Targeting Inflation Expectations?

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Abstract

Do inflation expectations respond to changes in monetary policy, namely, Inflation Targeting? Subjective expectations, a survey expectations of professional forecasters for 32 Inflation Targeting countries, and an event study methodology are used to find that countries with price stability as the single objective, have a reduction in short run forecast errors. Moreover, the reduction in forecast errors is the result of a change in inflation and not expectations. The key insight of the paper is that Inflation Targeting does not have a direct impact on short-run inflation expectations. In addition, the change in forecast errors but not expectations lends support to the idea that inflation leads expectations. Finally, the paper also performs a quantitative exercise which finds that the weight that agents attach some weight to the inflation target which central banks can leverage to build credibility ex-post by reducing inflation.

Keywords: *Inflation Expectations, Inflation Targeting, Subjective Expectations, Adaptive Learning, Inflation, Anticipation*

JEL Codes: D83, D84, E52, E58

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1 Introduction

An open question that has resurfaced during the Covid-19 outbreak and recent resurgence in inflation, is that of an appropriate monetary policy framework for central banks to achieve their objective of price stability.[1] Modern macroeconomic theory dictates that inflation expectations matter for the path of current and future inflation.[2] Several monetary policy frameworks such as Inflation Targeting (IT), Average Inflation Taregting (AIT), Price-Level Taregting (PLT) have the anchoring of inflation expectations as the main tenet. However, there is little consensus on how agents form expectations and whether agents' expectations adjust to changes in regimes and monetary policy frameworks.

With the objective of disentangling the effect of the introduction of a policy, namely, Inflation Targeting (IT) on inflation expectations, the paper asks three questions. First, do agents adjust expectations at the time of the implementation? If no, do they adjust them at the time of the announcement? Finally, do agents incorporate the announced inflation target in their rule for forming expectations?

There are several competing hypotheses describing the nature of expectations ranging from the rational expectations (RE) approach to the umbrella of deviations from RE. The paper uses the RE and adaptive learning framework as the theoretical basis to estimate the effect of IT on expectations. Data on six-month-ahead inflation expectations from professional forecasters for thirty countries is used to undertake the analysis. First, a test of the Rational Expectation Hypothesis (REH) on the data used which is followed by the use of an event study design. The specific method used is based on Borusyak et al. (2021) to elicit the impact of the change in policy on expectations and the forecast errors. The method suggested by Borusyak et al. (2021) allows one to use the full set of observations and also allows for heterogeneity in the treatment effects typically missing in the treatment effects literature.

Adaptive learning models are an attractive lens to understand inflation expectations. These models are able to match the properties of expectations and macroeconomic aggregates. Coibion and Gorodnichenko (2015a) document the fact that forecast errors are correlated with forecast revisions, a key feature of learning models. Additionally, Carvalho et al. (2021) develop a model with adaptive learning which has good out-of-sample properties[3].

Finally, in order to aid identification, the study documents an anticipation (announcement) date for the sample. This is one of the first studies to study the announcement and adoption of the policy as different events. Defining data on the announcement dates is particularly important since the study uses surveys of professional forecasters - agents who are well informed about the economy. The announcement is gleaned from the minutes

[1]For instance, the Federal Reserve shifted to Average Inflation Target in August 2020 only to reverse policy to Inflation Targeting in May 2022. One of the reasons for the reversals was to control the rise in expectations and prevent them from becoming unmoored (see Bullard et al. (2022))

[2]'a la Calvo (1983), amongst others

[3]The experimental literature Anufriev and Hommes (2012) also show that simple learning rules provide the best fit in a lab setting.

of the monetary policy meetings from each country by checking the first time the there is a discussion of a new regime.

One of the key aspects of IT is the anchoring of expectations in the long run as opposed to the short run, which is the data this study uses. However, (Carvalho et al., 2021, p. 19) suggest that the degree of anchoring depends on the endogenous link between long-term and short-term inflation expectations and the strength of this depends on the recent forecasting performance and monetary policy. They show that short-term forecasts accurately predict long term forecasts.[4] Nonetheless, the paper undertakes a quantitative exercise to assess whether there is an explicit change in the expectation rule after the structural break and if agents attach any weight to the target. This model encompasses long run expectations since, it should be the case that expectations converge to the target.

Figures 1 - 2 provide preliminary evidence to motivate the research question. The blue line represents realised inflation while the red dashed line represents inflation expectations based on a survey of professional forecasters. The vertical yellow line marks the year of the adoption of Inflation Targeting. Figure 1 portrays the evidence for Colombia while figure 2 presents evidence for the United States. Upon comparing the two figures, it is difficult for one to conclusively ascertain the impact of a regime change on expectations.

Figure 1 suggests that inflation expectations adjust significantly when IT is implemented and expectations track inflation with gradual adjustments also taking place in the period of the announcements. On the other hand, figure 2 shows no change in expectations following the announcement and implementation of the policy. The break in inflation and inflation expectations occurs at the time of the financial crisis, which has been documented in Gerko (2017). This evidence leads to the question regarding the direction of impact of the policy. Does IT impact inflation expectations which in turn impact inflation or does IT impact inflation which then leads to a response of inflation expectations?

Apart from confirming the deviations from rational expectations, the paper finds three key results. First, countries who have a single mandate, that is, they focus on price stability as their sole objective are able to adjust the short-run expectations with the adoption of inflation targeting. The mechanism is through a reduction in the forecast errors[5]. However, this reduction is the result of a change in inflation and not inflation expectations. For countries with dual mandates, there is increased volatility in forecast errors. This result holds despite the length of time period considered post the adoption of the policy. This result is different from the findings by Gürkaynak et al. (2010a) who suggest that IT leads to an anchoring of inflation expectations in the long run. However, this paper differs on two key dimensions. First, it uses a panel dataset of over 30 countries and modern econometric methods of event study analysis to produce the current findings. Second, Gürkaynak et al. (2010a) use a measure of forward interest rates and inflation compensation to elicit expectations. On the other hand, the current paper uses survey expectations from professional forecasters. While not a perfect measure, survey data provides a direct measure of expectations without the need to infer it from market information. This pa-

[4](Coibion et al., 2020, p. 34) also show the importance of short-term expectations for the financial sector

[5]Please see section 4 for a discussion on the construction of the forecast errors.

per also only finds an effect for countries with a single mandate as opposed to the focus on dual mandate economies by Gürkaynak et al. (2010a). This result also challenges the view of Coibion et al. (2018) who suggest no effect for the US and New Zealand (also based on individual country analysis) after the introduction of the policy.

Figure 1: Colombia: Inflation and Inflation Expectations

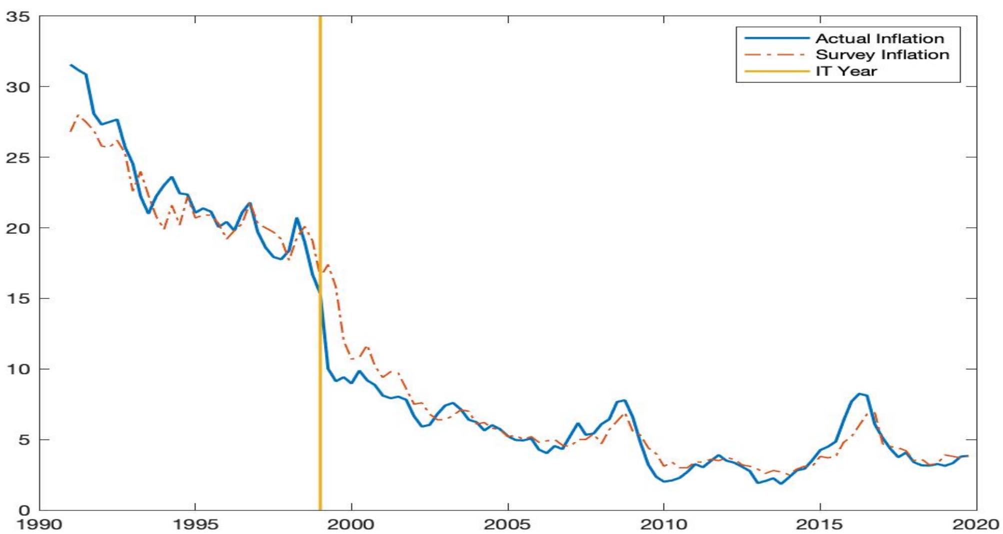
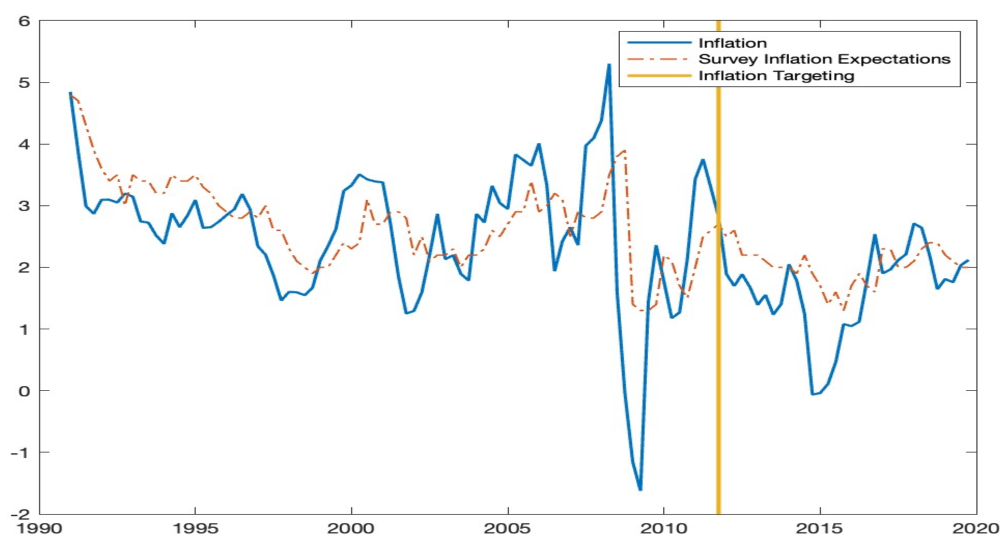


Figure 2: United States: Inflation and Inflation Expectations



There is a small adjustment in inflation expectations two quarters after the announcement of the policy. However, by the third quarter after the announcement, this effect also disappears. Overall, supporting the fact that expectations do not adjust to IT.

Finally, the quantitative exercise reveals that while agents do include the inflation target in the perceived law of motion after the adoption of IT, the weight that agents attach some weight to the inflation target (around 0.11). Consequently, agents rely on a longer history of inflation to predict future inflation. While a small value, one must note that the expectations being considered in this study are short run expectations. In addition, agents also rely on past inflation which is also affected by the policy. Importantly, central banks can leverage this and build credibility ex-post by reducing inflation (the part which is within the control of central banks).

Taken together, the results of the empirical estimation and quantitative exercise highlight two things. First and crucially, there is no direct impact of the policy on expectations. Second, the empirical evidence suggests that a single objective aids clarity of communication and facilitates the adjustment process even if not through the expected channel.

One of the main criticisms of using vastly different countries can be the credibility of the central bank. The paper uses data from Dincer and Eichengreen (2013) to run a robustness check by including information on central bank transparency. Despite controlling for "credibility", the results remain unchanged. Robustness checks are also based on different estimators such as those by Sun and Abraham (2021) and Callaway and Sant'Anna (2021) uphold the main results of the paper. There is no significant change in the response to new information when the policy is implemented. Although, with Callaway and Sant'Anna (2021), there is an increase in expectations after a few quarters. The significance of this result is not straightforward since the method requires grouping of the individual countries by date of adoption, reducing the sample size. Therefore, with the use of different estimators, the results remain robust. Additional results based on different splits of the data present results similar to those highlighted above.

Related Literature This paper lies at the intersection of and contributes to three strands of literature. First, assuming that agents behave like econometricians (as in Marcet and Sargent (1989b), Evans and Honkapohja (2012)) this paper studies how far expectations look back to the past to form expectations about the future before and after a change in the monetary policy framework. Thus, it is one of the only papers to tackle the impact of a policy change on expectations. This paper furthers the literature on inflation expectations such as Mankiw et al. (2003), Erceg and Levin (2003), Eusepi and Preston (2011), Coibion and Gorodnichenko (2015b), Coibion et al. (2018), and Bordalo et al. (2020), Carvalho et al. (2021), Gáti (2022). These papers document the deviation of the forecasts of the professional forecasters from the full information rational expectations (FIRE) framework. However, as stated above this literature has ignored the formation of expectations around a change in regime. Thus, beginning from the assumption that inflation expectations have always played a critical role in inflation. To the best of the author's knowledge, this is the first paper to address the question under adaptive learning.

A plethora of the literature has focused on the macroeconomic implications of IT on variables such as GDP and inflation, for example, Cecchetti and Ehrmann (1999), Ball and Sheridan (2004), and Levin et al. (2004). In addition, the effect of a policy change on expectations under RE has been relatively more researched for example, Castelnuovo et al. (2003), Gürkaynak et al. (2010b) Gürkaynak et al. (2010a), Beechey et al. (2011) there is limited work under deviations from RE. While Coibion et al. (2020) discuss the role that the introduction of Average Inflation Targeting plays on expectations of households, the evidence is limited on account of the policy application. To the best of the author's knowledge, this is the first paper to have a systematic and comprehensive comparison of surveys across a wide set of countries (advanced and developing), that differ substantially in their history of inflation and economic stability. Given the widespread implementation of IT as a monetary policy framework,[6], a rigorous study calls for using all available data.[7]

In addition, this paper distinguishes between the announcement and implementation of the policy. Thus, allowing the paper to focus on the transition period of the policy and consider an anticipation effect of the policy. The literature on the other hand, has ignored the transitory period.[8]

Finally, the paper adds to the literature on the credibility of the central bank building on papers such as Kostadinov and Roldán (2020) and King et al. (2020). The previous two papers build models where the agents need to infer the type of policy maker based on the policies implemented after a change in policy makers. In addition, Duggal and Rojas (2022) also use an adaptive learning model to measure central bank credibility based on announcement of intermediate targets.[9] This paper differs from the previous literature by assuming the new regime is announced and known to all individuals in the economy. However, this paper supports the credibility literature as learning is due to a lack of credibility and over time, expectations should converge to the objective of the central bank.

