Reduced Macroeconomic Volatility after Adoption of Inflation Targeting: Impulses or Propagation?*

Christopher John Cruz†

February 1, 2021

Abstract

This paper asks whether the notable decline in macroeconomic volatility after countries adopted inflation targeting can be attributed to a more stable structure (the propagation mechanism) or less volatile shocks (the impulses). Using quarterly data from a sample of advanced and emerging market economies, results show that the observed reduction in inflation variability may be attributed largely to a more stable structure while the decreased output volatility is driven solely by much calmer shocks. The result is robust to various specifications examined.

JEL Classification: E52, E58, E61, E63
Keywords: inflation targeting, inflation volatility, output volatility, macroeconomic stability

---

*I thank George Karras, Houston Stokes, Jin Man Lee, Paul Pieper, Ben Ost, Darren Lubotsky, Erik Hembre, Steve Rivkin, and Robert Kaestner for helpful comments and discussions. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

†Correspondence: Department of Economics, Seidman College of Business, Grand Valley State University, 50 Front Ave SW, Grand Rapids, MI 49504 USA; cruzch@gvsu.edu; (616)331-7122

1 Introduction

A very important development following the adoption of inflation targeting (IT) by a number of countries starting in the 1990s was the dramatic decline in the variability of both inflation and output. Advocates of inflation targeting argue that the desirability of the framework lies in its ability to maintain price stability and to support economic growth and stability. However, the question of why and how the monetary policy framework results in the volatility decline not only of inflation but also of output remains unsettled. The objective of this paper is to distinguish whether the decline in the volatility of inflation and output following the countries' switch to inflation targeting can be attributed to a supposedly more stable structure (the propagation mechanism) or shocks that originate in a less volatile environment.

The role of inflation targeting in promoting price stability and supporting economic growth has been the subject of intense study. In the literature, there is no conclusive evidence that inflation targeting is responsible for the decline in the variability of inflation among IT adopters. While some research work find that IT has inflation-stabilizing effects (Batini and Laxton (2007), Vega and Winkelried (2005), Lin and Ye (2009), King (2001) and Neumann and von Hagen (2002)), others find no significant evidence to conclude that IT led to a stabilization of inflation (Johnson (2002), Levin, Natalucci, and Piger (2004), Lin and Ye (2007), Brito and Bystedt (2010)). Similarly, the empirical evidence on the impact of IT on output volatility remains inconclusive. While some research work find that IT contributed to the the decline in output volatility (Goncalves and Salles (2008), Corbo, Landerretche, and Schmidt-Hebbel (2002), and (Pétursson, 2004)), others find no significant evidence to conclude the same (Brito and Bystedt (2010), Ball and Sheridan (2004)). Others take the view that the adoption of the IT framework simply coincided with increased stability in the global environment. In particular, global inflation showed a dramatic decline in both its level and variability in the 1990s when IT had been increasingly adopted by advanced economies initially, then followed by emerging market economies.[1]

While the effects of inflation targeting on macroeconomic stability will continue to be studied, this paper examines the variability of inflation and output from a different perspective.

[1] In fact, Ball and Sheridan (2004) note that in their research on 7 IT and 13 non-IT OECD countries, the observed increase in the stability of inflation and output growth among those switched to IT was also experienced by non-adopters around the same time.

In particular, utilizing the "counterfactual" Vector Autoregressive (VAR) method developed by James (1993), extended by Simon (2001), and employed by Stock and Watson (2002), Karras, Lee, and Stokes (2005), and Karras, Lee, and Stokes (2006), this paper tries to ascertain whether the observed moderation in macroeconomic volatility after countries switched to inflation targeting can be attributed to a more stable structure or less violent shocks. Using quarterly data for five advanced economics (New Zealand, Canada, United Kingdom, Sweden, Australia) and five emerging market economies (Thailand, Mexico, South Korea, the Philippines, Indonesia), the paper finds that the observed decline in the variability of inflation after the adoption of IT can be attributed largely to a more stable structure (the propagation mechanism) and partly to milder shocks (the impulses). The evidence shows that if the structure in the post-IT adoption period were combined with the shocks from the pre-IT period, the inflation environment during the pre-IT period would have been more tranquil. At the same time, results suggest that if shocks from the post-IT adoption period were combined with the pre-IT structure, inflation volatility in the pre-IT period would also have been lower. Meanwhile, focusing on output volatility, evidence shows that the reduced variability of output after countries switch to IT can be attributed mainly to calmer shocks, and not at all to the change in structure. In fact, combining the structure of the post-IT adoption period with the shocks from the pre-IT period would have made output in the pre-IT period more volatile.

The remainder of the paper is organized as follows. Section 2 discusses the econometric methodology and the data used in the estimation. Section 3 presents the empirical results, including a number of robustness checks. Section 4 presents some policy implications and concludes.

2 Methodology and Data Description

The counterfactual VAR method starts by estimating reduced-form VARs for each of the countries in the sample for the two-periods of interest: the pre-IT adoption period and the post-IT adoption period. New Zealand was the first to adopt the IT framework in January 1990, followed initially by advanced economies, and then by the emerging market economies. In my sample, Indonesia was the latest country to adopt IT in July 2005. As shown in Table (1), there was a dramatic decline in the variability of inflation and output growth after the IT framework was adopted in my sample countries.

Following Karras et al. (2005), Karras et al. (2006), and Stokes (2013), I outline the basic idea behind the counterfactual VAR method. Suppose we have VARs as

$$\mathbf{x}_t = \mathbf{A}_i(L)\mathbf{x}_{t-1} + \mathbf{u}_t, \tag{1}$$

where $\mathbf{x}$ represents the vector of k variables in the VAR model ($k \geq 1$), t indexes time periods (i.e., $t = 1$ for the pre-IT adoption and $t = 2$ for the post-IT adoption period), the $\mathbf{A}'s$ represent the matrices of polynomials in the lag operator L, and $\mathbf{u}$ is the error term with variance $\mathbf{\Sigma}_i$ in period i. Let $\mathbf{B}_i(L) = [\mathbf{I} - \mathbf{A}_i(L)L]^{-1}$ be the moving average representation of the model and define B_{ij} as j^{th} lag of $\mathbf{B}_i$. The variance of the k^{th} series of $\mathbf{x}$ in the i^{th} period can be written as

$$\mathrm{Var}(x_{kt}) = \left(\sum_{j=0}^{\infty} \mathbf{B}_{ij} \mathbf{\Sigma}_i \mathbf{B}'_{ij} \right)_{kk} = \sigma_k(\mathbf{A}_i, \mathbf{\Sigma}_i)^2. \tag{2}$$

