hodrick-Prescott Filter (lambda=14400) 60,000 50,000 40,000 8,000 30,000 40.000 4,000 20,000 20,000 0 10,000 0 -4,000 -20,000 -8,000 -12.000 -40.000 1990 2002 2006 1990 1998 2004 1988 1992 1994 1996 2000 1988 1994 1992 – Thailand Trend ---- Cycle



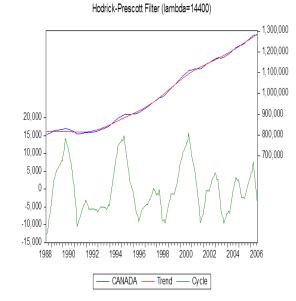


#### HODRICK - PRESCOTT FILTER PROCESS TO TREND FOR POTENTIAL GDP

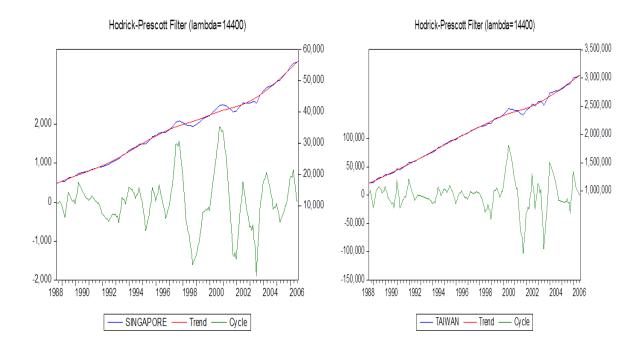


Hodrick-Prescott Filter (lambda=14400)

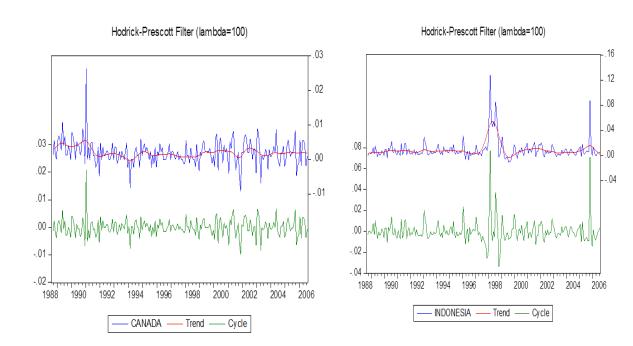
Hodrick-Prescott Filter (lambda=14400) 140,000 120,000 100,000 2,000 80,000 1,000 60,000 40,000 0 -1,000 -2,000 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 - NETHERLANDS -— Trend Cycle



#### HODRICK - PRESCOTT FILTER PROCESS TO TREND FOR POTENTIAL GDP



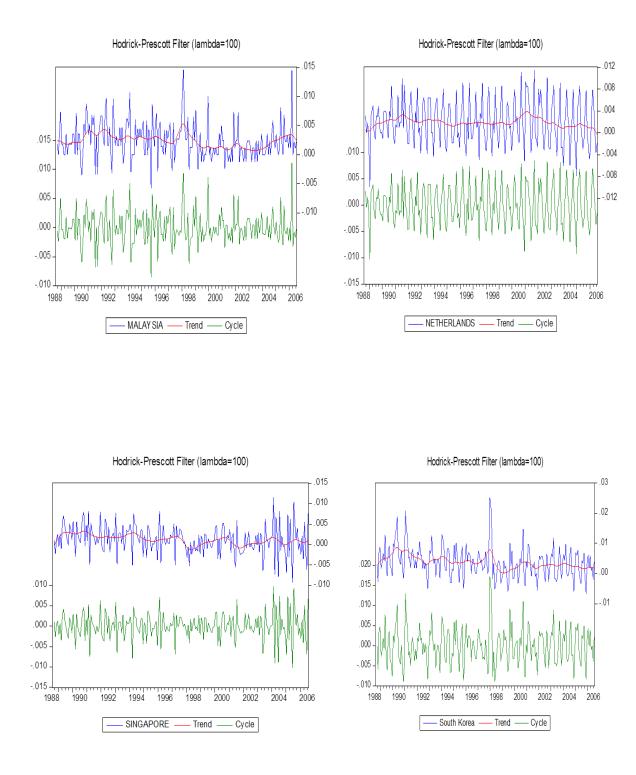
HODRICK – PRESCOTT FILTER PROCESS TO TREND TARGET FOR INFLATION



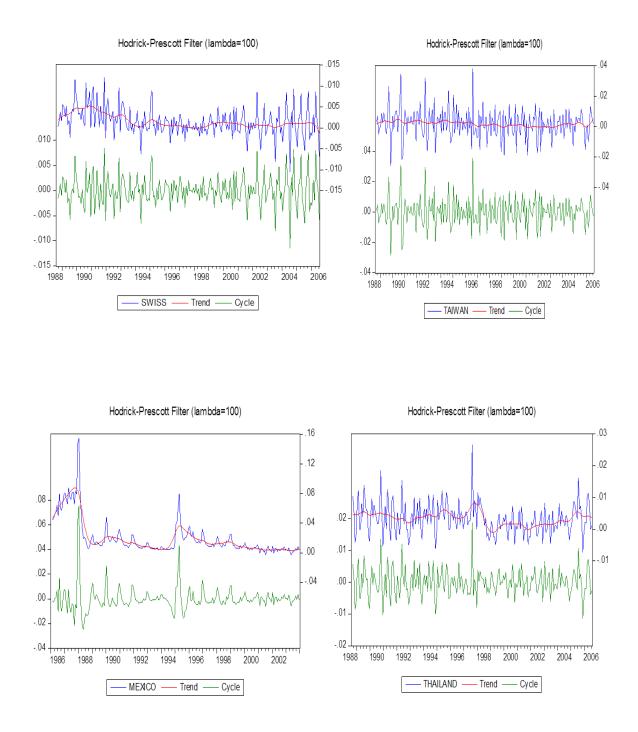
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#### HODRICK – PRESCOTT FILTER PROCESS TO TREND TARGET FOR INFLATION