Road map The paper is organised as follows. Section two discusses the model of expectations explored in the paper. Section three delineates the data and its properties. Section four presents the empirical framework and results. Section five discusses a Monte Carlo simulation of the model to check the performance of the empirical strategy. Section six encompasses robustness checks using different definitions and estimators. Finally, section seven concludes with directions for further research.

[6]Approximately 60 countries around the world have adopted Inflation Targeting as their Monetary Policy Framework.

[7]Most of the work pertaining to inflation expectations has been limited to the developed economies specifically, the United States

[8]While there is a strand of literature that focuses on anticipation pioneered by Garmel et al. (2008), Schmitt-Grohé and Uribe (2012), and Maliar et al. (2015). However, the results in these papers relate to policies such as the introduction of the enlargement of the EU with eastern European countries, and anticipated shocks to output. Thus, anticipation has been limited to discussion of policies outside regime changes in the monetary framework.

[9]Early version working paper available here

2 Agents' Expectations

Before turning to the empirical and quantitative models, it is important to have a framework in mind, which can be used to interpret the results of the models. The paper specifically builds on two frameworks which are later tested. First, is the standard rational expectations framework. The second is adaptive learning based on Marcet and Sargent (1989a) and Evans et al. (2001).

2.1 Inflation

To understand the formation of expectations let us first understand the model for inflation.

Let inflation evolve according to a uni-variate unobserved component model. Where inflation π_t is the sum of an unobserved permanent (λ_t) and transitory component (ε) . Before IT is implemented the permanent component evolves according to a unit root process.

$$\pi_t = \lambda_t + \varepsilon_t \tag{1}$$
$$\lambda_t = \lambda_{t-1} + \vartheta_t \tag{2}$$

Now, let IT be introduced at time $t = IT^I$ such that for all periods after the implementation of IT inflation follows,

$$\pi_t = \lambda_t + \varepsilon_t \tag{3}$$
$$\lambda_t = \rho\lambda_{t-1} + (1-\rho)\pi^T + \vartheta_t \tag{4}$$

Where, the key difference between the pre and post-IT periods is the change in the process for the permanent component of inflation (λ_t). λ_t now evolves according to an AR(1) process where ρ measures the persistence of the permanent component and $(1 - rho)$ is the weight on the inflation target. Therefore, inflation is now a mean reverting process for $\rho < 1$.

The variance of the errors in inflation is time varying. The discussion of the relevance of the time varying error structure is postponed till section 5 of the paper.

2.2 Rational Expectations

The rational expectations approach assumes that the economic agents have complete of knowledge about the economy. Specifically, knowledge about the structure of the economy, the mapping between the fundamentals, the values of the parameters and the value of the shocks. Agents therefore, fully know the path of inflation, output and other macroeconomic variables in an economy. This implies that forecasts under RE will always be given as per[10],

$$\mathbb{E}_t \pi_{t+h} = \pi_t \tag{5}$$

Under the Rational Expectations Equilibrium (REE), the perceived law of motion of the agents (PLM) and the actual law of motion (ALM) of the variable, coincide. Moreover, that the shocks to the economy are *independent and identically distributed*. This is because the REE imposes a consistency condition that each agent's choice is the best response to the choices of others.

In the pre inflation targeting period, the agents would have perfect knowledge about the underlying process for inflation. Therefore, they are able to predict inflation correctly. A well know example of this is referred to as the inflation bias as termed by Barro and Gordon (1983), where agents have rational expectations and they are able to anticipate how the government will respond to shocks and correctly forecast future inflation. For details on the Barro and Gordon (1983) model, please see appendix D.

Similarly, in the post-inflation targeting period, the agents know the central bank's inflation target, π^T for all t. This inflation target can also be interpreted as the long run mean of inflation or the inflation drift. Thus, under rational expectations and a credible inflation target, the expectations of the agents will coincide with the inflation target.

$$\mathbb{E}_t \pi_{t+h} = \pi^T$$

This implies that under RE, the history of the policy, inflation or any other variable does not matter. Every period, agents know perfectly how all the changes in the economy will take place.

While, the agents considered in this paper are relatively more informed agents (professional forecasters) about the economy, they are not endowed with full information about the structure of the economy. Thus, they must behave as econometricians to forecast future prices. This implies that the second framework being considered in this paper is that of adaptive learning.

[10] While the variance of the forecast and the forecast error will be given by (if assuming an underlying model of stochastic volatility),

$$\begin{aligned} Var(E_t \pi_{t+h}) &= \sum_{k=1}^{h} E_t \sigma^2_{\varepsilon_{t+k}} + E_t \sigma^2_{\vartheta_{t+k}} \\ &= \sigma^2_{\varepsilon_t} \sum_{k=1}^{h} exp^{-0.5\gamma} + \sigma^2_{\vartheta_t} exp^{-0.5\gamma} \end{aligned}$$

2.3 Subjective Expectations

There is sufficient literature which discusses that inflation expectations deviate from rational expectations[11]. Therefore, one can now use a model of adaptive learning specifically, constant gain learning to underpin the empirical framework discussed in section four. They implication of using learning models (independent of the fundamental being addressed) is the fact that agents form expectations based on the history of the variables of economy. Moreover, they are unaware of the interaction between the structural variables.

The assumption the paper makes is that agents use a constant gain model to predict future inflation with the updating equation given by,

$$\tilde{\beta}_t = \tilde{\beta}_{t-1} + \kappa_t(\pi_t - \tilde{\beta}_{t-1}) \tag{6}$$

$\tilde{\beta}$ represent the underlying inflation expectations which impact inflation and are the result of the standard Kalman Filter.

As suggested before, let inflation targeting be announced at $t = IT^I$ such that there are two possibilities for the formation of expectations,

$$\tilde{\beta}_t = \tilde{\beta}_{t-1} + \kappa(\pi_t - \tilde{\beta}_{t-1}) \tag{7}$$

Where, κ gives the strength at which agents update their beliefs and with a constant κ. That is, agents do not adjust the way they change their expectations.

The second alternative is that for $t \geq IT^I$,

$$\tilde{\beta}_{IT} < \tilde{\beta}_{IT-1} + \kappa(\pi_{IT} - \tilde{\beta}_{IT-1})$$

Intuitively, 2.3 refers to the idea of the jump in expectations. That is, the paper aims to check whether the announcement or the introduction of the policy makes people reduce their inflation expectations or they must see it to believe it. Under equations (7) and (2.3) the assumption is of a constant variance of priors and a constant Kalman gain (κ). Section 5 relaxes this assumption to check if maybe the variance of the prirors and therefore the Kalman Gain adjust after the introduction of inflation targeting.

As discussed in the introduction, the paper uses short-run inflation forecasts to answer the research question. Appendix E provides a small explanation regarding how expectation of short-run inflation matters for economic decisions. Moreover, long-run expectatiosn are the infinite sum of long-run expectations. Thus, making the study of the effect of a policy change on short-run expectations, relevant.

[11] For instance, Branch and Evans (2006), Eusepi and Preston (2011), Coibion and Gorodnichenko (2015a), Branch and Evans (2017)

3 Data

3.1 Data on Forecasts

The survey measure used comes from the Ifo World Economic Survey which is a survey of professional forecasters. The survey collects information about various variables such as current and future economic situation of a country, inflation and GDP expectations etc. The survey collects qualitative responses (+) for a positive assessment, (=) for a neutral assessment, and (−) for a negative assessment. These responses are then converted to point estimates for each country. The final point estimates are used for the analysis in this paper.

The data set includes a set of 32 Inflation Targeting countries covering the periods from 1991Q1 - 2019Q4 (the last year of the survey). The range of the countries in the data set span advanced economies such as the United States, Japan, and Germany. On the other hand, it also includes developing economies such as Brazil, Chile, and India. The range of countries used enables a systematic review of the impact of IT on inflation expectations.

3.2 Properties of Forecasts

Tables F.3 - F.14 present the summary statistics (mean, standard deviation and persistence) for three key variables namely, inflation, inflation expectations and forecast errors. The results are split around the period of announcement and the period of implementation. Further, given that most central bankers use IT to anchor expectations in the medium to long term the summary statistics are also presented five years prior to and five years post the announcement and implementation of the policy. The forecast horizon of the forecasts is a rolling six-month-ahead forecast.

The summary statistics present two preliminary facts which dictate the empirical grounding of the paper. First, there is no consistent change in persistence of inflation expectations before and after the introduction of Inflation Targeting. Some countries such as Argentina, Austria, United States experience a decline in persistence. On the other hand, Finland, Spain, and Ireland experience an increase in persistence.

Second, the forecast errors for many countries increase after the introduction of inflation targeting. This is true for the full sample and if one were to look at the five years after the introduction of IT, the result holds significantly. The persistent forecast errors despite the change in policy to one which promotes credibility is indicative of two things. First, that inflation expectations may not adhere to the rational expectations framework. Second, the channel through which monetary policy is operating may not be directed through inflation expectations.

3.2.1 Structural Break

Given that the summary statistics do not provide a clear indication of the change in expectations. Let us now turn to a structural break test to check if there is a significant change. The paper follows the structural break tests as described by Bai and Perron (1998), De Wachter and Tzavalis (2012) and Ditzen et al. (2021) for multiple structural breaks. The structural break test for the panel data serves as an initial test for whether inflation expectations evolve differently over time.

When using the full data set, the dates are set as unknown since there is no one common date of implementation or announcement for the IT economies. Testing for each individual country is based on known and unknown dates. This allows us to check whether the structural break recommended by the data is close to or similar to the dates of the announcement or implementation. The individual tests for structural breaks are relevant for section 5, where the paper simulates data for 30 countries over 200 periods to analyse a change in the expectation rule and compute the credibility of the central bank.

The test for the structural break is run by regressing inflation expectations on past inflation and vice-versa. This framework provides changes in both variables without imposing an external break point. It also will allow one to test the validity of the known break dates from the announcement and implementation of IT.

The specification used for the test is as follows,

$$y_{it} = \beta x_{it} + \delta(s) z_{i,t,s} + \epsilon_{it} \tag{8}$$

Where, x_{it} is a $(1 \times p)$ vector of variables without structural breaks, z_{it} is a $(1 \times q)$ vector of variables with structural breaks and ϵ_{it} is the error term which includes individual heterogeneity. For the purposes of the paper, the assumption of individual heterogeneity has been collapsed to $\alpha_i = \bar{\alpha}$. That is, it is assumed that the unobserved heterogeneity is constant across all units. This simplification will be important for the event study, later. s represents the number of the structural break. In this paper, the two variables which comprise z are time t and inflation expectations π_t^e while $y_{it} = \{\pi_t, \pi_t^e\}$.

The test is performed in two stages, allowing one to check the exact number of structural breaks possible in the data. This is important especially since there are countries (for instance, Colombia and the United States) which had a long length of time between announcing and implementing IT. Thus, allowing for multiple breaks facilitates additional checks for any differences that may occur between the two periods and help with causal inference.

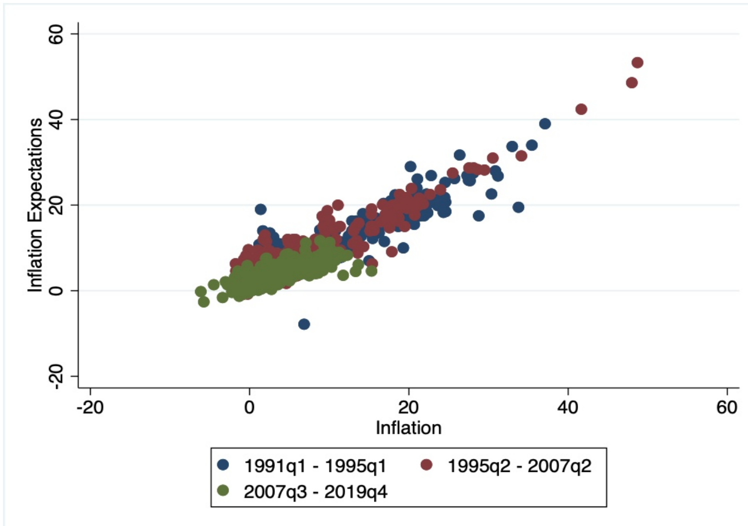
Test 1: H_0: $\delta_1 = \delta_2 = \cdots = \delta_s$ H_A: $\delta_j \neq \delta_k$ for some $j \neq k$

Test 2: H_0: $\delta_j = \delta_{j+1}$ for one $j = 1, \ldots s$ H_A: $\delta_j \neq \delta_{j+1}$ for some $\forall j = 1, \ldots s$

The first test checks the null hypothesis of no structural breaks against s structural breaks. The second hypothesis tests the null of s breaks versus $s + 1$ breaks.

The results from regressing inflation on expectations leads to two structural breaks in the data set. First, in $1955q1$ and the second in $2007q3$. Figure 3 suggests that inflation expectations have undergone a structural break twice in relation to observed inflation.

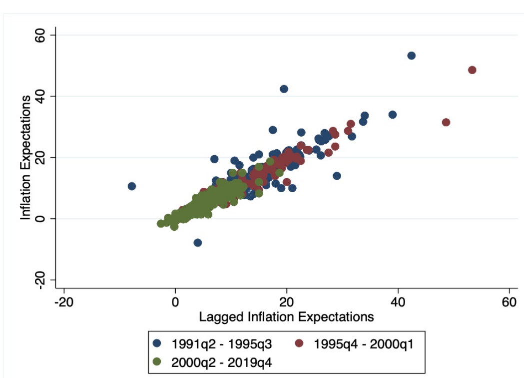
Figure 3: Structural Break in Inflation and Expectations



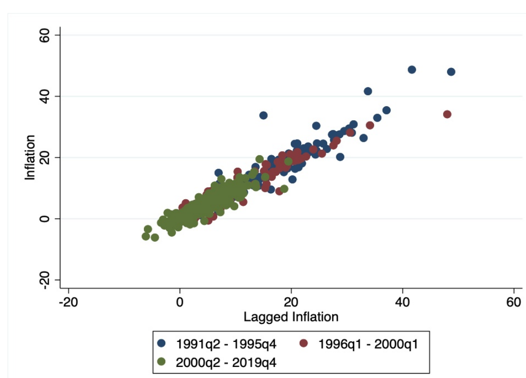
The second set of regressions entail computing the persistence of inflation and inflation expectations. Figures 4a and 4b represent the first order auto correlation of inflation and inflation expectations. While not noticeable in the graphs. There is a slight decrease in persistence in the mid 90s for both series from 0.96 to 0.90. However, the persistence increases again in the early 2000s to around 0.93 for both series. These finding suggest that there hasn't been a large break in inflation and expectations. It also supports the results from Stock and Watson (2007) who suggest that inflation remains a process which is close to a unit root.