This variance can be evaluated for various $\mathbf{A}_s$ and $\mathbf{\Sigma}s$, as Stock and Watson (2002) note. Define $\sigma_{kij} = \sigma_k(\mathbf{A}_i, \mathbf{\Sigma}_j)$ as the resulting variance if we combine the coefficients (structure) in period i ($\mathbf{A}_i$) and the variance (innovations) from period j ($\mathbf{\Sigma}_j$) for the k^{th} series. For illustration purposes, suppose the inflation rate is the first variable in the VAR ($k = 1$) model. The "factual" variance of inflation in the pre-IT and post-IT adoption periods can be written as $\sigma_{11} = \sigma_1(\mathbf{A}_1, \mathbf{\Sigma}_1)$ and $\sigma_{22} = \sigma_2(\mathbf{A}_2, \mathbf{\Sigma}_2)$. The counterfactual variance $\sigma_{12} = \sigma_1(\mathbf{A}_1, \mathbf{\Sigma}_2)$ represents the variance that would have been observed if the structure of the pre-IT period had been imposed with the shocks after the introduction of IT. Meanwhile, $\sigma_{21} = \sigma_2(\mathbf{A}_2, \mathbf{\Sigma}_1)$ represents the counterfactual variance when the pre-IT period shocks are imposed using the structure of the post-IT period.

The main idea of the counterfactual VAR test is to compare the factual and counterfactual variances and assess whether the difference in estimated variances can be attributed to a change with the structure or change with the shocks or both. Thus, the statistic of interest can be defined as $T_{i,j}\_T_{k,l} = |\sigma_{i,j} - \sigma_{k,l}|$. The statistics $T_{i,i}\_T_{j,i}$ tests the existence of a counterfactual structural change, i.e.,, whether the change in the structure that took place after IT was adopted had a statistically significant effect on the volatility of inflation or output. Meanwhile, $T_{i,j}\_T_{i,i}$ tests for a counterfactual shock change, i.e., whether the change in the shocks that occurred after the IT adoption had a statistically significant impact on inflation or output variability.

The next step is to formally test whether differences in estimated variances are significantly different from zero. However, the problem is that the distribution of these statistics are not known. Critical values can only be obtained using bootstrapping and Monte Carlo methods. Karras et al. (2005) propose a parametric method of bootstrapping, building on the work of Stine (1987), Runkle (1987), and Inoue and Kilian (2002). Their proposed methodology implements bootstrapping that is able to preserve the heteroskedasticity or serial correlation properties of the data, if these exist, in the process of resampling the data. Consequently, the resulting estimators become consistent unlike those from the traditional bootstrapping algorithm of time-dependent data which as Efron (1979) notes, assume that errors are independent and identically distributed.

I follow the bootstrapping algorithm proposed in Karras et al. (2005) and Karras et al. (2006) to generate consistent estimators. The algorithm has the following steps. First, I use Least Squares (LS) to estimate an AR or a VAR process of order p,

$$x_t = \beta_0 + \beta_1 x_{t-1} + ... + \beta_p x_{t-p} + \varepsilon_{p,t}, \tag{3}$$

which yields LS estimates $\hat{\beta}(p) = (\hat{\beta}_0, \hat{\beta}_1, ..., \hat{\beta}_p)$. I use the Schwarz Bayesian Information Criterion (SBIC) in selecting the appropriate order of p that removes the autocorrelation and cross-correlation of the residuals.[2] Second, including k initial observations, I generate by random sampling with replacement from the regression residuals $T+k+p$ bootstrap innovations ε_t^*, where $T = p+1, ..., t$. Third, I use the vector of initial observations $x_0^* = (x_1^*, ..., x_p^*)$ as starting values to preserve the scale of x_t, then I generate a sequence of pseudo-data of length $T+k+p$ from the recursion $x_t^* = \hat{\beta}_0 + \hat{\beta}_1^* x_{t-1} + ... + \hat{\beta}_p^* x_{t-p} + \varepsilon_{tt}^*$. Fourth, I remove k initial observations then I compute the factual and counterfactual variances of x_t^*. In order to build the empirical distribution of the test statistics, I repeat steps two, three, and four for the desired number of iterations. The results shown in this paper are all based on 1000 iterations, consistent with

[2]For quarterly VAR models, Ventzislav and Lutz (2005) recommends the use of SBIC especially for small sample sizes (i.e., less than 120) and Hannan-Quinn Criterion (HQC) for larger sample sizes. Hacker and Hatemi-J (2008) also show that SBIC is the optimal criterion for choosing lag length in many situations due to better lag-choice accuracy, least sensitivity to ARCH regardless of stability or instability of the VAR model, and best forecasting abilities.

those reported in Karras et al. (2005) and Karras et al. (2006).

The Monte Carlo algorithm to compute for critical values follows similar steps, except for the second step where the residual is replaced by $T + k + p$ independent and identically distributed random innovations μ_{t+k+p}. These are adjusted to the same variances of the estimated residuals from step one. Karras et al. (2005) and Karras et al. (2006) note that the Monte Carlo method has the advantage of having the disturbance free of heteroskedasticity and serial correlation.

To analyze macroeconomic stability, I focus on the volatility of inflation rate and real GDP growth. I use quarterly observations up to Q4 2017 mainly from the databases of the International Monetary Fund (2018) and the OECD (2018).[3] With respect to the sample countries, it may be noted that the number of countries that can be analyzed using the empirical approach in this paper is constrained by the length of time-series data for the post-IT adoption period, especially for those which have switched to IT fairly recently.[4] The countries chosen in the sample were some of the first countries to formally introduce the IT framework. I rely on IMF research, particularly on Roger (2009) in the identification of the effective adoption date of the IT framework (Table 1). In his research, Roger (2009) conducts a comprehensive examination of each country and uses the following criteria in determining the effective IT adoption date: (1) formal announcement of IT regime; (2) adoption of explicit forward-looking target; (3) publication of an Inflation Report; and (4) evidence of subordination of exchange rate objective to inflation objective.

3 Empirical Evidence

As starting point, I estimate a simple univariate model for inflation and for output growth for each country in the sample. I then expand the estimated system to a multivariate VAR model comprised of domestic interest rates, GDP growth and inflation. In addition, global inflation (proxied by US inflation) is included in the model to account for the impact of the global disinflation trend that happened when countries started to switch to IT. Thus, the baseline multivariate

[3]The key data used in this study were derived from the following resources available in the public domain: data.imf.org for the IMF data and stats.oecd.org for the OECD data. These were last accessed on August 1, 2018.

[4]As of 2015, about 47 countries have formally shifted to IT, 15 of which are advanced economies and the majority are emerging market economies(Schmidt-Hebbel & Carrasco, 2016).