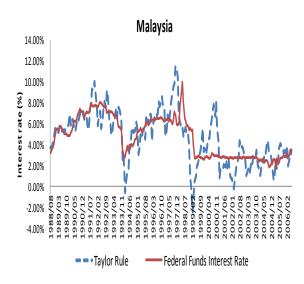


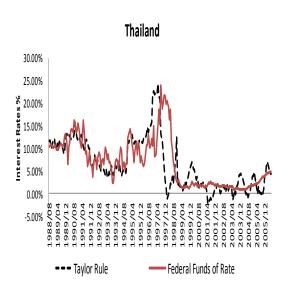
#### HODRICK – PRESCOTT FILTER PROCESS TO TREND TARGET FOR INFLATION

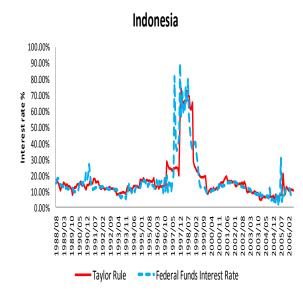


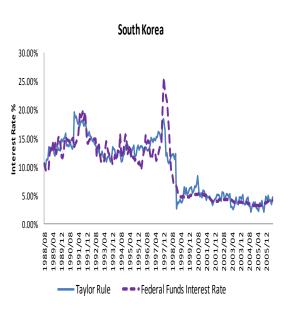
## ANNEXURE - III (Taylor Rule Estimation):

#### TAYLOR RULE ESTIMATION

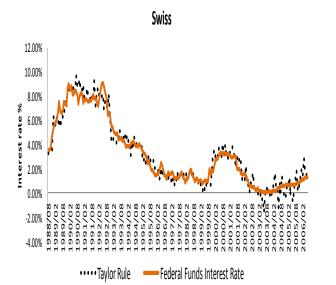


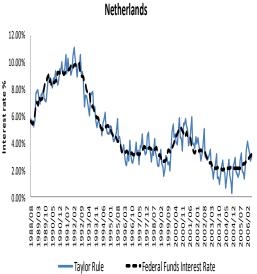


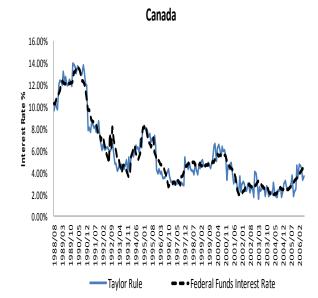


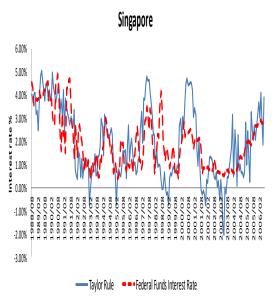


#### **TAYLOR RULE ESTIMATION**

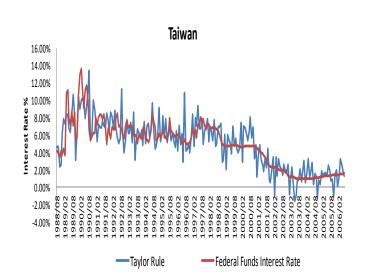








#### TAYLOR RULE ESTIMATION



## ANNEXURE – IV (Results of the VAR): VAR RESULTS FOR THE WHOLE DATA SAMPLE

#### TABLE 8:

Date:05/20/12Time:18:46Sample (adjusted): 1986M04 2003M12Included observations: 213 after adjustmentsStandard errors in ( ) & t-statistics on 1[ ]							
	STOCK	TIGHT	FX	DETM1			
STOCK(-1)	0.45	-0.14	0.032	0.02			
	(0.07)	(0.04)	(0.03)	(0.04)			
	[ 6.40]	[-3.26]	[ 1.22]	[ 0.46]			
STOCK(-2)	-0.13	-0.14	0.04	0.02			
	(0.07)	(0.05)	(0.03)	(0.05)			
	[-1.71]	[-3.14]	[ 1.27]	[ 0.50]			
TIGHT(-1)	0.21	0.84	-0.01	0.07			
	(0.10)	(0.06)	(0.04)	(0.06)			
	[ 2.12]	[ 14.06]	[-0.14]	[ 1.14]			
TIGHT(-2)	-0.17	-0.23	-0.023068	-0.02			
	(0.10)	(0.06)	(0.04)	(0.06)			
	[-1.73]	[-3.95]	[-0.63]	[-0.41]			
FX(-1)	-0.17	0.030	0.54	-0.01			
	(0.19)	(0.11)	(0.07)	(0.11)			
	[-0.89]	[ 0.26]	[ 7.58]	[-0.12]			
FX(-2)	0.37	0.62	-0.10	-0.09			
	(0.19)	(0.12)	(0.07)	(0.16)			
	[ 1.95]	[ 5.39]	[-1.35]	[-0.74]			
DETM1(-1)	0.081	0.12	0.02	0.05			
	(0.12)	(0.07)	(0.04)	(0.07)			
	[ 0.69]	[ 1.74]	[ 0.40]	[ 0.72]			
DETM1(-2)	0.08	0.12	0.02	0.011			
	(0.12)	(0.07)	(0.04)	(0.07)			
	[ 0.67]	[ 1.77]	[ 0.43]	[ 0.15]			
С	0.02	-0.00	0.01	0.00			
	(0.01)	(0.00)	(0.00)	(0.00)			
	[2.32]	[-0.08]	[2.14]	[ 0.03]			
-squared dj. R-squared	0.24 0.21	0.71 0.70	0.27 0.24	0.02 -0.02			
um sq. resids	1.90	0.70	0.24	-0.02 0.69			
E. equation	0.10	0.06	0.04	0.09			
-statistic	8.24	63.20	9.54	0.00			
og likelihood	200.66	307.41	407.65	307.51			
kaike AIC	-1.80	-2.80	-3.74	-2.80			
chwarz SC	-1.66	-2.66	-3.60	-2.66			
lean dependent	0.03	0.00	0.01	0.00			
.D. dependent	0.11	0.11	0.04	0.06			
eterminant resid covariance (dof ac eterminant resid covariance	dj.)	0.00 0.00					
og likelihood		1233.46					
kaike information criterion		-11.24					
Schwarz criterion		-10.68					

**Note:** '*Stock*' denotes stock returns from the Mexican national stock exchange, '*Tight*' denotes the tightness of the monetary policy in Mexico, '*FX*' denotes the exchange rate between the Mexican Peso and the U.S. Dollar, and '*DETM1*' denotes the de-trended monetary base (money supply) in Mexico