Figure 4: Structural Break in Inflation and Expectations

(a) Inflation Expectations



(b) Inflation



To check the significance of the results based on the figures above, one can run the structural break test suggested by Fuhrer (2010). Formally, the regression considered is as follows,

$$\pi_t^e = \alpha_{\pi_t^e} + \alpha_{\pi_t^e}\mathbb{1}_{\{t\geq t^*\}} + \rho_{\pi^e}\pi_{t-1}^e + \rho_{\pi^e}\mathbb{1}_{\{t\geq t^*\}}\pi_{t-1}^e + e_t \tag{9}$$

Where, $\mathbb{1}_{\{t\geq t^*\}}$ is the indicator variable for the period following $1995q3$. The advantage of relying on a specification like (9) is that the former allows us to verify if the structural change in the coefficients is statistically significant. A similar specification is used to compute the structural break in the persistence of inflation.

$$\pi_t = \alpha_{\pi_t} + \alpha_{\pi_t}\mathbb{1}_{\{t\geq t^*\}} + \rho_{\pi}\pi_{t-1}^e + \rho_{\pi}\mathbb{1}_{\{t\geq t^*\}}\pi_{t-1} + e_t \tag{10}$$

The results for the panel data set are presented in table 1 below. There is strong evidence of a structural break in 1995q3 for inflation expectations and inflation. While the persistence in expectations increases marginally, there is a decrease in persistence for inflation. Individual country wise structural break findings are available in Appendix H.

Table 1: Structural Break Test

	π_t^e		π_t	
	(1)	(2)	(1)	(2)
Lagged Var	0.939***	0.957***	0.944***	0.881***
	(0.005)	(0.008)	(0.004)	(0.007)
Lag$*\mathbb{1}_{\{t\geq t^*\}}$		-0.042***		0.108***
		(0.011)		(0.009)
Constant	0.194***	0.285***	0.136***	0.718***
	(0.032)	(0.093)	(0.028)	(0.079)
Constant$\mathbb{1}_{\{t\geq t^*\}}$		-0.042		-0.739***
		(0.100)		(0.085)

Note: HAC Robust standard errors in parenthesis. $*p < 0.10, **p < 0.05, ***p < 0.01$.

3.2.2 Rational Expectation Hypothesis

If surveys about inflation expectations convey information about true expectations of future inflation, then it is possible to construct a test that verifies whether the Rational Expectation Equilibrium (REE) holds in the data. Under the Rational Expectation Hypothesis (REH) forecast errors must be orthogonal to all the information that is available and relevant to the agents at the moment of making the forecasts. However, if agents form beliefs about inflation according to adaptive expectations then, the forecasting errors may not necessarily be orthogonal to the information agents use to form their forecasts.

This paper follows Adam et al. (2017), Gerko (2017) and Kohlhas and Walther (2018) to perform the test for the rational expectation hypothesis. Let $E_t^{\mathcal{P}}$ and E_t denote the measure for subjective and rational expectations, respectively. Let $y_{t,t+h}$ denote the actual value of inflation in period $t+h$ and $E_t^{\mathcal{P}}y_{t,t+h}$ represent the forecast of inflation in period $t+h$, reported at time t. Therefore, the forecast error is given by $y_{t,t+h} - E_t^{\mathcal{P}}y_{t,t+h}$. Thus, a negative value of the difference would imply that agents are over-predicting inflation. Therefore, the test run to check the validity of the the hypothesis is the following,

$$y_{t,t+h} = \alpha_1 + \rho_1 y_{t-h,t} + \epsilon_t \tag{11}$$
$$E_t^{\mathcal{P}} y_{t,t+h} = \alpha_2 + \rho_2 y_{t-h,t} + \eta_t \tag{12}$$

Under the null of rational expectations, we would expect, $E_t^{\mathcal{P}} = E_t$. Thus, $H_0 : \rho_1 - \rho_2 = 0$. We can re-write equation (1) and (2) to perform a joint test for the REH. Thus the test is now augmented such that the null hypothesis is, $H_0 : \rho = 0$. Table 2 presents the results for the REH test for the panel data. For both the pre and post IT period, the test is rejected.

Table 2: REH Test, Panel Data

Variable	Pre-IT	Post-IT
Π_t	0.338***	0.142**
	(0.061)	(0.058)
Constant	-7.56***	-0.872***
	(1.77)	(0.167)

Note: The regression is of the forecast error in $t+h$ on inflation in period t. Newey West standard errors are reported in Parenthesis. The null hypothesis of $H_0 : \rho = 0$ is rejected for this sample. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table G.15 provides the results for the REH test each country in the data set. It is unsurprising that the REH is rejected at the individual level for the expectations of professional forecasters. The Newey West standard errors are reported along with the coefficient on inflation (ρ). The coefficient for all countries in both the periods is significantly different from zero. Thus, it is possible to reject the test for almost all countries for the pre and post targeting period.

4 The Role of Inflation Targeting

4.1 Empirical Framework

To estimate the treatment effect as described in (7), the paper uses the event study methodology based on Borusyak et al. (2021). Specifically, the regression is of the form

$$\beta_{it} = \underbrace{\delta_i}_{0} + \beta_{it-1} + \kappa(\pi_{it} - \beta_{it-1}) + \gamma_1 t + \gamma_2 \bar{\pi}_t + \epsilon_{it} \tag{13}$$

Where, β_{it} are the inflation expectations as taken from the surveys of professional forecasters, y_{it} is the annualised inflation rate, t captures a time trend and $\bar{\pi}_t$ represents the world inflation with $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$ and is orthogonal to all previous information. The paper also uses a complementary regression to understand the impact on inflation through expectations namely,

$$\pi_{it} = \beta_{it-1} + \kappa(\pi_{it} - \beta_{it-1}) + \gamma_1 t + \gamma_2 \bar{\pi}_t + \epsilon_{it} \tag{14}$$

One way to interpret both equations 13 and 14 is to think of constant gain learning akin to the normal returns in the Finance literature[12]. Thus, $(\beta_{it} - \hat{\beta}_{it-1})$ and $(y_{it} - \hat{\beta}_{it-1})$ represent the "abnormal" expectations and inflation, allowing the measurement of the effect of the treatment.

In order to compute the effect of the change in the policy, the estimation needs to be done in three stages. Before describing the details, let us work through some notational details. Let $\{it : D_{it} = 1 \in \Omega_1\}$ be the set of observations that receive treatment (those periods where Inflation Targeting is active) and $\{it : D_{it} = 0 \in \Omega_0\}$ be the untreated observations (periods where Inflation Targeting is not active). Let τ_{it} be the effect of the policy on the variable of interest (β_{it}) and $\beta_{it}(0)$ be the potential outcome if the observations were not treated. In addition, let w_{it} be the weights attached to each unit in the computation of the treatment effect. Then, the treatment effect is computed based on the following,

1. For all untreated observations in Ω_0, compute β_{it} by OLS. Thus, for this paper the regression is given by equation 13 to estimate $\hat{\kappa}, \hat{\gamma}_1, \hat{\gamma}_2$.

2. For all the treated observations in Ω_1 and $w_{it} \neq 0$ compute $\beta_{it}(0) = \beta_{it-1} + \hat{\kappa}(\pi_{it} - \beta_{it-1}) + \hat{\gamma}_1 t + \hat{\gamma}_2 \bar{\pi}_t + \epsilon_{it}$.

3. Compute, $\beta_{it} - \beta_{it}(0) = \tau_{it}$ which gives us the treatment effect.

4. Finally, the effect for each period after the treatment is computed as per $w_{ih} = \frac{1}{\Omega_{1,h}}$ where $\Omega_{1,h} = \{it : h = t - IT\}$ which is the relative time since the adoption of the policy.

5. Finally, $\tau_h = w_{ih} \tau_{ih}$ is the estimand based on τ_{it} for the different horizons ($h = \{1, 2, 3, 4, 5, 6, 7, 8\}$).

To complement the estimation procedure above consider the following example. Let there be two economies $n1$ and $n2$ such that $n1$ is treated at time $IT = 2$ and $n2$ is treated at time $IT = 4$. Then, the average treatment effect τ for each period is given by,

[12] For instance, Fama et al. (1969)

$$\tau = \begin{bmatrix} 0 \\ \tau_{n1,2} \\ \vdots \\ \tau_{n1,T} \\ 0 \\ \vdots \\ \tau_{n2,4} \\ \tau_{n2,5} \\ \vdots \\ \tau_{n2,T} \end{bmatrix}$$

Therefore, the effect at each horizon (h) is computed according to the following,

$$\tau_h = \frac{1}{\Omega_{1,h}} \sum_{i=1}^{N \in \Omega_{1,h}} \tau_{ih}$$

Where, $\Omega_{1,h}$ is all the observations such that inflation targeting is implemented in period $h = t - IT^I$ after the introduction of IT and $h = \{0, 1, 2, 3, \dots\}$. Finally, this implies that $\tau_1 = \frac{1}{2}(\tau_{n1,3} + \tau_{n2,5})$. Thus, this methodology doesn't require a normalisation period since we are able to compute the effect on impact as well ($h = 0$).

4.1.1 A note on Identification

Having defined the procedure and formal regression which has been used to estimate the treatment effect, let us turn to the identification procedure. Specifically, checking if the assumptions such as *non-anticiaption* of the policy and *parallel trends* before the introduction of IT, holds for the study.

Anticipation: This is the main threat to identification for the study. In order to circumvent the anticipation effect, the paper uses the announcement date. The announcement (anticipation) date is constructed based on the minutes of the meetings of the monetary policy committees. The date is drafted based on the first time a change in monetary regime to either a Taylor type rule or Inflation Targeting is explicitly discussed. For some countries, there were also studies which were conducted before shifting to Inflation Targeting. For these countries, the paper uses the dates of the study. Addressing the question of anticipation is particularly important since the underlying data is that of Professional forecasters - agents who are well informed about the economy. By using the date of the first discussion of a change in regime one is able to capture the anticipation effect.

Unobserved Heterogeneity (Unit Fixed effects): The study assumes that the unobserved heterogeneity is constant across all the countries. Moreover, this unobserved heterogeneity is zero ($\delta_i = 0$). While a strong assumption, making this assumption is not unreasonable. With a constant gain model having unobserved heterogeneity, would imply that agents would always make mistakes. These mistakes would then have a mean value around which they osciallate, making it difficult to reach the Rational Expectation Equilibrium (which is the inflation target).

Reverse Causality: Second, the treatment effect literature often worries about issues relating to reverse causality (anticipation is a special case). However, the implementation of the policy in most countries was a response to high inflation or high inflation volatility with the objective of anchoring inflation expectations. Prior to the adoption of IT, most countries did not keep track of inflation expectations and did expectations were not a part of monetary policy. Therefore, it is unclear how expectations would have an impact on the introduction of the policy.

Control Group: The study only has data on countries which are treated, resultantly, missing a control group to compute the treatment effect as in the *difference-in-difference* literature. However, this is resolved by using the *not-yet-treated* group as the control for those treated. This implies for a country treated in say, 1999Q1, will have a companion country which is treated in 2010Q3 thus allowing the pre-trends to hold for the country treated in 1999Q1. Since the data set in the paper has countries whose announcement and implementation date range from 1995Q3 to 2016Q3, the study is able to build a credible control group.

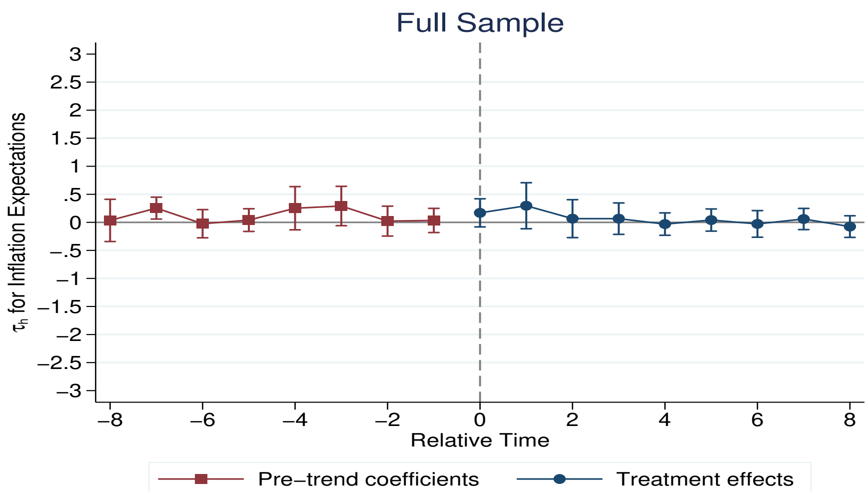
Finally, there are a few important *limitations* to address before discussing the results and stylised facts of the paper. First, the data is low frequency data, since the survey is a quarterly survey. This means there could be changes that could occur during a quarter which would could manipulate expectations, limiting the effect of the policy. Second, the data used is a survey. As with any survey, there will be a degree of measurement error. One redeeming factor of the survey is that it is based on professional forecasters. Therefore, given forecasters have a stake in how well their expectations perform, the contribution of the error should be minimal. Finally, given the data is from professional forecasters there is an open debate in the literature on whose expectations to consider while thinking about the monetary policy framework. This paper is unable to answer this question owing to data availability. Let us now turn to the stylised facts derived from the study and their implications.

4.2 Implementation

Figure 5 and 6 present the first set of findings. The red dots and confidence interval lines represent the period before IT while the blue dots and lines portray the post targeting period or the treatment period. First, the pretrends assumption is not violated since the confidence intervals cross zero. Second, after the introduction of IT there is no change in the level of inflation expectations. The magnitude remains similar to before IT and the results are insignificant.