VAR model is an augmented version of a simple domestic monetary policy transmission model. As stressed by Karras et al. (2005), the multivariate model is critical because relying on the univariate model would minimize the importance of structural stability and/or assign an excessively large role to the impulses owing to the omission of key variables. The Cholesky ordering used in the multivariate model is global inflation, domestic interest rates, GDP growth and inflation, with the appropriate lag length determined using the Schwarz Bayesian Information criterion.

In this section, I begin by analyzing in detail the results for inflation, specifically for New Zealand, the front runner in IT adoption. Then, I compare my findings to the rest of the countries in the sample. The idea is that the lengthy analysis for New Zealand's inflation results also serves as a guide in reading the results for the other countries.

3.1 Variability of Inflation

New Zealand

Results for New Zealand in Table (2) highlight the significant decline in the variability and mean of inflation after IT was introduced in 1989. The actual variance of inflation after the shift to IT is about nine times lower than that prior to the adoption. Focusing on the estimated variances, the univariate model appears to have estimated the dynamics quite well as the factual variances ($\sigma_{11} = 19.67$ and $\sigma_{22} = 1.29$) are close to the actual variances ($\sigma_1^2 = 19.29$ and $\sigma_2^2 = 2.07$) in the periods before and after the IT adoption. The factual variances estimated by the multivariate model ($\sigma_{11} = 15.75$ and $\sigma_{22} = 1.24$) are likewise close to the actual variances, though noticeably smaller in magnitude than the estimates from the univariate model. The estimated variances from both models capture the significant reduction in the variability of inflation after IT was adopted in New Zealand.

In assessing whether the counterfactual variances are significantly different from the factual variances, the analysis focuses on the results of the multivariate model to avoid putting too much weight on the role of shocks. Panel B of Table (2) indicates that the counterfactual estimate $\sigma_{12} = 3.24$, the variance of inflation that would have occurred if the structure of the pre-IT period had coincided with the post-IT shocks, is closer in magnitude with the actual and factual variances post-IT (σ_2^2 and σ_{22}, respectively). Meanwhile, the counterfactual variance that would have been observed when the post-IT structure is combined with pre-IT shocks,

$\sigma_{21} = 8.10$, seems closer in magnitude to the actual and factual variances prior to IT adoption (σ_1^1 and σ_{11}, respectively). This seems to suggest that in the case of New Zealand, the lower variability of inflation after IT was institutionalized can be attributed to calmer shocks, rather than to a more stable structure. In the language of time-series analysis, the moderation in the volatility of inflation can be attributed mainly to impulses, and not to the propagation mechanism.

However, a mere comparison of the factual and counterfactual variances is not sufficient to allow us to conclude whether the propagation mechanism or the impulses is responsible for the decline in inflation volatility. Whether or not the differences between pairs of variances are statistically significant can be determined if these are greater than the computed critical values using bootstrapping and Monte Carlo techniques as reported in Panel B of Table (2). Keep in mind that $|\sigma_{ii} - \sigma_{ji}|$ yields the difference in the counterfactual variances while holding the shocks constant, while $|\sigma_{ii} - \sigma_{ij}|$ holds the structure constant. This implies that if we want to find out whether there is a meaningful structural change, we should look at $|\sigma_{11} - \sigma_{21}|$ or $|\sigma_{12} - \sigma_{22}|$ and check if they are statistically significant. But if we would like to see whether there is a sizable change in the innovation variance, then the focus should be on $|\sigma_{11} - \sigma_{12}|$ or $|\sigma_{21} - \sigma_{22}|$.

It is also crucial to compare the magnitude of the factual and counterfactual variances when making the comparison of the variances. Table (3) summarizes what the different pairwise comparisons imply with respect to the change in structure or shocks in the post-IT period. As indicated in Table (3), if $|\sigma_{11} - \sigma_{21}|$ is statistically significant and the counterfactual variance σ_{21} is lower than the factual variance σ_{11}, then this is evidence suggesting that the more stable structure in the post-IT period helps reduce the variability of inflation. The same can be concluded if $|\sigma_{12} - \sigma_{22}|$ is significant and the counterfactual variance σ_{12} is higher than the factual variance σ_{22}. The other two cases lead us to the opposite conclusion. Meanwhile, if $|\sigma_{11} - \sigma_{21}|$ is statistically significant, but the counterfactual variance σ_{21} is higher than the factual variance σ_{11}, then the evidence points to a less stable structure after IT was adopted. The same can be said if $|\sigma_{12} - \sigma_{22}|$ is significant but the counterfactual variance σ_{12} is lower than the factual variance σ_{11}. The latter two cases do not explain the decline in the variability of inflation. In this case, we look at the role of impulses. It is likely that shocks are generally calmer after IT was adopted relative to those in the pre-IT period. This can be concluded if $|\sigma_{11} - \sigma_{12}|$ is statistically significant and the counterfactual variance σ_{12} is lower than the factual variance σ_{11}; or if $|\sigma_{21} - \sigma_{22}|$ is statistically significant and the counterfactual variance σ_{21} is higher than the factual variance σ_{11}.

In this section, I generally highlight the Monte Carlo critical values at the 5 percent significance level in determining the statistical significance of the differences in variances. Results in Panel B of Table (2) show that both $|\sigma_{11} - \sigma_{21}| = 7.65$ and $|\sigma_{12} - \sigma_{22}| = 2.00$ are not statistically significant as these are too small to exceed the Monte Carlo critical values of 14.78 and 16.03, respectively. However, directionally, the evidence points to a more stable structure in the post-IT period. The counterfactual variance $\sigma_{21} = 8.10$ is smaller than the factual variance $\sigma_{11} = 15.75$, while $\sigma_{12} = 3.24$ is slightly bigger than $\sigma_{22} = 1.24$. That is, in the pre-IT period, modifying the structure of the model while maintaining the shocks reduces the variance of inflation, while in the post-IT period, the same increases inflation variability. Meanwhile, $|\sigma_{11} - \sigma_{12}| = 12.51$ is large and decisively significant (greater than the Monte Carlo critical value of 6.87). In addition, $\sigma_{11} = 15.75$ is much larger than the counterfactual variance $\sigma_{12} = 3.24$. This implies that combining the pre-IT structure with post-IT shocks raises significantly the pre-IT variance of inflation. Furthermore, the difference $|\sigma_{21} - \sigma_{22}| = 6.86$ is bordering significant (Monte Carlo critical value=7.36), with the counterfactual variance $\sigma_{21} = 8.10$ turning out to be substantially higher than the factual variance $\sigma_{22} = 1.24$. This suggests that in the post-IT period, changing the shocks while keeping the post-IT structure increases the volatility substantially. All these results seem to suggest that the main reason behind the reduction in volatility after IT was adopted in New Zealand are calmer shocks (the impulses) and not a more stable structure (the propagation mechanism.)