		TABLE 9		
	Stock	Tight	FX	DetM1
Stock(-1)	0.45*	-0.14*	0.03	0.02
Stock(-2)	-0.13***	-0.14*	0.04	0.02
Tight(-1)	0.21**	0.84*	-0.01	0.07
Tight(-2)	-0.17***	-0.23*	-0.02	-0.02
FX(-1)	-0.17	0.03	0.54*	-0.01
FX(-2)	0.37***	0.62*	-0.10	-0.09
DetM1(-1)	0.08	0.12***	0.02	0.05
DetM1(-2)	0.08	0.12***	0.02	0.01
С	0.02**	-0.00	0.01**	0.00

Significance of VAR coefficients (Whole sample): Significant coefficients are marked in red and asterisks. \* Significant at 1% level. \*\* Significant at 5% level. \*\*\* Significant at 10% level.

#### **GRANGER CAUSALITY TESTS FOR WHOLE DATA SAMPLE**

#### **TABLE 10:**

VAR Granger Causality/Block Exogeneity Wald Tests Date: 07/31/12 Time: 13:05 Sample: 1986M02 2003M12 Included observations: 213

Dependent variable: STOCK							
Excluded	Chi-sq	df	Prob.				
TIGHT	4.52	2	0.10				
FX	3.81	2	0.15				
DETM1	0.98	2	0.61				
All	10.74	6	0.10				
Dependent variable: TIGHT							
Excluded	Chi-sq	df	Prob.				
STOCK	36.64	2	0.00				
FX	41.15	2	0.00				
DETM1	6.45	2	0.04				
All	96.02	6	0.00				
Dependent variable: FX							
Excluded	Chi-sq	df	Prob.				
STOCK	5.53	2	0.06				
TIGHT	1.27	2	0.53				
DETM1	0.36	2	0.83				
All	6.58	6	0.36				
Dependent variable: DETM1							
Excluded	Chi-sq	df	Prob.				
STOCK	0.81	2	0.67				
TIGHT	1.76	2	0.41				
FX	0.88	2	0.64				
All	3.41	6	0.76				

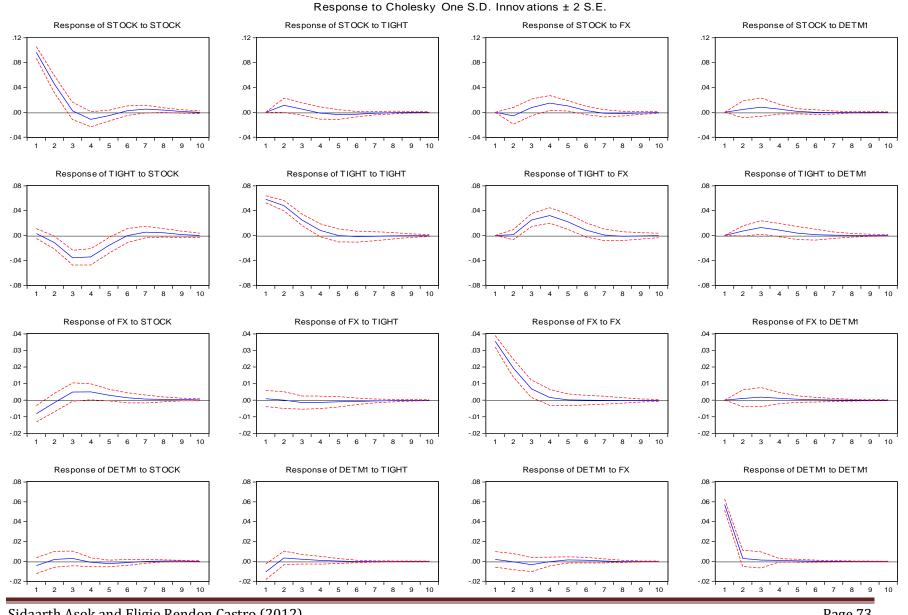
## TABLE 11:VAR Lag Exclusion Wald Tests for Whole sample

VAR Lag Exclusion Wald Tests Date: 07/31/12 Time: 13:40 Sample: 1986M02 2003M12 Included observations: 213

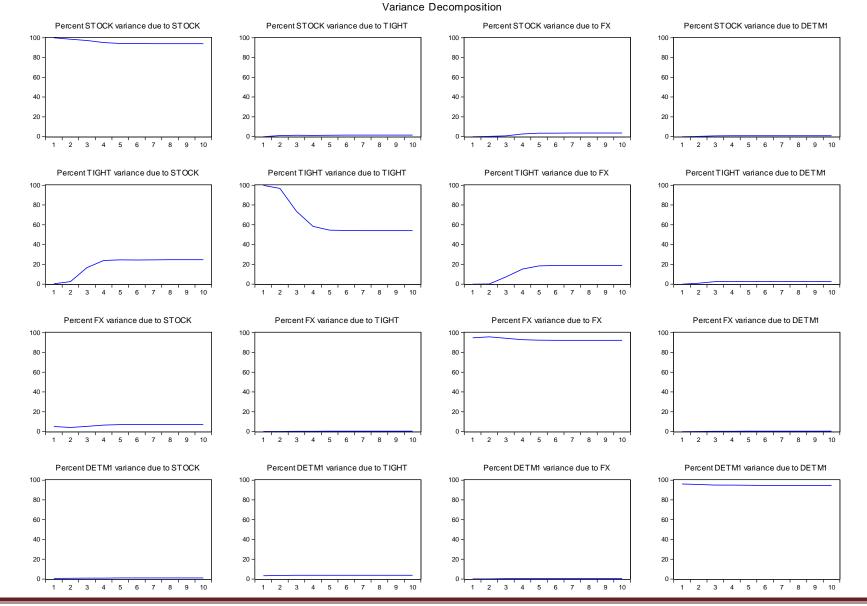
Chi-squared test statistics for lag exclusion: Numbers in [] are p-values