Fact 1: *Inflation expectations do not respond to the implementation of the policy.*

Figure 5: Inflation Expectations Around Implementation



Fact 2: *There is a significant but small change in the forecast errors around the implementation.*

Figure 6: Forecast Errors Around Implementation

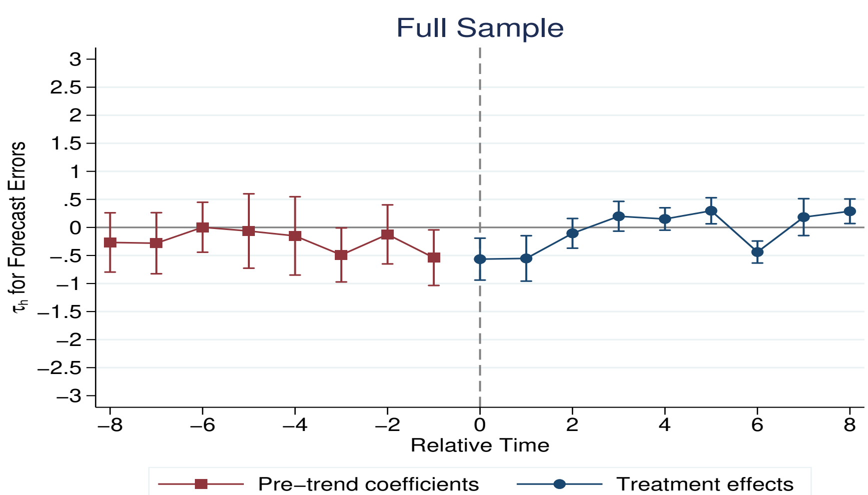
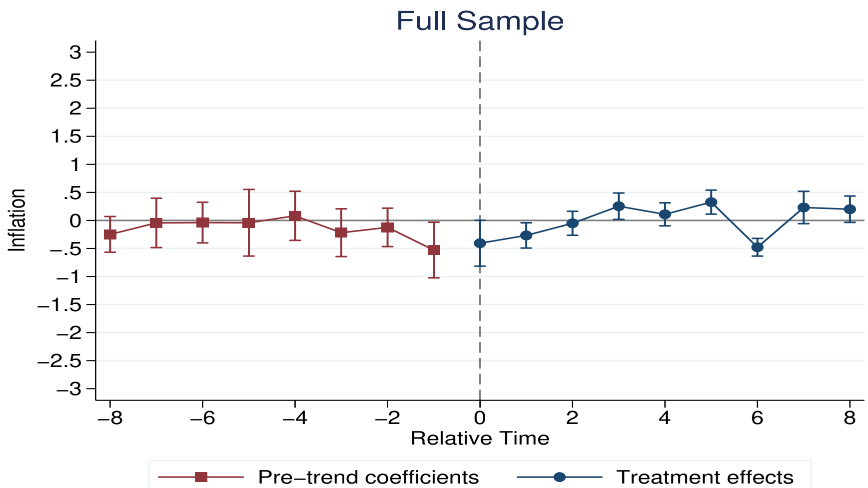


Figure 6 provides support to fact 1 with forecast errors adjusting after the implementation of the policy. In order to decompose this effect, note that forecast errors are defined as realised inflation − inflation forecasts. Therefore, a negative (positive) forecast error implies agents are over predicting (under predicting) inflation. Systematic changes of forecast errors is predictive of two things. First, agents do not form expectations according to the REH. In addition, it enables us to distinguish between changes in expectations that may occur due to inflation as opposed to inflation expectations. Figure 13 represents the path of inflation after the introduction of the policy. The results suggest that inflation declined after the policy was adopted however expectations did not change. As a result, the forecast errors increased with agents overpredicting inflation. This implies, inflation leads inflation expectations as opposed to inflation expectations leading inflation.

Figure 7: Inflation Around Implementation

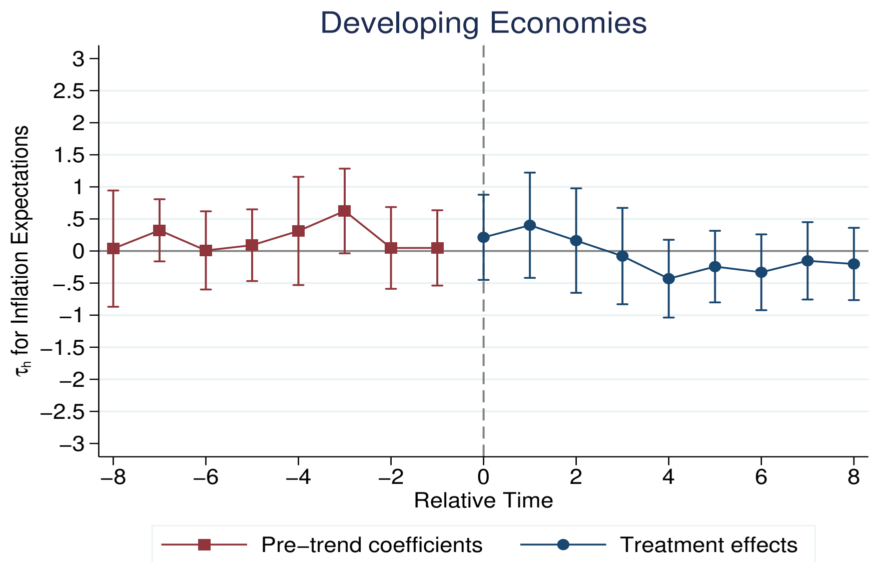


Inflation Targeting is often credited with success in developing economies. This paper tries to test this hypothesis as well. A decrease in the level of expectations for developing economies is to be expected since on average, these economies had higher inflation before the policy was adopted. Figure 8 presents the results from this hypothesis and are similar to those found previously. While there is a decline in expectations, the results are insignificant at the 95% level. Moreover, agents overpredict inflation in these economies (figure 14) upon implementation before the forecast errors return to around zero after roughly one year.

These results suggest two things. First, inflation targeting does not have a direct impact on inflation expectations. However, if countries have a single mandate after about a year of adopting the policy, expectations adjust.

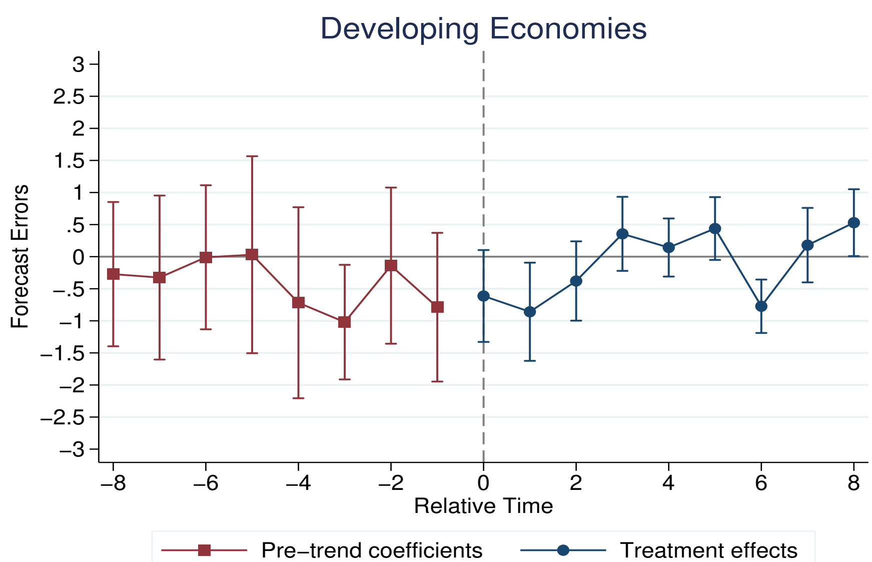
Fact 3: *Any change in expectations is insignificant in developing economies.*

Figure 8: Inflation Expectations Around Implementation



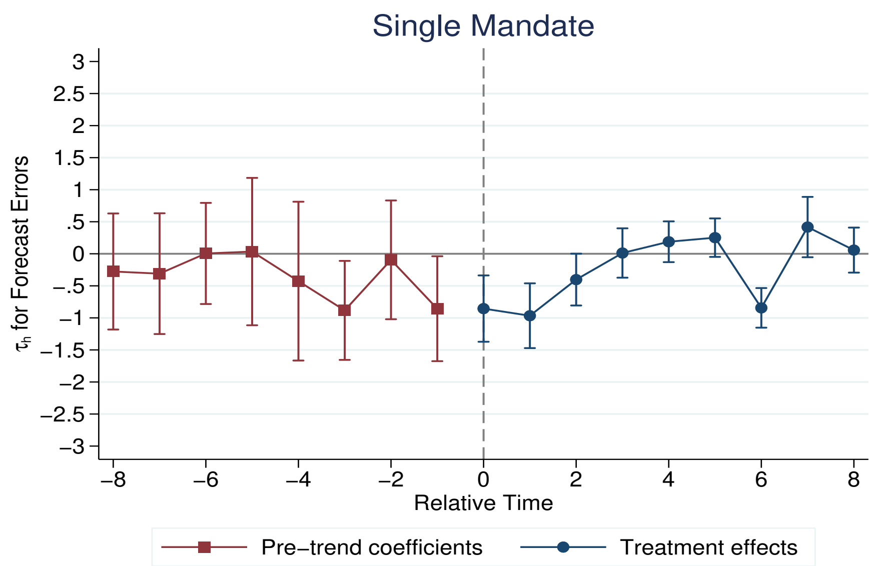
Fact 3a: *Significant but small change in forecast errors in developing economies.*

Figure 9: Forecast Errors



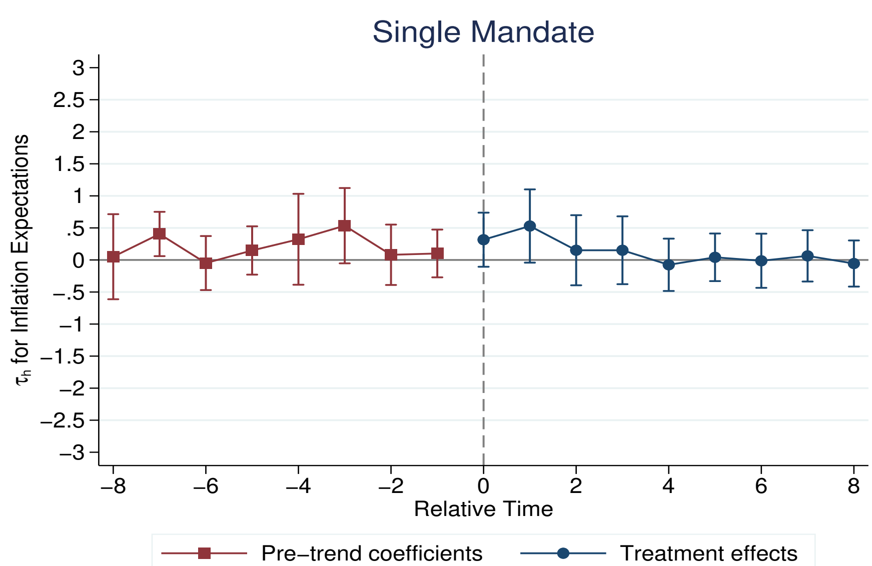
Fact 4: *Forecast errors for those countries whose central banks have single mandates are close to zero a few quarters after implementation.*

Figure 10: Forecast Errors Around Implementation



Fact 4a: *Inflation expectations for countries with single mandates do not adjust significantly after implementation.*

Figure 11: Forecast Errors Around Implementation



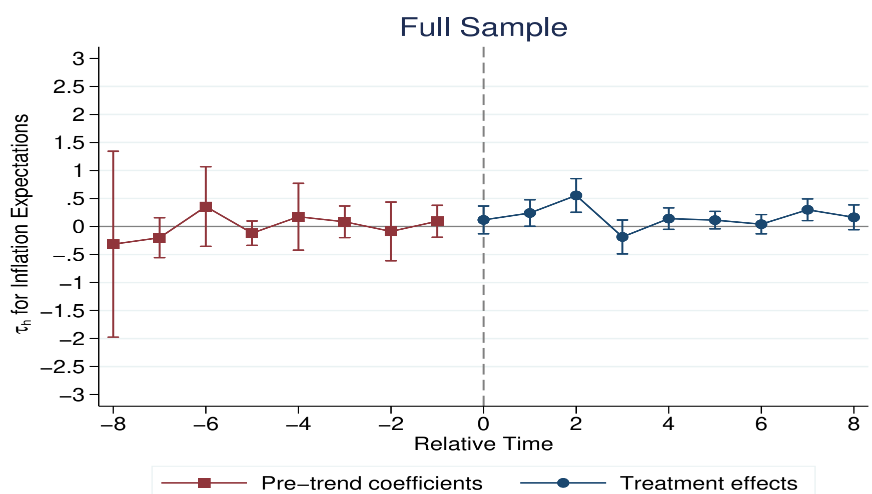
4.3 Announcement (Anticipation)

As discussed above the anticipation of the policy is a concern for determining causality (or lack thereof). Thus, let us now observe the findings from using the announcement dates as the date for agents becoming aware of the new policy. The results based on the date of the announcement are not very different to that of implementation. There is a small and statistically significant uptick in inflation expectations based after two quarters of the announcement. However, soon after, the changes become insignificant. There is however not a clearly distinguishable causal effect of the policy announcement on inflation expectations. This is because several countries preferred to make the announcement to switch to Inflation Targeting when inflation was lower than average[13]. Thus, the exogenous state of the economy dictated the introduction of the policy itself. Thus, this result is in line with the result around implementation of the policy.

Forecast errors around the announcement have the same behaviour as around the implementation, for the full sample. However, the behaviour of the forecast errors for single mandate economies differs slightly from before. On average, figure 15 suggests that agents continue to over predict inflation after the announcement of the policy. The mechanism behind this remains a decline in inflation as opposed to a rise in inflation expectations except for the small uptick in quarter 2.