Nine other IT countries

Table (4) summarizes the results of the multivariate model for the different countries in the sample.[5] Analysis of the results for the other countries reveals that UK exhibits the same result as New Zealand. The estimated factual variances are not only quite close to the actual variances pre- and post-IT, but also capture the substantial moderation in the volatility of inflation. After IT was adopted in the UK, shocks became less violent and the differences $|\sigma_{11} - \sigma_{12}|$ and $|\sigma_{21} - \sigma_{22}|$ are statistically significant, thus helping explain the considerable decline in the inflation variability. However, the statistics $(|\sigma_{11} - \sigma_{12}|, |\sigma_{12} - \sigma_{22}|)$, which show whether the change in structure helped reduced the variance of inflation, are not statistically significant. Nonetheless, direction-wise, the results point to a more stable structure after the adoption of IT.

Canada, the second country to directly target inflation, exhibits a totally different story. Analysis of the differences in the factual and counterfactual variances indicates that the sizable decline in inflation variability can be explained solely by a more stable structure. The counterfactual variance $\sigma_{21} = 0.99$ is smaller than the factual variance $\sigma_{11} = 4.93$ and the difference is statistically significant. In addition, the counterfactual variance $\sigma_{12} = 5.53$ is statistically significantly much larger than the factual variance $\sigma_{22} = 0.79$. That is, combining the post-IT structure with the pre-IT shocks would substantially lessen inflation variability in the pre-IT period, while accompanying the post-IT shocks with the pre-IT structure would increase the volatility in the post-IT period. Meanwhile, the statistics which test the impact of a counterfactual shock are both not statistically significant. That is, combining the pre-IT structure with the post-IT shocks or post-IT structure with the pre-IT shocks would not significantly change the variance of inflation.

Meanwnile, the results for the other advanced economies (Australia and Sweden) as well as all the emerging market economies (Indonesia, Korea, Mexico, Philippines and Thailand) suggest that the substantial reduction in inflation variability after the IT framework was adopted in these countries can be explained by a combination of a more stable structure and milder shocks. The differences in the pairs of variances are statistically significant, with the estimated variances declining when the post-IT structure is maintained while changing the shocks, or when the post-IT shocks are kept but the structure is altered. The models also yield factual

[5] See the online Appendix for the individual country results.

variances that are close in magnitude to the actual variances in the periods before and after IT was adopted.

3.2 Variability of Output Growth

Is the decline in output volatility following the shift to inflation targeting due to more stable structure or less violent shocks? Results from the counterfactual VAR analysis (Table 5) show that in most of the countries in the sample, the reduction in the variability of output can be traced solely to much calmer shocks, offsetting what appears to be a less stable structure in the post-IT period.

In most advanced economies (Canada, New Zealand, Sweden, and the United Kingdom) and emerging market economies (Korea, Mexico, Philippines), the statistics indicating a change in the shocks ($|\sigma_{11} - \sigma_{12}|$ and $|\sigma_{21} - \sigma_{22}|$) are statistically significant, pointing to much calmer shocks in the post-IT period. The results indicate that in the pre-IT period, holding the structure fixed but applying the post-IT shocks would have reduced the variability of output growth considerably. At the same time, in the post-IT period, combining the pre-IT shocks with the post-IT structure would have made output growth significantly more volatile. Meanwhile, the evidence for these countries suggest that the structure in the post-IT adoption period was significantly less stable compared to the pre-IT period. Looking at $|\sigma_{11} - \sigma_{21}|$, the estimates suggest that if the structure in the post-IT adoption period coincided with the pre-IT shocks, output volatility in the pre-IT period would have been significantly higher.

Meanwhile, results for Indonesia and Thailand seem to suggest the observed decline in output variability in these countries can be traced to a combination of more stable structure and calmer shocks. In both countries, the counterfactual variance σ_{21} (σ_{12}) is statistically significantly smaller (larger) than the factual variance σ_{11} (σ_{22}). That is, holding the shocks fixed, applying the post-IT structure reduces the volatility in the pre-IT period, while combining the pre-IT structure with post-IT shocks raises the variability in the post-IT period significantly. Calmer shocks in the post-IT period also helped reduce the variance of output. In the case of Australia, the decline in the variance of output growth can be traced solely to less volatile shocks. The evidence on the impact of the change in structure in Australia is inconclusive.

3.3 Summary of Results

Table (6) summarizes my findings on what drives the relatively benign inflation and output after IT was adopted in the sample countries. In sum, it appears that the remarkable decline in inflation variability can be traced to a combination of more stable structure after IT was adopted and generally less violent shocks.

As implemented in Karras et al. (2006), the counterfactual VAR approach allows the decomposition of the proportion of variability that is attributable to either the change in structure or the change in innovation variance. The estimated difference in the variances between the two periods can be decomposed as $\frac{\sigma_{22}-\sigma_{11}}{\sigma_{22}-\sigma_{11}} = \frac{\sigma_{22}-\sigma_{21}}{\sigma_{22}-\sigma_{11}} + \frac{\sigma_{21}-\sigma_{11}}{\sigma_{22}-\sigma_{11}}$. The change in the variance that can be attributed to the structure is given by $\frac{\sigma_{21}-\sigma_{11}}{\sigma_{22}-\sigma_{11}}$, which yields what would have been the variance during the pre-IT period if the structure during the post-IT period is adopted much earlier. Meanwhile, the contribution of the shocks given by $\frac{\sigma_{22}-\sigma_{21}}{\sigma_{22}-\sigma_{11}}$ looks at what would have been the variance during the post-IT period if we instead experience the pre-IT period shocks.[6]

Results in Table (7) show that for most of the countries in the sample, the propagation mechanism or the change in structure accounts for a larger proportion of the reduction in inflation volatility after the IT adoption. To get a sense of the magnitudes of the variances, let us take Canada, the country where the role of the change in structure is quite glaring. Given that $\sigma_{21} = 0.99$, my computation suggests that the structure accounts for about 95 percent $\left[\frac{\sigma_{21}-\sigma_{11}}{\sigma_{22}-\sigma_{11}} = \frac{-3.94}{-4.14} = .95\right]$ of the volatility decline, while shocks are responsible for the remaining 5 percent$\left[\frac{\sigma_{22}-\sigma_{21}}{\sigma_{22}-\sigma_{11}} = \frac{-0.20}{-4.14} = .05\right]$.[7] In terms of the relative importance of the propagation mechanism, countries following Canada include Indonesia (91 percent), Sweden (81 percent), Mexico (80 percent), Philippines (55 percent), New Zealand (53 percent), and Australia (53 percent). In the case of Thailand, the contribution of the propagation mechanism is more than 100 percent. The reason for this can be attributed to the finding that shocks appear to be slightly more violent in the post-IT period.[8]