	STOCK	TIGHT	FX	DETM1	Joint
Lag 1	58.91	198.71	58.51	2.10	331.60
	[ 0.00]	[ 0.00]	[ 0.00]	[ 0.72]	[ 0.00]
Lag 2	17.19	92.47	4.36	0.10	111.74
	[ 0.00]	[ 0.00]	[ 0.36]	[ 0.91]	[ 0.00]
df	4	4	4	4	16

#### Box 1: Impulse Responses for the whole sample period



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#### Box 2: Variance Decompositions for the whole sample period

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#### **BEFORE CRISIS VAR**

#### VAR RESULTS FOR THE PRE-CRISIS DATA SAMPLE

#### Table 12:

Vector Autoregression Estimates Date: 05/21/12 Time: 01:18 Sample (adjusted): 1986M04 1994M12 Included observations: 105 after adjustments Standard errors in ( ) & t-statistics in []

Standard errors in () & t-statist	STOCK	TIGHT	FX	DETM1
STOCK(-1)	0.55	-0.15	0.00	0.02
	(0.11)	(0.06)	(0.03)	(0.06)
	[5.12]	[-2.50]	[ 0.07]	[ 0.38]
	[ •···=]	[ =:••]	[ ••••• ]	[]
STOCK(-2)	-0.27	-0.22	0.08	0.03
	(0.12)	(0.06)	(0.03)	(0.07)
	[-2.34]	[-3.46]	[2.39]	[0.40]
TIGHT(-1)	0.05	0.77	0.017	0.06
	(0.14)	(0.08)	(0.04)	(0.08)
	[ 0.35]	[ 10.28]	[ 0.30]	[ 0.77]
TIGHT(-2)	-0.06	-0.20	-0.048	-0.016
	(0.13)	(0.07)	(0.04)	(0.08)
	[-0.48]	[-2.82]	[-1.28]	[-0.21]
FX(-1)	0.44	0.14	0.35	0.26
FX(-1)	(0.45)	(0.25)	(0.13)	(0.27)
	[ 0.97]	[ 0.58]	[ 2.76]	[ 0.96]
	[0.37]	[ 0.00]	[2.70]	[ 0.90]
FX(-2)	0.60	1.29	0.29	-0.16
( )	(0.45)	(0.25)	(0.13)	(0.27)
	[1.33]	[5.21]	[2.24]	[-0.60]
DETM1(-1)	-0.13	0.02	-0.02	0.06
	(0.18)	(0.10)	(0.05)	(0.11)
	[-0.74]	[ 0.19]	[-0.31]	[ 0.58]
DETM1(-2)	0.11	0.10	-0.03	0.06
	(0.17)	(0.10)	(0.05)	(0.10)
	[ 0.66]	[ 1.03]	[-0.63]	[ 0.61]
С	0.02	-0.01	0.00	-0.00
8	(0.02)	(0.001)	(0.00)	(0.01)
	[ 1.16]	[-0.94]	[ 1.07]	[-0.47]
R-squared	0.32	0.82	0.32	0.04
Adj. R-squared	0.27	0.80	0.27	-0.04
Sum sq. resids	1.31	0.39	0.10	0.47
S.E. equation	0.12	0.06	0.03	0.07
F-statistic	5.88	53.02	5.75	0.46
Log likelihood	81.25	144.35	214.48	134.95
Akaike AIC	-1.38	-2.58	-3.91	-2.40
Schwarz SC	-1.15	-2.35	-3.69	-2.17
Mean dependent	0.05	0.00	0.02	0.00
S.D. dependent	0.14	0.14	0.04	0.07
Determinant resid covariance (	dof adj.)	0.00		
Determinant resid covariance		0.00		
Log likelihood		591.47		
Akaike information criterion		-10.58		
Schwarz criterion		-9.67		

		TABLE 13		
Variable	Stock	Tight	FX	DetM1
Stock(-1)	0.55*	-0.15**	0.00	0.02
Stock(-2)	-0.27**	-0.22*	0.08**	0.03
Tight(-1)	0.05	0.77*	0.01	0.06
Tight(-2)	-0.06	-0.20*	-0.05	-0.02
FX(-1)	0.44	0.14	0.35*	0.26
FX(-2)	0.60	1.29*	0.29**	-0.16
DetM1(-1)	-0.13	0.02	-0.02	0.06
DetM1(-2)	0.11	0.01	-0.03	0.06
С	0.02	-0.01	0.00	-0.00

Significance of *VAR* coefficients (Pre-Crisis sample):

Significant coefficients are marked in red and asterisks.

\*Significant at 1% level.

**\*\***Significant at 5% level.

\*\*\*Significant at 10% level.

#### **GRANGER CAUSALITY TESTS FOR PRE-CRISIS DATA SAMPLE**

#### Table 14:

VAR Granger Causality/Block Exogeneity Wald Tests Date: 05/20/12 Time: 22:22 Sample: 1986M02 1994M12 Included observations: 105