Fact 1: *There is minimal change in inflation expectations upon announcement.*

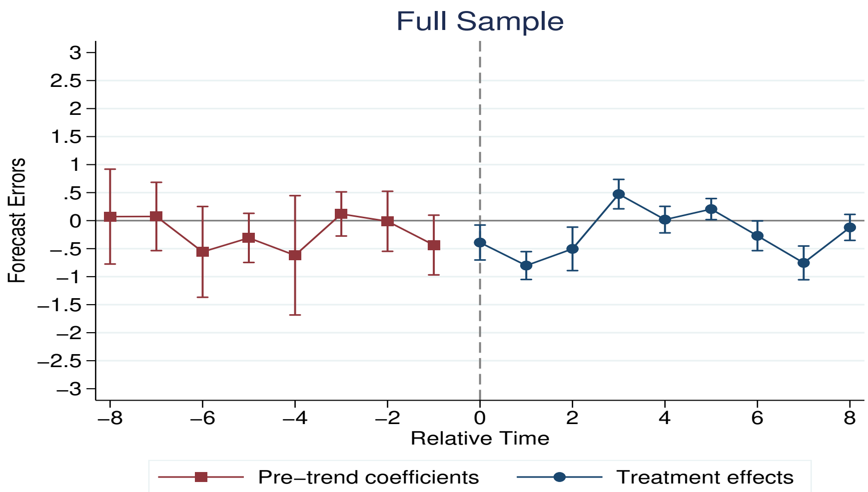
Figure 12: Inflation Expectations Around Announcement



Fact 2: *Forecast errors decline after the announcement of IT.*

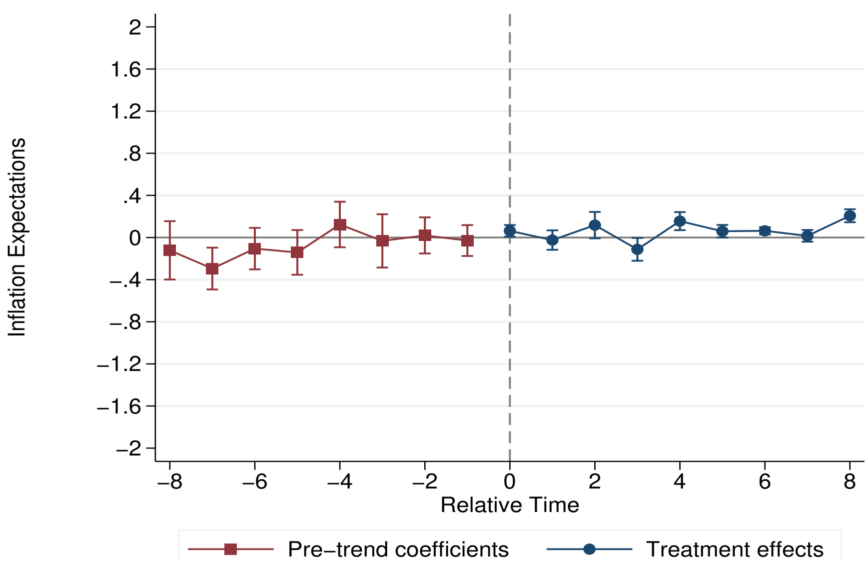
[13]For more details, please see Hammond et al. (2012)

Figure 13: Forecast Errors Around Announcement



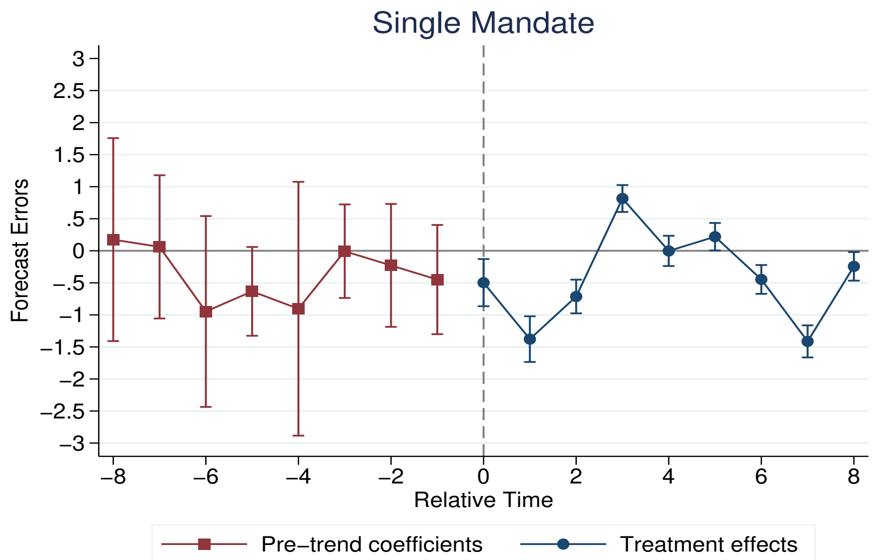
Fact 3: *No change in the advanced economies even after 8 quarters of the announcement.*

Figure 14: Inflation Expectations Around Announcement



Fact 4: *Forecast errors for single mandate countries decline after 3 quarters.*

Figure 15: Forecast Errors Around Announcement



The above stated facts are the key findings of the paper. However, appendix I and J provide a detailed breakdown of each variable observed around the change in policy. In addition, it provides graphs which look at the impact up to five years after the implementation and announcement of the policy. The results remain largely unchanged. One interesting fact arises from looking at the results five years ahead, though. There appears to be some form of cyclicality in inflation and inflation expectations roughly about every two years. This is an aspect that is left for further investigation as this could be influenced by individual countries and their varying adoption dates.

4.4 Dynamic Panel Data

One of the assumptions this paper makes to be able to undertake the analysis in the previous section is to assume, $\alpha_i = \bar{\alpha}$, which is the unobserved heterogeneity for each country. The previous assumption was important because it dealt with the inconsistency of the estimator under the setting of a dynamic panel. Without the previous assumption, equation 13 would need to be estimated using panel data models such as those by Anderson and Hsiao (1981) and Arellano and Bond (1991). The paper now makes the assumption flexible in order to allow for unobserved heterogeneity. Therefore, the estimation now takes the following form in addition to equation (13),

$$\beta_{it} = \delta_i + \beta_{it-1} + \gamma_1 t + \kappa(\pi_{it} - \beta_{it-1}) + \gamma_2 \bar{\pi}_t + \epsilon_{it} \tag{15}$$

The instruments will be for the forecast error since the forecast errors and lagged inflation expectations. The paper uses $(y_{t-1} - \beta_{t-2})$, β_{t-2}, $(\Delta y_{t-1} - \Delta\beta_{t-2})$, $\Delta\beta_{t-2}$ as the instruments for the forecast errors and lagged expectations. The table below presents the results from the Arellano-Bond estimator. Notice, this estimation is not an exact replication of the previous estimation. This is because (15) produces the estimate of a version of the gain parameter. Whereas under Borusyak et al. (2021) the estimate is the treatment effect, τ_t. Moreover, the paper follows the strategy of Borusyak et al. (2021) and performs the estimation in two stages. First, on only pre-IT observations (periods) and then on post-IT observations (periods).

The interpretation of regression (15) is as follows. The left hand side (LHS) of the equation measures the revision of the agents' forecasts. Thus, if the forecast revision responds significantly to the forecast errors, it implies agents are responding to inflation surprises. If this coefficient increases after the introduction of IT, it would suggest low credibility of the central bank. Since, agents should stop responding to significant forecasts errors if the central bank is able to keep inflation close to the target.

Table 3 presents the results from the Arellano-Bond estimation. The table is divided into four columns. Column (1) presents the findings based on the regression for the pre-IT observations. The results suggest that there is a positive correlation between inflation expectations and the forecast errors. Moreover, it is a measure of the gain parameter which is roughly 0.40 and significant at the 5% level. Columns (2) - (4) present the findings for the post IT period after 1 year, 2 years, and for the full sample, respectively. There are two things worth noticing in the post IT results. First, there is a marginal decline in the gain parameter from 0.40 to 0.31. This decline is surprising because if the policy is credible, the agents should immediately adjust their forecasts to reflect new information which should lead to an increase in the gain.

Table 3: Arellano-Bond Estimation results for equation (13)

VARIABLES	Pre-IT	Post-IT		
	(1)	(2)	(3)	(4)
	π_t^e	π_t^e (1 year)	π_t^e (2 years)	π_t^e (Full Sample)
$\pi_{t-1}^e(\rho)$	0.903***	0.954***	0.996***	0.935***
	(0.0616)	(0.198)	(0.097)	(0.045)
$\pi_{t,fe}(\kappa)$	0.402**	0.156	0.226	0.316***
	(0.160)	(0.210)	(0.079)	(0.044)
Constant	0.491	0.152	0.079	0.221
	(0.496)	(0.155)	(0.227)	(0.129)
Observations	947	115	207	1,683
Number of countries	23	23	23	23

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Second, the decline in the gain is not statistically significant for the first 2 years while the full sample has a marginal and statistically significant decline. Therefore, this result supports the result from section 4.3, of no significant change in expectations following an introduction of IT. To change the implementation dates for the announcement dates does not change the result. There is no statistical change in expectations even with an announcement. Results for this regression are provided in Appendix L. One difference between the announcement dates and the implementation dates is the estimated value of the gain for the full sample under the Post-IT regime is significant at the 10% level. However, contrary to what one would expect, the gain falls from 0.473 to 0.305 after the announcement of the policy. Thus, indicative of a lack of credibility of the announcement by the central bank.

Finally, while the estimated value of the gain might seem high relative to what is found in the asset pricing literature (for example, Adam et al. (2016)). The value of the gain is comparable to those found by Gáti (2022).

5 Quantitative Model

The previous results are striking, particularly in comparison to the previous literature which develops on Rational Expectations (Gürkaynak et al. (2010a)). Let us now turn to a quantitative model to check if the announced inflation target is taken into consideration in the PLM of the agents and the weight attached to the target, if any.

5.1 Model Description

Before identifying the process for inflation expectations around the policy change, it is important to first and foremost understand the variation in true inflation during the same period. Thus, allowing for the closest approximation of expectations given the inflation dynamics in a specific country.

Consider an economy, with inflation evolving according to a uni variate unobserved component model,based on Stock and Watson (2007) and Stock and Watson (2016). Specifically, let inflation be the sum of two unobserved components, a trend given by τ_t and a transitory component, ε_t, where the variances of the two disturbances change over time.

$$\pi_t = \tau_t + \varepsilon_t, \text{ where, } \varepsilon_t = \sigma_{\varepsilon,t}\zeta_{\varepsilon,t} \tag{16}$$

$$\tau_t = \tau_{t-1} + \vartheta_t, \text{ where, } \vartheta_t = \sigma_{\vartheta,t}\zeta_{\vartheta,t} \tag{17}$$

$$\ln \sigma^2_{\varepsilon,t} = \ln \sigma^2_{\varepsilon,t-1} + \nu_{\varepsilon,t} \tag{18}$$

$$\ln \sigma^2_{\vartheta,t} = \ln \sigma^2_{\vartheta,t-1} + \nu_{\vartheta,t} \tag{19}$$

$\zeta_t = (\zeta_{\varepsilon,t}, \zeta_{\vartheta,t}) \sim iid(0, I_2)$ and $\nu_t = (\zeta_{\nu,t}, \zeta_{\nu,t}) \sim iid(0, \gamma I_2)$. Moreover, $Cov(\zeta_t, \nu_t) = 0$. Where, γ is a smoothing parameter for the stochastic volatility process.

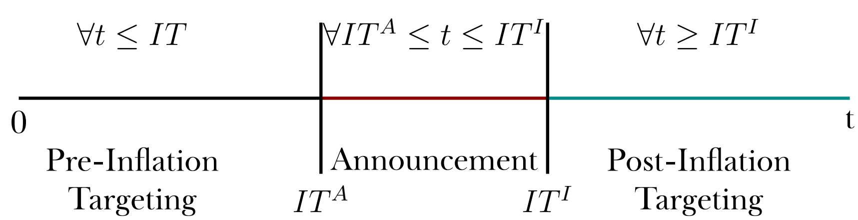
Stock and Watson (2007) argue that post the 1980s a lower order auto regressive process became a less accurate approximation of the inflation process. In addition, they suggest that the changing nature of the processes for inflation requires a time varying process. Thus, developing a model with stochastic volatility. This paper builds on the stochastic volatility model.

The paper assumes that the process for inflation in the pre and post inflation targeting period remains the same. This is because the choice of a stochastic volatility model allows for accounting for a regime shift without imposing one. Specifically, a regime shift would imply, that subject to well anchored inflation expectations, the variance to the trend (or) permanent component of inflation (ϑ_t), will decrease over time. Figure A.1 portrays the evolution of the estimated ϑ_t for Colombia. It portrays a decline in the variance of the permanent shock after the introduction of Inflation Targeting in 1999.

Thus, given the properties of an unobserved components process to map inflation, this paper assumes the same for the model economy. Let us now turn to the timing in the model and the formation of beliefs. Let an economy live infinitely, with the introduction of Inflation targeting at time IT. For all $0 < t < IT$, agents follow one updating rule to compute their forecasts for inflation. For all $t \geq IT$, agents change their updating rule to include the policy change introduced with the new monetary framework.

Figure 16 summarises the model. The only changes that occur post inflation targeting are the changes to the updating equation of the agents. Given that the agents we are modelling are professional forecasters (individuals with extensive knowledge of the economy), one would expect that they use the information provided by the central bank about the inflation target. Section 3.2 provides details on the beliefs structures of the agents of the economy and their updating equations.

Figure 16: Timing of the model



5.2 Belief Formation

Given that the rational expectations hypothesis does not hold with the survey data, I assume a more flexible information structure for the agents. That is, agents have subjective expectations about the evolution of the aggregate price level in the economy and form expectations using an unobserved component model[14].

Pre Inflation Targeting

Consider agents who think that the process for inflation is the sum of a persistent component β_t and a transitory component ϵ_t.

[14]This model is similar to the statistical IMA model introduced by Stock and Watson (2007)

$$\pi_t = \beta_t + \epsilon_t \tag{20}$$
$$\beta_t = \beta_{t-1} + \eta_t \tag{21}$$

Equations (1) and (2) represent the Perceived Law of Motion (PLM) for the agents, $\epsilon_t \sim ii\mathcal{N}(0, \sigma^2_\epsilon)$ and $\eta_t \sim ii\mathcal{N}(0, \sigma^2_\eta)$ are independent of each other and jointly iid. This implies that $E[(\epsilon_t, \eta_t)|I_{t-1}] = 0$, where I_{t-1} includes all the variables in the agents' information set up to $t-1$. Assume that agents' prior beliefs are given by,

$$\tilde{\beta}_0 \sim N(\bar{\beta}_{-1}, \sigma^2_{\tilde{\beta},0})$$

The priors here are computed using a training sample of realised inflation. Regressing inflation on a presample period allows one to avoid over sensitivity of the data to the current temporary shocks. Furthermore, the updating equations are given by,

$$\tilde{\beta}_t = \tilde{\beta}_{t-1} + \kappa(\pi_t - \tilde{\beta}_{t-1}) \tag{22}$$
$$\kappa_t = \frac{\tilde{\sigma}^2_{\tilde{\beta},t}}{\tilde{\sigma}^2_{\tilde{\beta},t} + \sigma^2_{\epsilon,t}} \tag{23}$$
$$\tilde{\sigma}^2_{\tilde{\beta}} = \tilde{\sigma}^2_{\tilde{\beta},t} - \kappa\tilde{\sigma}^2_{\tilde{\beta},t} + \sigma^2_{\eta,t} \tag{24}$$

Where, κ gives the strength at which agents update their beliefs. The choice of using a constant gain learning algorithm to model expectations is in line with the literature. It is commonly noted that a constant gain parameter can track structural changes better than a decreasing gain parameter. However, this comes at an additional cost of increased asymptotic variability. Given that the paper is considering a change in policy regime. It is therefore reasonable to use a constant-gain algorithm.