[6] Alternatively, the change in the variance can be decomposed as $\frac{(\sigma_{22}-\sigma_{12})+(\sigma_{12}-\sigma_{11})}{\sigma_{22}-\sigma_{11}}$, where the relative importance of the structure is given by $\frac{\sigma_{22}-\sigma_{12}}{\sigma_{22}-\sigma_{11}}$ while that of shocks is $\frac{\sigma_{12}-\sigma_{11}}{\sigma_{22}-\sigma_{11}}$. While this is a reasonable decomposition, it answers a slightly different research question. For instance, it asks what would have been the variance during the post-IT period if the structure during the pre-IT period is maintained. Based on the alternative decomposition, the resulting level of shares will be different but the qualitative results are not very different for most countries.

[7] See the online Appendix for the detailed computation for each country in the sample.

[8] Numerically, this is reflected in the negative sign in the contribution of the impulses. This "negative" effect is offset by the more than 100 percent contribution of the change in structure.

Meanwhile, in other countries, shocks seem to have played a bigger role. In Korea and the UK, calmer shocks are responsible for about 87 percent and 58 percent of the respective reduction in inflation volatility, respectively. More stable structure accounted for the remaining 13 percent for Korea and 42 percent for the UK. While there could be some variation in their relative importance, it must be stressed that both the propagation mechanism and the impulses have a role to play in explaining the relative tranquility in inflation after the adoption of the IT framework.

With respect to output volatility (Table 7), evidence from the sample countries suggest that the relative stability of output growth can be attributed largely to milder shocks (impulses) after IT was adopted. In fact, these shocks are relatively much less violent than the pre-IT period to offset what appears to be a less stable structure in the post-IT period. As can be seen in Table (7), the contribution of the structure is negative in the majority of the countries which implies that shocks account for more than 100 percent of the decline in output variability. Consistent with the earlier findings of increased stability in structure for Indonesia and Thailand, the computed contribution of structure in the decomposition is positive. In particular, the structure is responsible for about 78 percent and 72 percent of the output volatility decline in Indonesia and Thailand, respectively, while shocks account for the remaining 22 percent and 28 percent.

3.4 Robustness Checks and Placebo Test

Various specifications are estimated to check the robustness of the estimates and implications of the counterfactual VAR approach.[9] First, I investigate whether it is in fact crucial to account for global developments in the model. Results show that if global inflation is excluded in the main specification, the conclusion would have been that the contribution of the propagation mechanism would seem minimal. This finding provides support to the concern that the variation due to global inflation would be relegated to the shock change if it were not included in the VAR system. I also estimate other specifications using other variables and the results are broadly the same as the baseline model. These specifications include: (a) a 4-variable VAR model, replacing world inflation with world oil price inflation as the most exogenous variable in the system; (b) a 4-variable VAR model where I replace world inflation with US output growth as an indicator of global output performance; and (c) a 5-variable VAR model comprised of

[9] See the online Appendix.

US inflation, US output growth, domestic interest rates, domestic output growth, and domestic inflation. Overall, the evidence suggests that the main specification, though only accounts for the impact of global inflation, is sufficient to provide convincing evidence on what underlies the more stable macroeconomic environment after the adoption of inflation targeting.

An alternative approach to do some sort of a placebo test is to apply the counterfactual VAR method to the pre-IT sample period and use the midpoint of the sample as the arbitrary breakpoint. However, this approach is not a foolproof placebo test because the counterfactual VAR approach tests whether there has been significant changes in the coefficients or the changes in the innovation variance of a VAR model at some meaningful break point.[10] Hence, the results should be interpreted with caution. The evidence shows that during the sample period prior to the shift to IT, the counterfactual VAR method either does not detect significant structural change for a number of countries or yields inconsistent results.

4 Discussion and Conclusion

This paper investigates the dramatic decline in inflation variability as well as the smoother business cycle that have been observed in many countries since the 1990s. Focusing on countries which adopted the IT framework in various years from 1989 to 2005, it examines whether the remarkable decline in macroeconomic volatility after the switch to inflation targeting has been the result of a more stable structure (the propagation mechanism) or less volatile shocks (the impulses.) This paper employs the technique developed by James (1993), enhanced by Simon (2001), and applied to business cycle volatility by Stock and Watson (2002), Stock and Watson (2003), Karras et al. (2006), and to exchange rate variability by Karras et al. (2005). I estimate univariate and multivariate VAR models in the period before IT was adopted and after its adoption using quarterly data for five advanced economies and five emerging market economies. The technique estimates "factual variances," the variability in the pre-IT period and in the post-IT period, as well as "counterfactual variances," the hypothetical variances that would have been observed if one period's structure is accompanied by the other period's shocks. A

[10] When the counterfactual VAR method is used on the pre-IT period, even using an arbitrary breakpoint, there could be country-specific shocks that could influence the results. A straightforward placebo test would have not detected any statistically significant result on the pre-IT period. But this pseudo-placebo test on the pre-IT period could potentially detect one for reasons unrelated to the monetary policy framework.

comparison of these estimated variances with each other and to the actual variances, with the aid of critical values generated from bootstrapping and Monte Carlo techniques, provides evidence as to what factor/s could have been responsible for the more stable inflation and output growth after countries introduced the inflation targeting framework.

The baseline model augments a simple monetary policy transmission model (interest rates, GDP growth, inflation) with the global inflation (proxied by US inflation) to account for the impact of a more tepid global inflation environment. Results show that the reduced inflation variability among the IT countries in my sample can be attributed to a combination of more stable structure (propagation mechanism) and milder shocks (impulses), but the former appears to account for a more significant stabilization role. The approach allows the computation of the relative contribution of the propagation mechanism and the impulses in bringing down inflation volatility. There is a variation in the computed shares, with the propagation mechanism explaining at least half of the volatility decline in Thailand, Canada, Indonesia, Sweden, Mexico, Philippines, New Zealand, and Australia; while the impulses seem to be much more important in Korea and the United Kingdom.

Meanwhile, evidence suggests that the observed moderation in output volatility after the adoption of inflation targeting can be attributed mainly to calmer shocks (impulses) and not at all to the change in structure. In fact, the evidence from the propagation mechanism points to a less stable structure in the post-IT adoption period.The shocks appear to be much calmer, thus offsetting what appears to a less stable structure in the post-IT adoption period. Results from the main model are robust to various specifications, including one which jointly accounts for the impact of global inflation and output developments.