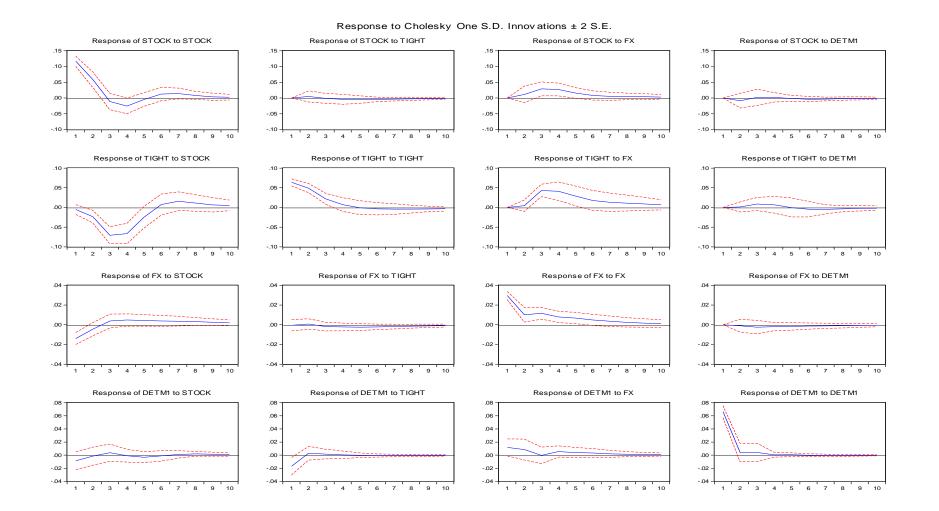
Excluded	Chi-sq	df	Prob.
TIGHT	0.24	2	0.89
<mark>FX</mark>	<mark>6.73</mark>	<mark>2</mark> 2	0.03
DETM1	0.92	2	0.63
All	9.61	6	0.14
endent variable: TIGHT			
Excluded	Chi-sq	df	Prob.
STOCK	40.50	2	0.00
FX	49.13	2	0.00
DETM1	1.13	2	0.57
All	106.38	6	0.00
endent variable: FX Excluded	Chi-sq	df	Prob.
Excluded	Chi-sq 8.56	-	Prob.
	Chi-sq 8.56 2.85	2	
Excluded STOCK	8.56	-	0.01
Excluded STOCK TIGHT	8.56 2.85	2 2	0.01 0.24
Excluded STOCK TIGHT DETM1 All	8.56 2.85 0.51	2 2 2	0.01 0.24 0.77
Excluded STOCK TIGHT DETM1 All	8.56 2.85 0.51	2 2 2	0.01 0.24 0.77
Excluded STOCK TIGHT DETM1 All endent variable: DETM1	8.56 2.85 0.51 10.58	2 2 2 6	0.01 0.24 0.77 0.10
Excluded STOCK TIGHT DETM1 All endent variable: DETM1 Excluded	8.56 2.85 0.51 10.58 Chi-sq	2 2 2 6 df	0.01 0.24 0.77 0.10 Prob.
STOCK TIGHT DETM1 All endent variable: DETM1 Excluded STOCK	8.56 2.85 0.51 10.58 Chi-sq 0.69	2 2 2 6 <u>df</u> 2	0.01 0.24 0.77 0.10 Prob. 0.71

#### Table 15:VAR Lag Exclusion Wald Tests for the pre-crisis sample

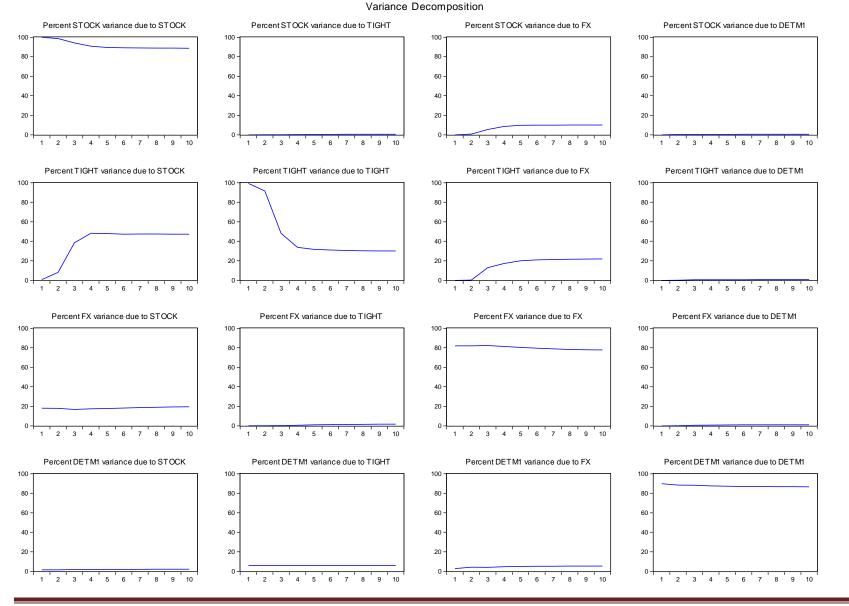
VAR Lag Exclusion Wald Tests					
Date: 07/31/12 Time: 15:24					
Sample: 1986M02 1994M12					
Included observations: 105					

Chi-squared test statistics for lag exclusion: Numbers in [] are p-values

	STOCK	TIGHT	FX	DETM1	Joint
Lag 1	32.59	115.33	9.57	2.19	178.68
	[ 0.00]	[ 0.00]	[ 0.048351]	[ 0.70]	[ 0.00]
Lag 2	16.19	101.36	8.22	1.02	143.50
	[ 0.00]	[ 0.00]	[ 0.08]	[ 0.90]	[ 0.00]
df	4	4	4	4	16



#### Box 3: Impulse Responses for the pre-crisis sample period



#### Box 4: Variance Decompositions for the pre-crisis sample period

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#### AFTER CRISIS VAR

#### VAR RESULTS FOR THE POST-CRISIS DATA SAMPLE

#### Table 16:

Vector Autoregression Estimates Date: 05/21/12 Time: 00:29 Sample: 1995M01 2003M12 Included observations: 108 Standard errors in ( ) & t-statistics in [ ]

	STOCK	TIGHT	FX	DETM1
STOCK(-1)	0.15	-0.14	-0.04	0.08
	(0.10)	(0.06)	(0.06)	(0.07)
	[ 1.53]	[-2.32]	[-0.66]	[ 1.08]
STOCK(-2)	0.03	0.16	-0.04	-0.09
	(0.10)	(0.06)	(0.06)	(0.07)
	[ 0.33]	[ 2.68]	[-0.67]	[-1.32]
TIGHT(-1)	0.39	0.73	-0.18	-0.10
	(0.16)	(0.10)	(0.10)	(0.12)
	[ 2.36]	[ 7.63]	[-1.84]	[-0.44]
TIGHT(-2)	-0.16	-0.13	0.089	-0.08
	(0.16)	(0.09)	(0.10)	(0.12)
	[-0.98]	[-1.40]	[ 0.89]	[-0.67]
FX(-1)	-0.33	-0.01	0.51	-0.19
	(0.16)	(0.09)	(0.10)	(0.11)
	[-2.13]	[-0.06]	[ 5.39]	[-1.67]
FX(-2)	0.10	0.38	-0.24	-0.16
	(0.16)	(0.09)	(0.10)	(0.12)
	[ 0.60]	[ 3.97]	[-2.49]	[-1.41]
DETM1(-1)	0.30	0.08	0.024	-0.12
	(0.15)	(0.09)	(0.09)	(0.10)
	[ 2.08]	[ 0.94]	[ 0.27]	[-1.11]
DETM1(-2)	-0.01	-0.08	0.05	-0.16
	(0.15)	(0.09)	(0.09)	(0.11)
	[-0.07]	[-0.91]	[ 0.52]	[-1.53]
С	0.01	-0.00	0.01	0.00
	(0.01)	(0.00)	(0.00)	(0.00)
<b>D</b>	[ 1.80]	[-0.92]	[ 1.85]	[ 0.75]
R-squared Adj. R-squared	0.20 0.14	0.55 0.51	0.33 0.28	0.11 0.04
Sum sq. resids	0.14	0.13	0.28	0.04
S.E. equation	0.06	0.13	0.04	0.20
F-statistic	3.14	15.00	6.14	1.52
Log likelihood	151.37	209.57	204.67	187.77
Akaike AIC	-2.64	-3.71	-3.62	-3.31
Schwarz SC	-2.41	-3.49	-3.40	-3.09
Mean dependent	0.01	0.00	0.01	-0.00
S.D. dependent	0.07	0.05	0.04	0.05
Determinant resid covariance (dof adj	.)	0.00		
Determinant resid covariance Log likelihood		0.00		
Akaike information criterion		761.82 -13.44		
Schwarz criterion		-12.55		