Furthermore, agents in this model only use past inflation and their forecast error to form expectations about inflation. The paper abstract from using other variables as part of the PLM since with just inflation data the PLM does well in capturing the formation of expectations. This is discussed in detail in the next section.

Under this assumption, agents behave like econometricians and use estimations to forecast future variables. That is they use all available data up to period $t-1$ to estimate β_{t-1}. Then, they forecast y_t.

Equation 22 reflects the model agents use to forecast inflation until period $t < IT$. At $t = IT$, targeting is implemented with an announced inflation target given by π^T (which is known by the agents).

Post Inflation Targeting

Given the change in policy $\forall t \geq IT^I$, the agents adjust their beliefs to include the announced target as follows,

$$\pi_t = \alpha\pi^T + (1-\alpha)\beta_t + \epsilon_t \tag{25}$$
$$\beta_t = \beta_{t-1} + \eta_t \tag{26}$$

Optimal updating then implies that $\tilde{\beta}_t$ evolves recursively according to,

$$\tilde{\beta}_t = \tilde{\beta}_{t-1} + \kappa(\pi_t - \alpha\pi^T - \tilde{\beta}_{t-1}(1-\alpha)) \tag{27}$$
$$\kappa_t = \frac{\tilde{\sigma}^2_{\tilde{\beta},t}(1-\alpha)}{(1-\alpha)^2\tilde{\sigma}^2_{\tilde{\beta},t} + \sigma^2_{\epsilon,t}} \tag{28}$$
$$\tilde{\sigma}^2_{\beta} = (1-\kappa(1-\alpha))\tilde{\sigma}^2_{\tilde{\beta},t} + \sigma^2_{\eta,t} \tag{29}$$

The key difference in the model between equations 20 and 25 is that now the inflation target is an additional source of information that the agents use to form their expectations.

An important note here is that agents change their perceived law of motion (PLM) before and after inflation targeting. The introduction of the inflation target to the Perceived Law of Motion of the agents' beliefs is an important addition. There are two reasons for this difference. First, there was an explicit adoption of the new policy regime with amendments to the objectives of the central bank. Second, the agents being modelled are professional forecasters who have extensive knowledge of the economy. In addition, the aim of IT is the anchoring of inflation expectations. Specifically, reducing the mean and variance of expectations. Therefore, if the agents do not use the inflation target as an additional source of information in their PLMs, it would imply that the expectation channel of monetary policy may not be as strong as it is thought to be.

Another parameter of importance here is the Gain κ. The Gain represents how much agents respond to new information. That is, how quickly they take into account the previous prediction error. The higher the value of the Kalamn Gain, the more weight the agents attach to the recent past. Therefore, $\kappa \approx 1$ would imply agents update their information immediately in every period and discount all previous information. On the other hand, $\kappa \approx 0$ would imply that agents take into account all the information from all the previous periods available to them. This would then imply that agents use a decreasing gain algorithm as opposed to a constant gain algorithm.

The choice of using a constant gain learning algorithm to model expectations is in line with the literature. It is commonly noted that a constant gain parameter can track structural changes better than a decreasing gain parameter. However, this comes at an additional cost of increased asymptotic variability. Given that the paper is considering a change in policy regime. It is therefore reasonable to use a constant-gain algorithm.

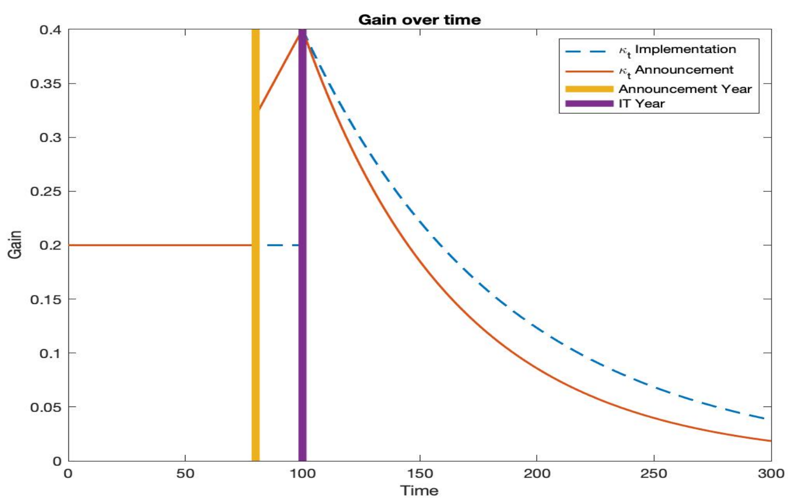
Under this assumption, agents behave like econometricians and use estimations to forecast future variables. That is they use all available data up to period $t-1$ to estimate β_{t-1}. Then, they forecast π_t. Furthermore, agents in this model only use past inflation and their forecast error to form expectations about inflation[15].

[15] Coibion and Gorodnichenko (2015a) show that the Kalman Filter represents the inflation forecasts of professional forecasters well.

Based on the constant gain learning model, figure 17 provides some intuition regarding the change in expectations. The yellow and purple lines represent the date when the change in policy is announced and the date of implementation of the policy, respectively. The dashed blue line and the solid red line represent the potential path of the Kalman gain after the change in policy. Assuming that the Kalman Gain is at steady state prior to the announcement and implementation of Inflation Targeting[16].

As can be seen, there are two possibilities for how inflation expectations adjust (κ) based on past experiences. Under constant gain learning, when agents notice that there has been a change in the policy on implementation and the policy is credible, agents will immediately discount the distant past and adjust expectations quickly. This is what the constant gain ($0 < \kappa < 1$) will capture. The higher (lower) the value of the gain ($\kappa \approx 1$), the more (less) the agents discount the distant (recent) past and use the recent (distant) history to forecast future inflation. Therefore, as central banks continue to build credibility - defined as inflation being at or near its target - after the introduction of Inflation Targeting, agents would become less sensitive to external shocks implying that the constant gain model would eventually become a decreasing gain model.

Figure 17: Hypothesis: Gain over time



The other alternative is that agents believe the announcement as soon as it is made (before the implementation of the policy). Consequently, the constant gain (κ) adjusts before the policy is implemented and then steadily declines as the central bank delivers on its targets and mandate.

This paper therefore exploits two properties of the agents' beliefs. First, introducing the inflation target to the PLM of the agents and therefore a change in the priors. Second,

[16]This is not an unreasonable assumption. Since the period prior to Inflation Targeting witnessed high inflation volatility, one can assume that agents discounted information almost at a constant rate since agents would not necessarily expect policy changes to sustain.

the kalman gain specifically, the weight that agents attach to the inflation surprise agents witnessed in the previous period. Given it can be a measure of elasticity of information. That is, how much agents respond to new information on observing inflation and perceived permanent and temporary shocks.

A drawback of the expectation model is the assumption of the information set of the agents. In addition, the exclusion of the fact that professional forecasters might be able to anticipate the policy of the central bank and incorporate that into their models while forming expectations. Finally, the model for expectations currently assumes that agents expect that inflation is a random walk process. That is, it is extremely persistent. This might be an assumption that could be extreme for the post inflation targeting period since the objective of Inflation targeting was not only to reduce the mean of inflation and inflation expectations. But also the persistence and the volatility of the same. Some of these drawbacks will be addressed in later sections of the paper.

5.3 Quantitative Performance of the Model

Whether the simulated model reflects reality from the perspective of the agents' is something that needs to be tested. Following Adam et al. (2016), Adam et al. (2017) and Duffie and Singleton (1993) this paper uses the Method of Simulated Moments (MSM) to estimate and test the model. Using this method, allows us to focus on the ability of the model to explain specific moments of the data.

One of the objectives of Inflation Targeting as a policy is to reduce the mean, volatility, and persistence of inflation expectations. As table C.2 shows there are several countries where agents over estimate inflation in the pre and post inflation targeting periods. Specifically, countries such as Colombia and the Czech Republic where agents appear to over-estimate inflation after the change in monetary policy. Therefore, we also test the ability of the model to explain the ability the forecast errors. Depending how agents interpret the change in policy (as a temporary or permanent shock), agents could have higher or lower forecast errors.

Therefore, the moments that the paper uses to measure the performance of the model are given by,

$$\hat{\theta}_{pre} = \{\sigma^2_\epsilon, \sigma^2_\eta, \sigma^2_\beta\},\ M_{pre} = \left(\widehat{E(\pi^e)}, \widehat{\sigma_{\pi^e}}, \widehat{\rho_{\pi^e}}, \widehat{E(\pi - \pi^e)}, \widehat{\sigma_{\pi-\pi^e}}, \widehat{\rho_{\pi-\pi^e}}\right)$$
$$\hat{\theta}_{post} = \{\sigma^2_\epsilon, \sigma^2_\eta, \sigma^2_\beta, \alpha\},\ M_{post} = \left(\widehat{E(\pi^e)}, \widehat{\sigma_{\pi^e}}, \widehat{\rho_{\pi^e}}, \widehat{E(\pi - \pi^e)}, \widehat{\sigma_{\pi-\pi^e}}, \widehat{\rho_{\pi-\pi^e}}\right)$$

Accounting for the model above the only free parameters that remain are the variance of the transitory and permanent shocks to inflation expectations which are pinned by the MSM. In addition, the variance of the priors. Moreover, in the post-IT period there is 1 additional parameters which will be pinned by MSM namely, the weights attached to the target in the beliefs (α).

Let $\hat{S}_N \in R^s$ denote the sample moments that will be matched in the estimation with N denoting the sample size and $s \leq 6$. Furthermore, let $\tilde{S}(\theta)$ denote the moments implied by the model for some parameter θ. The MSM parameter estimate $\hat{\theta}_N$ is defined as,

$$\hat{\theta}_N = \arg\min_{\hat{\theta}}[\hat{S}_N - \tilde{S}(\theta)]'\hat{\Sigma}^{-1}_{S,N}[\hat{S}_N - \tilde{S}(\theta)] \tag{30}$$

The estimate of $\hat{\theta}$ chooses the model parameter such that that the model moments $\tilde{S}(\theta)$ fit the observed moments $\hat{S}_N$ as closely as possible in terms of a quadratic form with a weighting matrix $\hat{\Sigma}^{-1}_{S,N}$.

The variance-covariance matrix given by $\hat{\Sigma}_{S,N}$ is an estimate of the variance-covariance of the sample moments $\hat{S}_N$. The Newey West estimator is used to compute the matrix of moments of the sample. The variance of the for the sample statistics is given by the following,

$$\hat{\Sigma}_{S,N} \equiv \frac{\partial S(M_N)}{\partial M'}\hat{S}_{w,N}\frac{\partial S(M_N)'}{\partial M} \tag{31}$$

Where, M_N contains the sample moments and $\hat{S}_N$ contains any functions of these moments. For example, M_N would contain the $\hat{v}ar(\pi^e_t)$ and $\hat{S}_N$ contains the serial correlation of inflation.

This approach also provides an overall test for the model. Under the null hypothesis that the model is correct, we have

$$\hat{W}_N \equiv N[\hat{S}_N - \tilde{S}(\hat{\theta}_N)]'\hat{\Sigma}^{-1}_{S,N}[\hat{S}_N - \tilde{S}(\hat{\theta}_N)] \to \chi^2_{s-4} \text{ as } N \to \infty \tag{32}$$

It is important to note that for the method of simulated moments, one requires the property of geometric ergodicity to be satisfied. This paper uses the results from Adam et al. (2016) and Duffie and Singleton (1993) to allow for an asymptotic distribution for constant gain models.

5.4 Discussion

Figure 18 - 21 and Tables 4, 5 present the results from the preliminary model presented in Section 3. The graphs in Figure 21 plot the model implied inflation (solid line) and the model implied inflation expectations (dashed line). There are a few things to notice from the results. First, in the pre-inflation targeting period, expectations are unable to capture some of the volatility in inflation. However, this is not true in the post IT period.

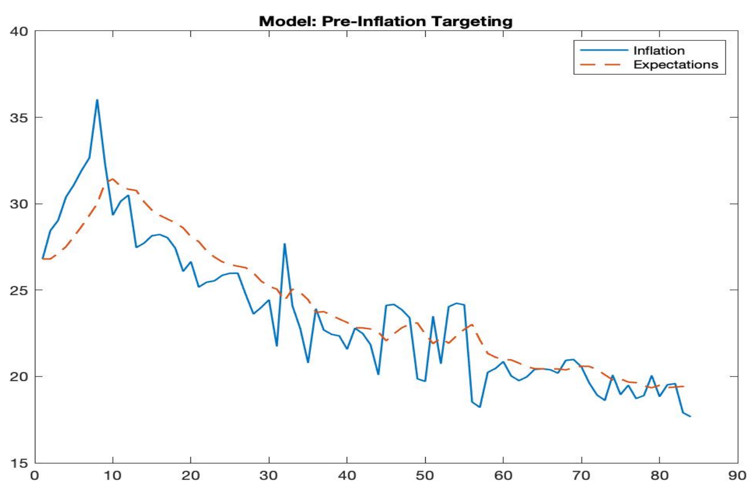
This inability to capture the volatility in inflation might be reflective of the inflation bias that has received significant attention in the literature. Given several of these countries experienced episodes ranging from high to hyperinflation. This could make it much harder to forecast inflation and therefore harder to pin down a model that could match the expectations.