What is the economic significance of these results? Consider the finding that inflation volatility in the pre-IT period would have been significantly lower if the post-IT adoption structure had coincided with the pre-IT shocks. This implies that in the hypothetical case where IT was adopted much earlier, we could have seen a more tranquil inflation environment earlier as well. Meanwhile, the opposing finding on the impact of the propagation mechanism on inflation and output seem to support the view that there is a trade-off between inflation volatility and output volatility. While the conventional understanding of the Phillips curve trade-off is between the inflation and output (or the unemployment rate), Taylor (1994) and Fuhrer (1997) posit the existence of a policy trade-off between the volatility of inflation and of output. Providing direct evidence to support the policy trade-off is beyond the scope of the paper and not amenable to the methodology employed here and thus, maybe explored for future research. Another interesting question for future work is what have been the causes of the calmer shocks in the post-IT adoption period and whether one of these causes may have been linked to the change in the monetary policy framework itself.

References

Alesina, A., & Stella, A. (2010). The Politics of Monetary Policy. In B. M. Friedman & M. Woodford (Eds.), *Handbook of Monetary Economics* (Vol. 3, p. 1001-1054). Elsevier.

Ball, L., & Sheridan, N. (2004). Does Inflation Targeting Matter? In *The Inflation-Targeting Debate* (p. 249-282). National Bureau of Economic Research, Inc.

Batini, N., & Laxton, D. (2007). Under What Conditions Can Inflation Targeting Be Adopted? The Experience of Emerging Markets. In F. S. Miskin, K. Schmidt-Hebbel, N. L. S. Editor), & K. S.-H. (Se (Eds.), *Monetary Policy under Inflation Targeting* (Vol. 11, p. 467-506). Central Bank of Chile.

Brito, R., & Bystedt, B. (2010). Inflation targeting in emerging economies: Panel evidence. *Journal of Development Economics*, *91*(2), 198 - 210.

Cecchetti, S., & Ehrmann, M. (2002). Does Inflation Targeting Increase Output Volatility?: An International Comparison of Policymakers' Preferences and Outcomes. In N. Loayza, K. Schmidt-Hebbel, N. L. S. Editor), & K. S.-H. (Series (Eds.), *Monetary Policy: Rules and Transmission Mechanisms* (Vol. 4, p. 247-274). Central Bank of Chile.

Corbo, V., Landerretche, O., & Schmidt-Hebbel, K. (2002). Does Inflation Targeting Make a Difference? In N. Loayza, R. Soto, N. Loayza, & K. Schmidt-Hebbel (Eds.), *Inflation Targeting: Design, Performance, Challenges* (Vol. 5, p. 221-270). Central Bank of Chile.

Efron, B. (1979). Bootstrap Methods: Another Look at the Jackknife. *The Annals of Statistics*, *7*(1), 1-26.

Fuhrer, J. C. (1997). Inflation/Output Variance Trade-Offs and Optimal Monetary Policy. *Journal of Money, Credit and Banking*, *29*(2), 214-234.

Goncalves, C. E. S., & Salles, J. M. (2008). Inflation targeting in emerging economies: What do the data say? *Journal of Development Economics*, *85*(1-2), 312-318.

Hacker, R. S., & Hatemi-J, A. (2008). Optimal lag-length choice in stable and unstable VAR models under situations of homoscedasticity and ARCH. *Journal of Applied Statistics*, *35*(6), 601-615.

Inoue, A., & Kilian, L. (2002). Bootstrapping Smooth Functions of Slope Parameters and Innovation Variances in VAR(∞) Models. *International Economic Review*, *43*(2), 309-332.

International Monetary Fund. (2018). *International Financial Statistics.* `data.imf.org`. (Online; accessed August 1, 2018)

James, J. A. (1993). Changes in Economic Instability in 19th-Century America. *American Economic Review*, *83*(4), 710-731.

Johnson, D. (2002). The effect of inflation targeting on the behavior of expected inflation: evidence from an 11 country panel. *Journal of Monetary Economics*, *49*(8), 1521-1538.

Karras, G., Lee, J. M., & Stokes, H. (2005). Sources of exchange-rate volatility: Impulses or propagation? *International Review of Economics & Finance*, *14*(2), 213-226.

Karras, G., Lee, J. M., & Stokes, H. (2006). Why are postwar cycles smoother? Impulses or propagation? *Journal of Economics and Business*, *58*(5-6), 392-406.

King, M. (2001). *The Inflation Target Ten Years On* (Bank Of England Quarterly Bulletin No. Winter 2002). London: Bank of England.

Levin, A., Natalucci, F., & Piger, J. (2004). The macroeconomic effects of inflation targeting. *Review*, 51-80.

Levin, A., & Piger, J. (2004). *Is inflation persistence intrinsic in industrial economies?* (Working Paper Series No. 0334). Frankfurt: European Central Bank.

Lin, S., & Ye, H. (2007). Does inflation targeting really make a difference? Evaluating the treatment effect of inflation targeting in seven industrial countries. *Journal of Monetary Economics*, *54*(8), 2521-2533.

Lin, S., & Ye, H. (2009). Does inflation targeting make a difference in developing countries? *Journal of Development Economics*, *89*(1), 118-123.

Mishkin, F., & Schmidt-Hebbel, K. (2007). *Does Inflation Targeting Make a Difference?* (NBER Working Papers No. 12876). Massachusetts: National Bureau of Economic Research.

Neumann, M., & von Hagen, J. (2002). *Does inflation targeting matter?* (ZEI Working Papers No. B 01-2002). Bonn, Germany: University of Bonn, ZEI - Center for European

Integration Studies.

OECD. (2018). *OECD Statistics.* `stats.oecd.org`. (Online; accessed August 1, 2018)

Pétursson, T. (2004). *The Effects of Inflation Targeting on Macroeconomic Performance* (Working Paper No. 23). Reykjavik: Central Bank of Iceland.

Roger, S. (2009). *Inflation Targeting at 20 - Achievements and Challenges* (IMF Working Papers No. 09/236). Washington D.C.: International Monetary Fund.

Runkle, D. (1987). *Vector autoregressions and reality* (Staff Report No. 107). Minneapolis: Federal Reserve Bank of Minneapolis.

Schmidt-Hebbel, K., & Carrasco, M. (2016). The Past and Future of Inflation Targeting: Implications for Emerging-Market and Developing Economies. In C. Ghate & K. Kletzer (Eds.), *Monetary Policy in India: A Modern Macroeconomic Perspective* (pp. 583–622). Springer Indi.

Simon, J. (2001). *The Decline in Australian Output Volatility* (RBA Research Discussion Papers No. rdp2001-01). Sydney: Reserve Bank of Australia.