TABLE 17						
Variable	Stock	Tight	FX	DetM1		
Stock(-1)	0.15	-0.14**	-0.04	0.08		
Stock(-2)	0.03	0.16*	-0.04	-0.09		
Tight(-1)	0.39**	0.73*	-0.19***	-0.05		
Tight(-2)	-0.16	-0.13	0.09	-0.08		
FX(-1)	-0.33**	-0.01	0.51*	-0.19***		
FX(-2)	0.10	0.38*	-0.25**	-0.16		
DetM1(-1)	0.30	0.08	0.023	-0.12		
DetM1(-2)	-0.01	-0.08	0.05	-0.16		
С	0.01***	-0.00	0.01***	0.00		

Significance of *VAR* coefficients (Post-Crisis sample):

Significant coefficients are marked in red and asterisks.

\* Significant at 1% level.

\*\* Significant at 5% level.

\*\*\* Significant at 10% level.

#### **GRANGER CAUSALITY TEST AFTER THE CRSIS**

#### Table 18:

VAR Granger Causality/Block Exogeneity Wald Tests Date: 05/21/12 Time: 01:47 Sample: 1995M01 2003M12 Included observations: 108

Dependent variable: STOCK

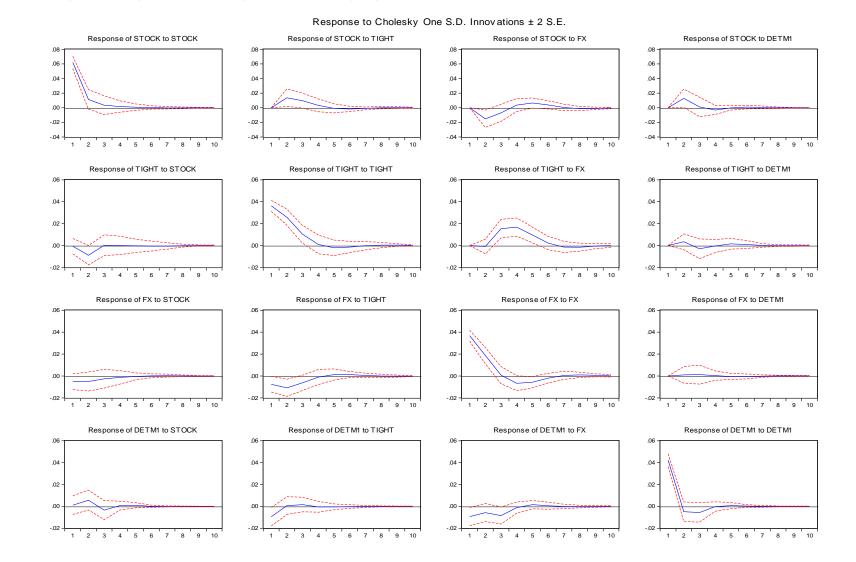
Dependent variable. 51	201		
Excluded	Chi-sq	df	Prob.
TIGHT FX	<b>5.85</b>	<mark>2</mark> 2 2	<mark>0.05</mark> 0.10
DETM1	4.59 4.38	2	0.10
All	18.86	6	0.00
Dependent variable: TIG	внт		
Excluded	Chi-sq	df	Prob.
STOCK	11.24	2	0.00
FX	18.09	2	0.00
DETM1	1.90	2	0.39
All	36.63	6	0.00
Dependent variable: FX			
Excluded	Chi-sq	df	Prob.
STOCK	1.00	2	0.61
TIGHT	3.45	2	0.18
DETM1	0.32	2	0.85
All	4.78	6	0.57
Dependent variable: DE	TM1		
Excluded	Chi-sq	df	Prob.
STOCK	2.60	2	0.27
TIGHT	1.55	2	0.46
FX	7.55	2	0.02
All	11.08	6	0.09

#### Table 19: VAR Lag Exclusion Wald Tests for the post-crisis sample

VAR Lag Exclusion Wald Tests Date: 05/21/12 Time: 01:55 Sample: 1995M01 2003M12 Included observations: 108

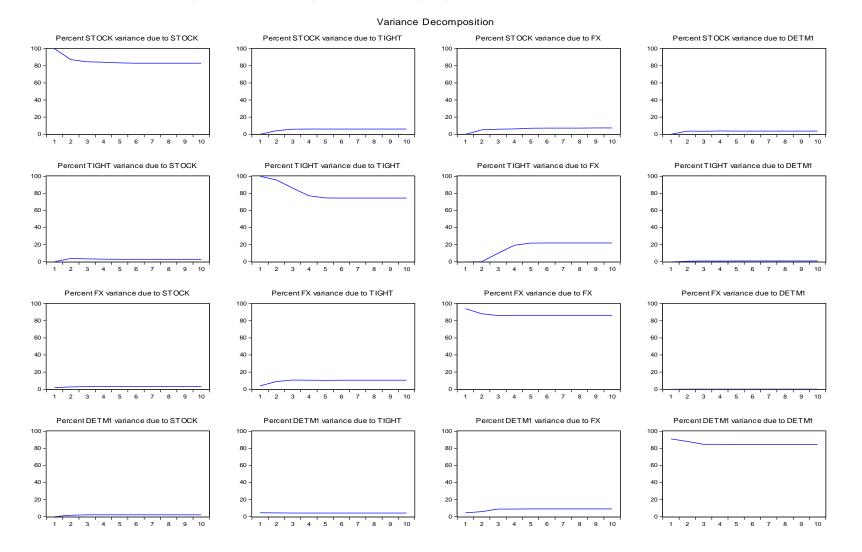
Chi-squared test statistics for lag exclusion: Numbers in [] are p-values