On the other hand in a seminal paper, Marcet and Nicolini (2003) show that adaptive learning models are effective in being able to explain the hyperinflation periods witnessed by several Latin American countries in the 80s and 90s. One key difference between the model for the pre-IT period in this paper and Marcet and Nicolini (2003) is the measure used to predict prices. Before Inflation Targeting was introduced, in several countries, the measure for monetary policy was the Money Supply as opposed to the interest rate. This fundamental distinction could be the reason for the simple model in this paper not being representative of the pre-Inflation Targeting period.

As noted above, in the pre-inflation targeting period there were different instruments that were used to control prices. For instance, some countries used the money supply as a measure others used the interest rate but with the "wrong" coefficients on the Taylor Rule. Resultantly, there would be a difference in the information sets that the agents use to forecast inflation prior to and post the adoption of inflation targeting.

It is important to note here that we are making two assumptions about the post inflation targeting period. First, the target is publicly announced and the agents have complete knowledge about the target. Second, the target is time invariant. That is, the central bank commits to using the same target until the end of the regime. These assumptions are innocuous since one of the objectives of the IT framework is to have a publicly announced inflation target. However, in practice, there are several countries[17] that evaluate the inflation target on an annual basis. The implications of a changing target are not captured at this moment.

Figure 18: Model based Inflation and Inflation Expectations Pre-IT



[17] For instance, Brazil, Chile and Colombia

Figure 19: Model based Inflation and Inflation Expectations: Post-IT based on the pre-IT model

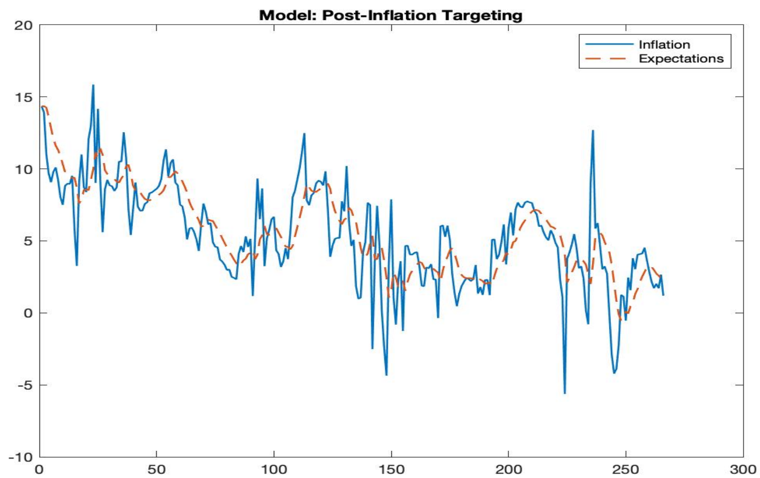


Figure 20: Model based Inflation and Inflation Expectations: Post-IT

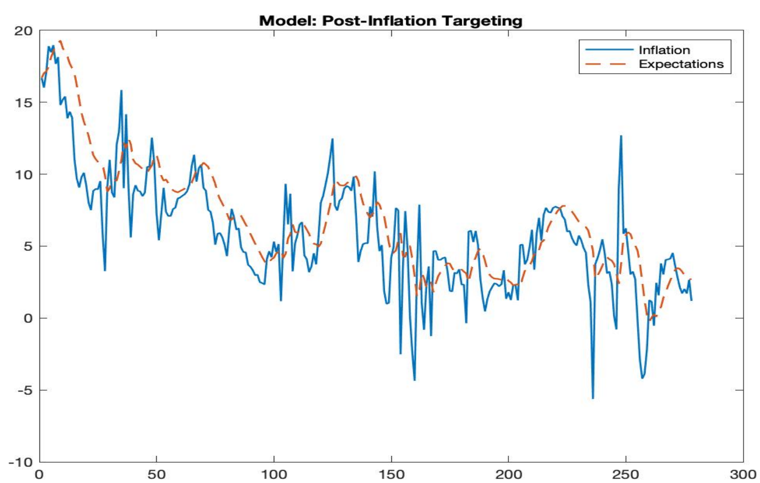
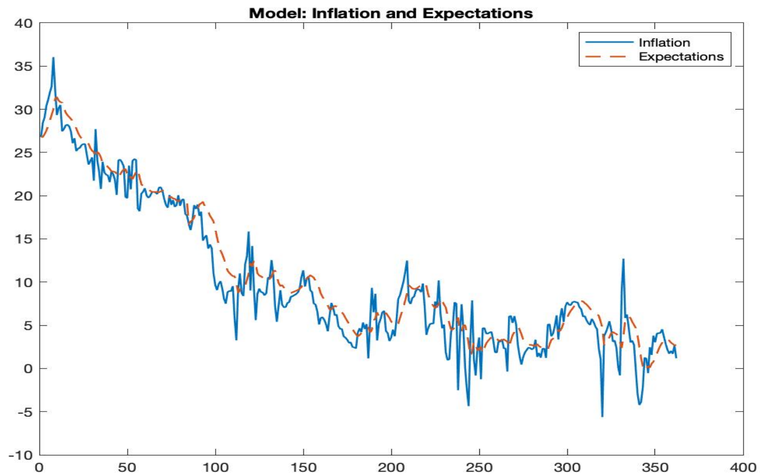


Figure 21: Model based Inflation and Inflation Expectations: Full Sample



One of the key differences between figure 19 and 20 is the model used for post IT. The former uses the model without including the inflation target while the latter uses the model with the inflation target. On a cursory look, one can see that the model which uses the inflation target tends to have inflation expectations overshoot inflation at different times. Thus, possibly indicating that the target might force a larger forecast error for agents.

However, in order to differentiate the models and check which one works better, we use information from the Method of Simulated Moments.

Table 4: Moments

	Pre-IT		Post-IT	
Moment	Model	Data	Model	Data
$\widehat{E(\pi_t^e)}$	22.67	22.03	5.78	5.636
$\widehat{\sigma_{\pi_t^e}}$	1.92	2.87	4.64	3.041
$\widehat{\rho_{\pi_t^e}}$	0.938	0.447	0.82	0.780
$\widehat{E(\pi_t - \pi_t^e)}$	0.570	0.684	-0.35	-0.366
$\widehat{\sigma_{\pi_t - \pi_t^e}}$	0.871	1.65	0.049	1.395
$\widehat{\rho_{\pi_t - \pi_t^e}}$	0.216	0.217	0.417	1.017

Table 4 portrays how well the model captures inflation expectations and the forecast error, pre and post targeting for Colombia. While the unobserved component model is able to match the mean of inflation expectations in the pre-IT period, it fails in capturing the variance and persistence of the same. In addition, the model captures over prediction in the agent's beliefs, whereas the data suggests agents are continuously surprised by inflation. Similar patterns exist in the post inflation targeting period but the model which includes the target is able to match the data moments better than the model without.

However, these results, require some additional changes[18], which are currently a work in progress.

One of the cornerstones of Inflation Targeting as the monetary policy framework is the anchoring of inflation expectations. In the context of the model, well anchored expectations would imply that the Kalman Gain should be small. That is, the agents believe that the shocks to the economy are temporary and inflation will revert to the mean, which is the target. Under the assumption of perfect anchoring, one would expect that the Kalman Gain is zero. That is, any shocks to inflation are temporary and the agents believe in the ability of the central bank to impact inflation and achieve the target in the next period.

Another result that would arise from the properties of learning models and the Kalman Gain is the reaction to a change in policy. Given that the gain parameter measures how much agents react to new information, one can anticipate that the adoption of Inflation Targeting would lead to a high gain parameter as soon as the policy is adopted. If the agents believe the central bank and the monetary policy regime is credible. The gain parameter will not show significant changes if the agents do not believe the change in monetary policy regime and believe that the shocks to inflation are permanent in nature. Therefore, agents would react to changes inflation the same way before and after inflation targeting.

Table 5: Parameters

Parameters	Pre-IT	Post-IT		
		2 years	5 years	Full Sample
κ	0.0553	0.057	0.110	0.639
α	-	0.10	0.109	0.113

Table 5 provides the results of the Kalman Gain for three different samples namely, pre Inflation Targeting and post Inflation Targeting. The results for the post inflation targeting period are split into three. This is to see the evolution of the Kalman Gain over time. It is possible to directly introduce a time varying gain to the model. However, given that a time varying gain would require a large number of parameters one for every period, there would be a degrees of freedom problem with the estimation. To circumvent the cost of a time varying gain, the paper uses varying time periods to estimate the speed of adjustment. The sample is split into two periods after the implementation of inflation targeting, five years after the implementation and using the full sample available post the implementation.

Contrary to what the hypothesis in Figure 17 suggests, we find the Kalman Gain is increasing over time. That is agents react more to recent news and update their forecasts at a higher rate. This results suggests two aspects. First, agents are constantly surprised by inflation, the further away the economy is from the implementation date. As a result and

[18]The results require the inclusion of data from other countries and a change to panel data. Currently, the results are based on Colombia. In addition, some testing to ensure the results are statistically significant.

second, inflation expectations are not anchored. Perfect anchoring would require that the gain parameter $\kappa \approx 0$. However, as can be seen, the gain parameter is closer to 1. This is result is surprising and not, at the same time. First, the result is in line with recent evidence on anchoring from Kumar et al. (2015), Coibion et al. (2020). However, it is surprising because the survey evidence in this paper is based on professional forecasters agents who are better informed about the state of the economy as well as the policy. One reason for this discrepancy might be that all the effect is taken in at the time of the announcement and with central banks successively implementing the policy, the interpretation of the actions might differ[19]

Finally, if one were to convert the gain parameter to check the length of period for which the data is used. The model suggests that on average agents use about 20 quarters worth of data to predict future inflation[20]. This calculated based on $\frac{1}{\kappa}$, which is the halving time for the constant gain algorithm. That is, after the first 5 years, less than 50% of the data is used for the computation of the forecast, in the pre and post IT period. Which decreases to about 2 quarters if one were to consider the full sample period after the adoption of the policy. However, the full sample also contains periods from the financial crisis, where agents might have been more sensitive to any new information. For the moment, the paper does not deal with this aspect of the economy and expectations.

6 Robustness Checks

The main finding of the paper is surprising and not encouraging for central banks. Therefore, performing robustness tests becomes more critical. The following section provides details on the different robustness exercises that the paper undertakes. There are two main categories. The first set of checks uses different definitions of rational expectations to check for changes in the policy. Second, different estimators are used as a way to ensure that the results are not in fact driven by the methods used.

6.1 Forecast Revisions and Forecast Errors

Adapted from the FIRE framework and in line with adaptive learning, it is possible to run the following regression by a re-write of 13 in the following way,

$$\underbrace{\beta_{it} - \beta_{it-1}}_{\text{Forecast Revision}} = \bar{\alpha} + \kappa\underbrace{(y_{it} - \beta_{it-1})}_{\text{Forecast Errors}} + \gamma_1 t + \gamma_2 \bar{\pi}_t + \epsilon_{it} \tag{33}$$

Writing (33) allows one to measure the gain directly by using a form of the Huber-Robust regressions as suggested by Coibion et al. (2020) to control for any outliers in the data. The regression is adjusted in the following way to compute the gain parameter.

[19] This is currently work in progress.
[20] Based on Ormeño and Molnár (2015)

$$\underbrace{\beta_{it} - \beta_{it-1}}_{\text{Forecast Revision}} = \bar{\alpha} + \bar{\alpha}\mathbb{1}_{t \geq t^*} + \kappa\underbrace{(y_{it} - \beta_{it-1})}_{\text{Forecast Errors}} + \underbrace{\kappa_{IT}(y_{it} - \beta_{it-1})\mathbb{1}_{t \geq t^*}}_{\text{Forecast Errors after IT}} + \gamma_1 t + \gamma_2 \bar{\pi}_t + \epsilon_{it} \quad (34)$$

Using the break point as the announcement and implementation date for each country. The key finding is that for most countries the changes after the implementation or announcement are insignificant. There are some countries which find an increase in the estimated gain after IT is announced and implemented. Thus, this result supports the finding that there is no change with either implementation of announcement of the policy. The table below presents the results for a select few countries where there are some significant changes.

Tables 6 and 7 report the findings of regression (34) for Colombia and the US. It can be seen that the gain parameter (κ - coefficient on the forecast errors) does not have a significant change after the policy introduction. The same is also true when using the anticipation dates of IT. Thus, the results are robust to this new definition.

6.1.1 Volatility of Expectations

Apart from anchoring expectations around the inflation target the goal of IT is to reduce the volatility of inflation expectations. To measure the change in volatility of expectations, this paper follows a regression similar to Gürkaynak et al. (2010a). The previous paper suggests regressing a change in inflation compensation on the surprise component of macroeconomic data and policy announcements. Formally, the regression is of the form,

$$\Delta\beta_t = \bar{\alpha} + \gamma_1(y_t - \beta_{t-1}) + \gamma_2\mathbb{1}_{t \geq t^*} + \epsilon_t \quad (35)$$

Here, γ_1 and γ_2 are the parameters of interest. Since these capture the effect of inflation surprises on the volatility of expectations. Note, if one were to re-write equation 35, it would lead to equation 33. And as shown before, this regression leads to the result of no significant change in the level of volatility of expectations after the implementation or adoption of the policy.

Table 6: Forecast Revisions on Forecast Errors: Colombia

(a) Implementation

VARIABLES	1	2
Forecast Errors	0.213***	0.413
	(0.0584)	(0.334)
Cons$*\mathbb{1}_{t\geq t^*}$		0.715**
		(0.310)
FE$*\mathbb{1}_{t\geq t^*}$		-0.361
		(0.111)
Constant	0.0217	0.0429
	(0.0855)	(0.0898)
Observations	115	115

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Forecast Errors	0.213***	0.292***
	(0.0584)	(0.0183)
Cons$*\mathbb{1}_{t\geq t^*}$		0.728***
		(0.0724)
FE$*\mathbb{1}_{t\geq t^*}$		-0.0759
		(0.0533)
Constant	0.0217	0.616***
	(0.0855)	(0.0775)
Observations	115	115

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Forecast Revisions on Forecast Errors: United States

(a) Implementation

VARIABLES	1	2
Forecast Errors	0.0722**	0.0687**
	(0.0311)	(0.0339)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.0451
		(0.0486)
FE$*\mathbb{1}_{t\geq t^*}$		0.00428
		(0.0497)
Constant	-0.0153	0.222***
	(0.0220)	(0.0276)
Observations	115	115

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Forecast Errors	0.0722**	0.0706*
	(0.0311)	(0.0366)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.00952
		(0.0463)
FE$*\mathbb{1}_{t\geq t^*}$		9.36e-05
		(0.0704)
Constant	-0.0153	0.224***
	(0.0220)	(0.0274)
Observations	115	115

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6.2 FIRE Framework

In addition to the regression in the previous section above, one can check the coefficients of the *Full Information Rational Expectations (FIRE)* framework. Following, Coibion and Gorodnichenko (2015a), Bordalo et al. (2020) the following test is run.

$$\underbrace{y_{it} - \beta_{it-1}}_{\text{Forecast Errors}} = \bar{\alpha} + \bar{\alpha}\mathbb{1}_{t \geq t^*} + \gamma_\kappa \underbrace{(\beta_{it} - \beta_{it-1})}_{\text{Forecast Revision}} + \underbrace{\gamma_{\kappa_{IT}}(\beta_{it} - \beta_{it-1})\mathbb{1}_{t \geq t^*}}_{\text{Forecast Revision after IT}} + \gamma_1 t + \gamma_2 \bar{\pi}_t + \epsilon_{it} \quad (36)$$

The regression above is based on the idea that forecast errors should not be predictable by the forecast revisions. One can run the test for each country to check if there have been changes in the predictability of forecast errors. This would capture any changes that might have occurred post the announcement and adoption of IT and therefore an impact of the policy.