Stine, R. (1987). Estimating Properties of Autoregressive Forecasts. *Journal of the American Statistical Association*(82), 1072-1078.

Stock, J., & Watson, M. (2002). *Has the Business Cycle Changed and Why?* (NBER Working Papers No. 9127). Massachusetts: National Bureau of Economic Research.

Stock, J., & Watson, M. (2003). *Understanding changes in international business cycle dynamics* (NBER Working Papers No. 9859). Massachusetts: National Bureau of Economic Research.

Stokes, H. (2013). *Specifying and Diagnostically Testing Econometric Models.*

Taylor, J. (1994). The inflation/output variability trade-off revisited. *Conference Series ; [Proceedings]*, *38*, 21-24.

Vega, M., & Winkelried, D. (2005). Inflation Targeting and Inflation Behavior: A Successful Story? *International Journal of Central Banking*, *1*(3).

Ventzislav, I., & Lutz, K. (2005). A Practitioner's Guide to Lag Order Selection For VAR Impulse Response Analysis. *Studies in Nonlinear Dynamics & Econometrics*, *9*(1), 1-36.

Table 1: IT adoption and Variances of Inflation and GDP Growth

	Advanced Economies					**Emerging Market Economies**			
	Adoption	**Period**	**Inflation**	**Output**		**Adoption**	**Period**	**Inflation**	**Output**
NZ	Jan 2001	1974Q1-1989Q4	19.3	13.0	TH	May 2000	1994Q1-2000Q1	7.7	41.0
		1990Q1-2017Q4	2.1	5.1			2000Q2-2017Q4	3.9	9.5
CA	Feb 1991	1962Q1-1990Q4	10.3	6.3	MX	Jan 2001	1980Q1-2000Q4	1,519.5	16.4
		1991Q1-2017Q4	1.2	3.7			2001Q1-2017Q4	1.2	6.0
UK	Oct 1991	1979Q1-1992Q3	19.3	7.0	KR	Jan 2001	1980Q1-2000Q4	43.1	22.4
		1992Q4-2017Q4	0.7	3.3			2001Q1-2017Q4	1.4	3.9
SE	Jan 1993	1982Q1-1992Q4	6.4	3.7	PH	Jan 2002	1982Q1-2001Q4	123.9	17.8
		1993Q1-2017Q4	1.8	6.7			2002Q1-2017Q4	4.2	3.2
AU	May 1993	1968Q1-1993Q1	15.8	6.5	ID	Jul 2005	1991Q1-2005Q2	239.9	32.6
		1993Q2-2017Q4	1.6	1.2			2005Q3-2017Q4	12.6	0.4

Table 2: Implied inflation volatility: New Zealand
4-variable VAR (World Inflation, Interest Rates, GDP Growth, Inflation)

	Actual				
	Period 1		Period 2		
Variance (σ^2)	19.29		2.07		
Mean	12.61		2.16		
CV	0.35		0.67		
	(A) Univariate Model				
	Factual			Counterfactual	
	$\sigma_{11} = \sigma(A_1, \Sigma_1)$	$\sigma_{22} = \sigma(A_2, \Sigma_2)$		$\sigma_{12} = \sigma(A_1, \Sigma_2)$	$\sigma_{21} = \sigma(A_2, \Sigma_1)$
	19.67	1.29		2.83	8.98
	$\|\sigma_{11} - \sigma_{21}\|$	$\|\sigma_{12} - \sigma_{22}\|$	$\|\sigma_{11} - \sigma_{12}\|$	$\|\sigma_{21} - \sigma_{22}\|$	$\|\sigma_{12} - \sigma_{21}\|$
	10.69	1.54	16.84*	7.69	6.15
BT-95%	23.14	24.15	20.67	21.82	29.89
BT-99%	36.58	36.54	34.70	33.01	51.06
MC-95%	22.29	22.10	9.01	10.74	23.84
MC-99%	33.54	29.47	12.98	15.19	36.08
	(B) Multivariate Model				
	Factual			Counterfactual	
	$\sigma_{11} = \sigma(A_1, \Sigma_1)$	$\sigma_{22} = \sigma(A_2, \Sigma_2)$		$\sigma_{12} = \sigma(A_1, \Sigma_2)$	$\sigma_{21} = \sigma(A_2, \Sigma_1)$
	15.75	1.24		3.24	8.10
	$\|\sigma_{11} - \sigma_{21}\|$	$\|\sigma_{12} - \sigma_{22}\|$	$\|\sigma_{11} - \sigma_{12}\|$	$\|\sigma_{21} - \sigma_{22}\|$	$\|\sigma_{12} - \sigma_{21}\|$
	7.65	2.00	12.51*	6.86	4.86
BT-95%	15.80	17.12	12.15	11.50	19.08
BT-99%	22.58	22.62	19.78	18.66	28.95
MC-95%	14.78	16.03	6.87	7.36	16.62
MC-99%	20.86	23.39	10.78	11.31	22.51

Notes: *Denotes significance at the 5 percent significant level using Monte Carlo critical values. BT and MC provide the Bootstrap and Monte Carlo critical values, respectively, from 1,000 replications. Period 1 = 1974Q1 - 1989Q4; Period 2= 1990Q1 - 2017Q4.

Table 3: Analysis of Test Statistics

Test Statistics	Condition	Conclusion for post-IT period
$(\sigma_{11} - \sigma_{21})*$	$\sigma_{11} > \sigma_{21}$	More stable structure
$(\sigma_{12} - \sigma_{22})*$	$\sigma_{12} > \sigma_{22}$	More stable structure
$(\sigma_{11} - \sigma_{12})*$	$\sigma_{11} > \sigma_{12}$	Calmer shocks
$(\sigma_{21} - \sigma_{22})*$	$\sigma_{21} > \sigma_{22}$	Calmer shocks

Table 4: Implied Inflation Volatility, Multivariate Model: 4-variable VAR (World Inflation, Interest Rates, GDP Growth, Inflation)