	STOCK	TIGHT	FX	DETM1	Joint
Lag 1	21.21	68.94	44.50	5.51	128.23
	[ 0.00]	[ 0.00]	[0.00]	[ 0.24]	[ 0.00]
Lag 2	1.71	26.34	9.33	5.02	36.58
	[ 0.79]	[ 0.00]	[ 0.05]	[ 0.29]	[ 0.00]
df	4	4	4	4	16



#### Box 5: Impulse Responses for the post-crisis sample period

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#### Box 6: Variance Decompositions for the post-crisis sample period

# ANNEXURE – V (Results of *OLS*, *Chow* test and other tests):

#### Table 20:

Estimation output of the multiple linear regression using OLS

Dependent Variable: STOCK Method: Least Squares Date: 05/21/12 Time: 21:39 Sample: 1986M02 2003M12 Included observations: 215

Variable	Coefficient	Std. Error	t-Statistic	Prob.
С	0.04	0.01	4.31	0.00
TIGHT	0.17	0.01	2.49	0.01
FX	-0.50	0.17	-2.86	0.00
M1	0.06	0.12	0.48	0.63
R-squared	0.06	Mean dependent var		0.03
Adjusted R-squared	0.05	S.D. dependent	0.11	
S.E. of regression	0.11	Akaike info criterion		-1.64
Sum squared resid	2.36	Schwarz criteric	on	-1.57
Log likelihood	179.86	Hannan-Quinn	criter.	-1.61
F-statistic	4.86	Durbin-Watson	stat	1.14
Prob(F-statistic)	0.00			

Table 21:

#### White test for heteroscedasticity

Heteroskedasticity Test: White			
F-statistic	54.79	Prob. F(9,205)	0.00
Obs*R-squared	151.87	Prob. Chi-Square(9)	0.00
Scaled explained SS	767.13	Prob. Chi-Square(9)	0.00

Test Equation:

Dependent Variable: RESID^2 Method: Least Squares Date: 05/22/12 Time: 15:48 Sample: 1986M02 2003M12 Included observations: 215

Variable	Coefficient	Std. Error	t-Statistic	Prob.
С	0.01	0.00	3.58	0.00
TIGHT	-0.01	0.02	-0.39	0.70
TIGHT^2	-0.01	0.03	-0.30	0.76
TIGHT*FX	2.34	0.55	4.28	0.00
TIGHT*M1	-0.54	0.27	-2.00	0.05
FX	-0.18	0.06	-2.82	0.01
FX^2	3.35	0.35	9.55	0.00
FX*M1	5.30	0.48	11.01	0.00
M1	-0.08	0.04	-2.20	0.03
M1^2	0.11	0.17	0.66	0.51
R-squared	0.71	Mean dependent var		0.01
Adjusted R-squared	0.69	S.D. dependent var		0.04
S.E. of regression	0.02	Akaike info criterion		-4.97
Sum squared resid	0.08	Schwarz criterion		-4.81
Log likelihood	543.86	Hannan-Quinn criter.		-4.90
F-statistic	54.79	Durbin-Watson stat		1.76
Prob(F-statistic)	0.00			

#### Table 22: Test for multicollinearity

Covariance Analysis: Ordinary Date: 05/22/12 Time: 16:01

Sample: 1986M02 2003M12 Included observations: 215						
Correlation t-Statistic						
Probability	TIGHT	M1	FX			
TIGHT	1.00					
M1	-0.07	1.00				
	-0.97					
	0.33					
FX	-0.02 -0.27	0.08 1.13	1.00			
	0.79	0.26				

## Table 23:Estimation output of the multiple linear regression using OLS after accounting<br/>for serial correlation and heteroscedasticity among residuals

Dependent Variable: STOCK Method: Least Squares Date: 05/22/12 Time: 16:07 Sample: 1986M02 2003M12 Included observations: 215 White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
С	0.036	0.01	4.33	0.00
TIGHT	<mark>0.17</mark>	0.09	1.96	<mark>0.05</mark>
FX	-0.50	0.41	-1.21	0.23
M1	0.06	0.17	0.35	0.73
R-squared	0.06	Mean depender	0.03	
Adjusted R-squared	0.05	S.D. dependent var		0.11
S.E. of regression	0.11	Akaike info criterion		-1.64
Sum squared resid	2.36	Schwarz criterion		-1.57
Log likelihood	179.86	Hannan-Quinn criter.		-1.61
F-statistic	4.86	Durbin-Watson stat		1.14
Prob(F-statistic)	0.00			

# Table 24: *Ramsey RESET* test to check for the correctness of the functional form of the regression

Ramsey RESET Test
Equation: UNTITLED
Specification: STOCK C TIGHT FX M1
Omitted Variables: Squares of fitted values
ennited Vanabiee. Equalee of hited Valuee

	Value	df	Probability
t-statistic	1.17	210	0.24
F-statistic	1.37	(1, 210)	0.24
Likelihood ratio	1.40	1	0.24
F-test summary:			
			Mean
	Sum of Sq.	df	Squares
Test SSR	0.02	1	0.02
Restricted SSR	2.36	211	0.01
Unrestricted SSR	2.35	210	0.01
Unrestricted SSR	2.35	210	0.01
LR test summary:			
	Value	df	
Restricted LogL	179.86	211	-
Unrestricted LogL	180.56	210	

Unrestricted Test Equation: Dependent Variable: STOCK Method: Least Squares Date: 05/22/12 Time: 17:04 Sample: 1986M02 2003M12 Included observations: 215 White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
С	0.03	0.00	3.46	0.00
TIGHT	0.09	0.14	0.62	0.54
FX	-0.53	0.42	-1.24	0.21
M1	0.07	0.16	0.46	0.64
FITTED^2	3.70	3.73	0.99	0.32
R-squared	0.07	Mean depende	ent var	0.03
Adjusted R-squared	0.05	S.D. dependent var		0.11
S.E. of regression	0.11	Akaike info criterion		-1.63
Sum squared resid	2.35	Schwarz criterion		-1.55
Log likelihood	180.56	Hannan-Quinn criter.		-1.60
F-statistic	3.99	Durbin-Watsor	n stat	1.10
Prob(F-statistic)	0.00			

#### Table 25: Chow test to check for structural break-point

Chow Breakpoint Test: 1994M12 Null Hypothesis: No breaks at specified breakpoints Varying Regressors: All equation variables Equation Sample: 1986M02 2003M12

F-statistic	2.72	Prob. F(4,207)	0.03
Log likelihood ratio	11.02	Prob. Chi-Square(4)	0.03
Wald Statistic	14.35	Prob. Chi-Square(4)	0.01
Wald Statistic	14.35	Prob. Chi-Square(4)	0.01

#### Table 26: OLS regression on pre-crisis sub-sample

Dependent Variable: STOCK Method: Least Squares Date: 05/22/12 Time: 17:16 Sample: 1986M02 1994M12 Included observations: 107 White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
С	0.06	0.02	3.84	0.00
TIGHT	<mark>0.20</mark>	0.07	2.99	<mark>0.00</mark>
FX	-0.79	0.89	-0.89	0.38
M1	0.00	0.15	0.02	0.98
R-squared	0.08	Mean dependent var		0.05
Adjusted R-squared	0.06	•		0.14
S.E. of regression	0.13	Akaike info criterion		-1.17
Sum squared resid	1.81	Schwarz criterion		-1.07
Log likelihood	66.42	66.42 Hannan-Quinn criter.		-1.13
F-statistic	3.06	Durbin-Watson	stat	0.99
Prob(F-statistic)	0.03			

#### Table 27: OLS regression on post-crisis sub-sample

Dependent Variable: STOCK Method: Least Squares Date: 05/22/12 Time: 17:39 Sample: 1995M01 2003M12 Included observations: 108 White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C TIGHT <mark>FX</mark> M1	0.01 0.03 <mark>-0.44</mark> 0.05	0.01 0.16 0.21 0.17	2.11 0.16 -2.07 0.28	0.04 0.87 <mark>0.04</mark> 0.78
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood F-statistic Prob(F-statistic)	0.10 0.07 0.06 0.43 144.55 3.64 0.02	Mean dependent var S.D. dependent var Akaike info criterion Schwarz criterion Hannan-Quinn criter. Durbin-Watson stat		0.01 0.07 -2.60 -2.50 -2.56 1.75

### ANNEXURE – VI (DID regression)

Table 28: Estimation output of the DID regression

Dependent Variable: STOCK Method: Panel EGLS (Period weights) Date: 05/23/12 Time: 00:05 Sample: 1988M08 2006M07 Periods included: 216 Cross-sections included: 10 Total panel (unbalanced) observations: 2155 Linear estimation after one-step weighting matrix White cross-section standard errors & covariance (d.f. corrected)

Variable	Coefficient	Coefficient Std. Error		Prob.
C	<mark>0.0</mark> 1	0.00	2.25	<mark>0.02</mark>
D1S	0.00	0.00	0.64	0.52
D2T	-0.00	0.00	-0.57	0.57
D1S*D2T	0.00	0.00	0.16	0.87
TIGHT	-0.07	0.22	-0.33	0.74
FX	0.25	0.22	1.14	0.25
M1	<mark>0.29</mark>	0.07	3.85	<mark>0.00</mark>
TIGHT*D1S*D2T	<mark>-0.99</mark>	0.39	-2.57	<mark>0.01</mark>
FX*D1S*D2T	<mark>-1.22</mark>	0.36	-3.42	<mark>0.00</mark>
M1*D1S*D2T	-0.09	0.16	-0.54	0.59
TIGHT*D1S	0.22	0.21	1.01	0.31
FX*D1S	0.35	0.29	1.22	0.22
M1*D1S	-0.07	0.08	-0.81	0.42
TIGHT*D2T	<mark>0.75</mark>	0.38	1.95	<mark>0.05</mark>
FX*D2T	0.23	0.29	0.80	0.43
M1*D2T	-0.034	0.142	-0.25	0.80
	Weighted	Statistics		
R-squared	0.06	Mean dependent	var	0.01
Adjusted R-squared	0.05	S.D. dependent v		0.08
S.E. of regression	0.08	Sum squared res	id	14.28
F-statistic	9.26	Durbin-Watson st	at	1.80
Prob(F-statistic)	0.00			
	Unweighted	d Statistics		
R-squared	0.02	Mean dependent	var	0.01
Sum squared resid	14.76	Durbin-Watson st		1.73

### ANNEXURE – VII (Findings)

Whole sample						
Approach Monetary Tightness Exchange Rate Monetary Aggregate						
VAR R^2(24.42%)	+ -Significant**	+Significant**	Insignificant			
OLS R^2(6.46%)	+Significant **	Insignificant	Insignificant			
** 10% significance level Chow Tests Null Hypotheses: Rejected at 5% significance level						

#### Table 29: Summary of findings (Whole sample)

#### Table 30: Summary of findings (Two subsamples)

Two Subsamples (Before-After Crisis)							
Approach	Approach Monetary Tightness			Exchange Rate		Monetary Aggregate	
	Before	After Before After		Before	After		
VAR	Insignificant	+Significant*	Insignificant	-Significant*	Insignificant	Insignificant	
OLS +Significant* Insignificant Insignificant -Significant* Insignificant Insignificant							
*5% significant	*5% significance level						

#### Table 31: Summary of findings (DID)

Difference in Difference Approach					
Approach	Monetary Tightness	Exchange Rate	Monetary Aggregate		
-	Insignificant	Insignificant	Insignificant		
-	Insignificant	Insignificant	Insignificant		
-	Insignificant	Insignificant	+Significant*		
D1S	Insignificant	Insignificant	Insignificant		
D2T	+Significant*	Insignificant	Insignificant		
D1S * D2T	-Significant*	-Significant*	Insignificant		
*5% significance level					