		AU	CA	ID	KR	MX	NZ	PH	SE	TH	UK
Actual	σ_1	15.77	10.26	239.86	43.10	1519.47	19.29	123.91	6.35	7.73	19.25
	σ_2	1.63	1.24	12.57	1.42	1.23	2.07	4.22	1.81	3.95	0.72
Estimates	σ_{11}	10.29	4.93	221.50	9.07	1391.00	15.75	122.90	9.67	7.12	10.15
	σ_{22}	1.40	0.79	4.85	0.97	1.02	1.24	3.43	1.50	3.74	0.71
	σ_{12}	3.54	5.53	115.70	2.73	20.65	3.24	27.45	7.70	29.88	6.04
	σ_{21}	5.59	0.99	24.42	8.02	273.90	8.10	57.32	3.02	3.56	6.20
Statistics	$\|\sigma_{11} - \sigma_{21}\|$	4.70*	3.94*	197.10*	1.05	1118.00*	7.65	65.62*	6.64*	3.56	3.95
(MC-95%)		(3.97)	(2.79)	(97.63)	(4.12)	(647.30)	(14.78)	(55.31)	(3.36)	(5.55)	(5.06)
	$\|\sigma_{12} - \sigma_{22}\|$	2.14	4.74*	110.90*	1.76	19.63	2.00	24.02	6.21*	26.14*	5.33
		(4.03)	(2.66)	(87.11)	(3.81)	(573.70)	(16.03)	(55.98)	(3.79)	(7.23)	(5.35)
	$\|\sigma_{11} - \sigma_{12}\|$	6.75*	0.61	105.80*	6.34*	1371.00*	12.51*	95.49*	1.96*	22.76*	4.11*
		(1.99)	(1.23)	(54.73)	(2.08)	(297.90)	(6.87)	(30.71)	(1.73)	(4.24)	(2.69)
	$\|\sigma_{21} - \sigma_{22}\|$	4.19*	0.20	19.57	7.05*	272.90	6.86	53.89*	1.53	0.18	5.49*
		(1.95)	(1.20)	(58.71)	(2.09)	(294.60)	(7.36)	(28.92)	(1.89)	(3.88)	(2.73)
	$\|\sigma_{12} - \sigma_{21}\|$	2.05	4.54*	91.28	5.29*	253.20	4.86	29.88	4.68*	26.32*	0.16
		(4.25)	(2.83)	(111.60)	(4.05)	(640.40)	(16.62)	(61.19)	(3.62)	(7.97)	(5.70)

Note: * indicates statistical significance at the 5 percent level using the critical values generated from the Monte Carlo method

Table 5: Implied Output Growth Volatility, Multivariate Model: 4-variable VAR (World Inflation, Interest Rate, GDP Growth, Inflation)

		AU	CA	ID	KR	MX	NZ	PH	SE	TH	UK
Actual	σ_1	6.53	6.25	32.57	22.38	16.41	13.04	17.77	3.70	41.02	7.05
	σ_2	1.20	3.68	0.43	3.91	5.98	5.09	3.19	6.75	9.49	3.26
Estimates	σ_{11}	5.74	4.61	30.82	19.09	15.14	11.46	17.03	3.90	33.74	5.24
	σ_{22}	1.16	2.65	0.25	3.64	5.80	4.55	2.61	4.80	9.30	3.27
	σ_{12}	1.22	1.34	15.96	5.00	4.63	3.18	2.96	2.73	63.88	1.70
	σ_{21}	5.79	7.32	8.81	35.33	485.50	17.84	24.80	7.53	14.64	23.77
Statistics	$\|\sigma_{11} - \sigma_{21}\|$	0.05	2.70*	22.00*	16.25*	470.40*	6.38*	7.77*	3.60*	19.09*	18.53*
(MC-95%)		(1.69)	(2.66)	(15.62)	(10.18)	(6.86)	(3.31)	(7.29)	(3.51)	(13.46)	(2.19)
	$\|\sigma_{12} - \sigma_{22}\|$	0.06	1.31	15.71*	1.36	1.18	1.37	0.35	2.07	54.57*	1.56
		(1.63)	2.67)	(13.95)	(9.56)	(6.42)	(3.69)	(6.59)	(4.01)	(18.51)	(2.45)
	$\|\sigma_{11} - \sigma_{12}\|$	4.52*	3.27*	14.85*	14.08*	10.51*	8.28*	14.07*	1.17	30.14*	3.54*
		(1.20)	1.52)	(8.28)	(5.93)	(3.75)	(2.81)	(3.43)	(2.23)	(12.81)	(1.31)
	$\|\sigma_{21} - \sigma_{22}\|$	4.63*	4.66*	8.56*	31.69*	479.70*	13.29*	22.19*	2.73*	5.34	20.50*
		(1.22)	(1.41)	(8.53)	(5.76)	(3.42)	(2.69)	(3.64)	(2.12)	(10.04)	(1.29)
	$\|\sigma_{12} - \sigma_{21}\|$	4.57*	5.97*	7.15	30.33*	480.90*	14.66*	21.83*	4.80*	49.23*	22.06*
		(2.03)	(3.15)	(17.15)	(11.08)	(7.28)	(4.72)	(7.77)	(4.13)	(22.10)	(2.65)

Note: * indicates statistical significance at the 5 percent level using the critical values generated from the Monte Carlo method

Table 6: Model Implications: 4-variable VAR
(World Inflation, Interest Rates, GDP Growth, Inflation)

	Inflation		Output Growth	
	Structure	Shocks	Structure	Shocks
AU	More stable	Calmer*	Less stable*	Calmer*
CA	More stable*	Mixed	Less stable*	Calmer*
ID	More stable*	Calmer*	More stable*	Calmer*
KR	More stable	Calmer*	Less stable*	Calmer*
MX	More stable*	Calmer*	Less stable*	Calmer*
NZ	More stable	Calmer*	Less stable*	Calmer*
PH	More stable*	Calmer*	Less stable*	Calmer*
SE	More stable*	Calmer*	Less stable*	Calmer*
TH	More stable*	More volatile*	More stable*	Mixed*
UK	More stable	Calmer*	Less stable*	Calmer*

Note: * indicates significance at the 5 percent level

Table 7: Decomposition of the Sources of Volatility

	Inflation		Output	
	Propagation $\left[\frac{\sigma_{21}-\sigma_{11}}{\sigma_{22}-\sigma_{11}}\right]$	Impulses $\left[\frac{\sigma_{22}-\sigma_{21}}{\sigma_{22}-\sigma_{11}}\right]$	Propagation $\left[\frac{\sigma_{21}-\sigma_{11}}{\sigma_{22}-\sigma_{11}}\right]$	Impulses $\left[\frac{\sigma_{22}-\sigma_{21}}{\sigma_{22}-\sigma_{11}}\right]$
AU	0.53	0.47	-0.01	1.01
CA	0.95	0.05	-1.38	2.38
ID	0.91	0.09	0.72	0.28
KR	0.13	0.87	-1.05	2.05
MX	0.8	0.2	-50.38	51.38
NZ	0.53	0.47	-0.92	1.92
PH	0.55	0.45	-0.54	1.54
SE	0.81	0.19	4.04	-3.04
TH	1.05	-0.05	0.78	0.22
UK	0.42	0.58	-9.39	10.39