Similar to the findings in section (6.1) there is no pattern in the way there are changes in the predictability of forecast errors. However, for some countries such as Colombia and the US, forecast errors have become more predictable after IT compared to before the announcement. The tables below (8 and 9) present the results for Colombia and the US. The results do not alter significantly if using the date of intervention as the announcement or the implementation of the policy.

Table 8: Forecast Revisions on Forecast Errors: Colombia

(a) Implementation

VARIABLES	1	2
Forecast Errors	0.0699	-0.356
	(0.185)	(0.436)
Cons$*\mathbb{1}_{t \geq t^*}$		-0.204
		(0.540)
FE$*\mathbb{1}_{t \geq t^*}$		1.073**
		(0.468)
Constant	-0.283**	-0.0297
	(0.128)	(0.988)
Observations	115	115

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Forecast Errors	0.0699	1.545***
	(0.185)	(0.235)
Cons$*\mathbb{1}_{t \geq t^*}$		-1.559***
		(0.279)
FE$*\mathbb{1}_{t \geq t^*}$		-1.459***
		(0.307)
Constant	-0.283**	1.225***
	(0.128)	(0.171)
Observations	115	115

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Forecast Revisions on Forecast Errors: United States

(a) Implementation

VARIABLES	1	2
Forecast Errors	0.742***	0.844***
	(0.227)	(0.156)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.0957
		(0.214)
FE$*\mathbb{1}_{t\geq t^*}$		-1.395***
		(0.495)
Constant	-0.176**	0.756***
	(0.0846)	(0.0839)
Observations	115	115

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Forecast Errors	0.742***	0.563
	(0.227)	(0.410)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.155
		(0.171)
FE$*\mathbb{1}_{t\geq t^*}$		0.226
		(0.464)
Constant	-0.0525	-0.344**
	(0.0719)	(0.155)
Observations	115	115

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6.3 New versus Old Targeters

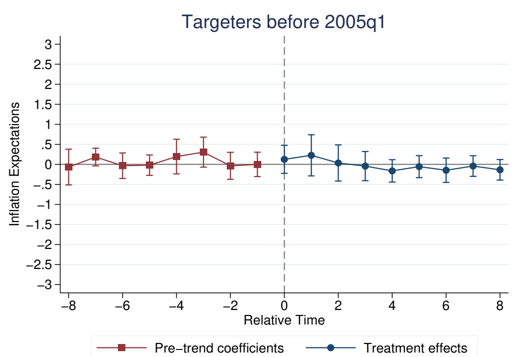
One of the features that is exploited in the event study is the different start dates of the policy. The different dates allow for the construction of the hypothetical which considers how the economies would respond if the policy was not implemented. However, there is one big factor that plays a role in these days. Some of the countries adopted IT after the financial crisis while others in the late 90s and early 2000s. The nature of global shocks was different at both these times. In addition, countries which adopted targeting later had evidence from previous adopters on how implementation. Therefore, this paper now tests whether new adopters of the policy had an advantage and if they were able to capitalise on it.

The data set is now split as per countries which adopted targeting before and after 2005Q1 (as per the announcement date). 2005Q1 is roughly the middle date of the sample period and allows the econometric methodology to still hold with a variety of adoption dates.

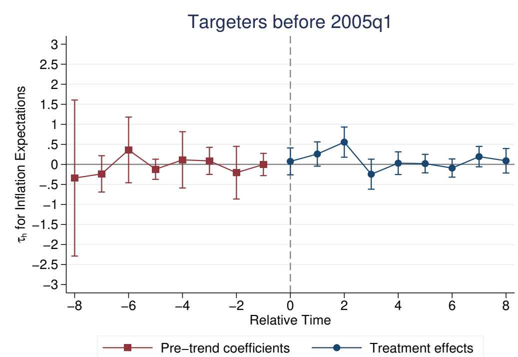
Figure 22 presents the findings upon dividing the sample between those who adopted targeting prior to and post 2005q1. An additional variable that controls for the Great Financial Crisis (GFC) is used to capture any effects of the time effects of the crisis. The results remain the same as those found previously. There is no significant change in inflation expectations on announcement or implementation of the policy. One interesting feature of this study however is the increased volatility of expectations for the countries which adopt IT after 2005q1.

Figure 22: Old and New Targeters: Inflation Expectations

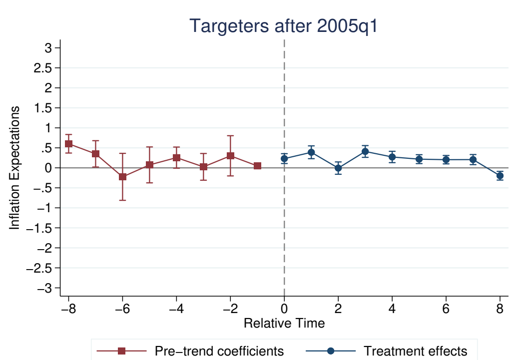
(a) Implementation: Old



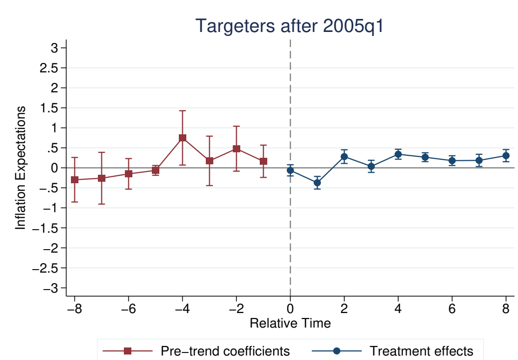
(b) Announcement: Old



(c) Implementation: New



(d) Announcement: New



6.4 Central Bank Transparency

Credibility is an important factor for inflation expectations. A simple example of this is the experience of the Latin American economies prior to the independence of the central bank. While monetary policy was still under the government's control, monetary policy had a credibility crisis and there were hyper inflationary cycles. However, after the independence of the central bank many of these countries have seen a steady decline in inflation[21].

While there are no direct measures available for the credibility of the central bank, there is an index of transparency and independence created by Dincer and Eichengreen (2013). This paper uses the index as a proxy for central bank credibility. The more transparent and independent the central bank, the higher the control it has on monetary policy and the ability to reach its objective, thus, making this variable a good proxy. Formally, the following regression is run,

$$\beta_{it} = \bar{\alpha} + \beta_{it-1} + \kappa(y_{it} - \beta_{it-1}) + \gamma_1 t + \gamma_2 \bar{\pi}_t + \gamma_3 TR + \epsilon_{it} \tag{37}$$

Where, the variables except TR which, measures the transparency of the central bank, are the same as before. The data is available from the period 1998-2019 and is available for all countries except those which are part of the European Monetary Union (EMU), Paraguay, and Uruguay. There is a combined index available for the EMU. However, given the countries announced the implementation of IT in different years, this paper does not include the data for the EMU. Moreover, given the index for central bank transparency is available for a shorter period, the regression is based on a shorter set of countries. The countries used for this analysis are Hungary, India, Japan, Korea, Mexico, Norway, Philippines, South Africa, Switzerland, Thailand, and the United States. An important caveat to highlight here is that the data being used is not weighted by the country GDP or population. The weighted data is not as freely available and is left for further research.

Figure 23 show the findings of the paper when central bank transparency is controlled for in the regression. The result for the implementation date remains unchanged. There is no significant change in expectations when the policy is introduced. On the other hand, there is a significant decline in expectations when the policy is announced. However, this decline is not sustained and overturns the following quarter albeit, at a lower level then prior to the announcement.

It is key to note here that the sample is significantly reduced making it difficult to draw convincing conclusions of the effect of central bank transparency. Therefore, the paper very cautiously amidst that there is a decline in the level of expectations.

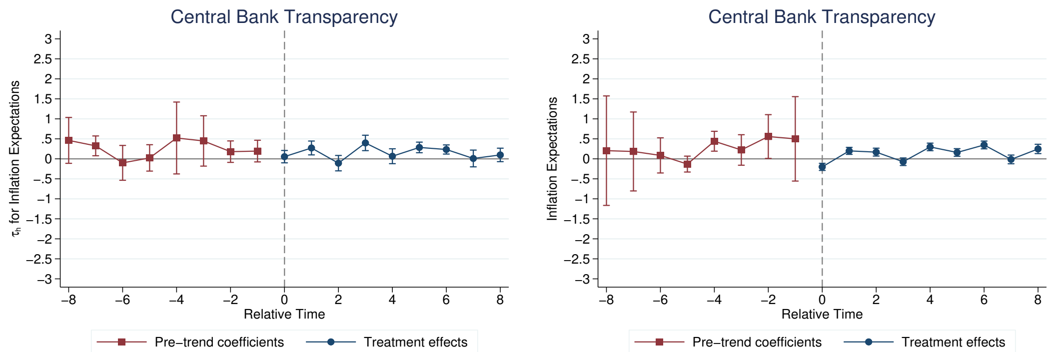
6.5 Other Estimators

The last couple of years have seen a burgeoning literature on the Two Way Fixed Effect literature with an effort to correct the bias in event studies. Two such studies are those

[21] Duggal and Rojas (2022) show how credible announcements led to a decline in expectations.

Figure 23: Inflation Expectations After controlling for Transparency

(a) Implementation (b) Announcement



of Sun and Abraham (2021) (SA) and Callaway and Sant'Anna (2021) (CS). One key difference between Borusyak et al. (2021) and SA, CS is how the data is used to construct the control group.

First, both CS and SA are group based estimators. That is, the data is grouped according to the year the policy is implemented. Given that the panel data being used in this study is small, this is a limitation to use the estimators. Second, both estimators aim to balance data in event time. This leads to a loss of further information for this study. This can lead to two problems, larger standard errors and inconsistent estimates. Since the imputation strategy in Borusyak et al. (2021) requires one to regress the treatment group to build the control group from all the periods before implementation, the estimator is more robust for this study.

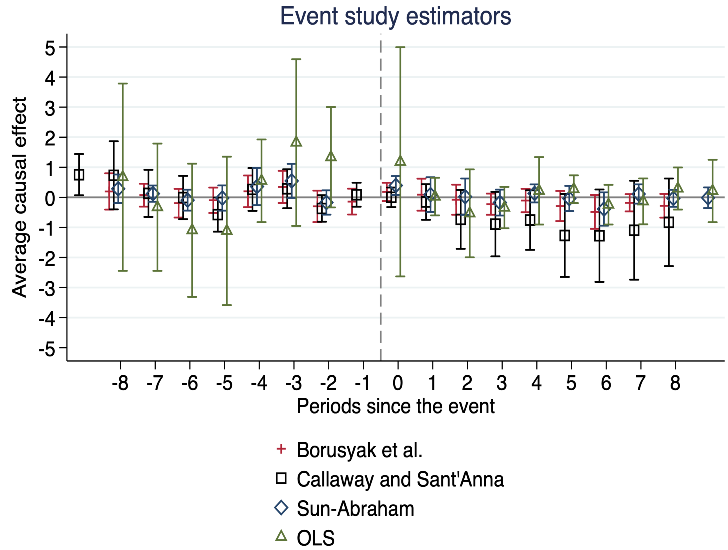
Nonetheless, figure 24 presents findings based on 4 different estimators those by OLS, Sun and Abraham (2021), Callaway and Sant'Anna (2021) and Borusyak et al. (2021). As expected, OLS has the worst performance in terms of the estimates and the standard errors. While all estimators provide no evidence of a change in expectations it is important to rely on the estimator which enables the use of the most data.

7 Conclusion

Employing an adaptive learning model and the event study methodology, the paper studies the response of inflation expectations to a change in the monetary policy regime. Specifically, it studies whether agents discount the distant past information in favour of the commitment made by the central bank on keeping inflation low.

The paper finds that countries with a single mandate are able to adjust short-run forecast errors. However, this change in forecast errors is a result of an adjustment in inflation and not inflation expectations. Therefore, the paper delineates that Inflation Targeting does not directly impact short-run expectations. Several robustness checks carried out on

Figure 24: Treatment Effect of Implementation



the bases of different estimators and definitions also further consolidate this result. Using a simple

While striking there are some limitations of the results. First and foremost, the data used is for a short-run horizon as opposed to long-run data. This is an important drawback since the purpose of Inflation Targeting is to anchor long-run expectations. However, as Carvalho et al. (2021) comment, short run expectations have a direct impact on how anchored on unanchored inflation expectations are. In addition, at the moment the paper is assuming a constant kalman gain. While convenient, it is a potential channel through which adjustment might be taking place and therefore leading to the result which suggests expectations are not the channel impacting inflation. Resolving these issues are left for further research. Finally, further research aims to build a model that can exploit a change in inflation but not expectations.

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Appendices

A List of IT Countries

Table A.1: List of IT countries

Name of Country	Start Year	Announcement Year
Argentina	2016Q3	2015Q4
Austria	1999Q1	1998Q2
Belgium	1999Q1	1996Q1
Brazil	1999Q2	1995Q4
Chile	1999Q3	1990Q3
Colombia	1999Q1	1993Q1
Czech Republic	1998Q1	1997Q4
Finland	1995Q1	1993Q1
Germany	1999Q1	1998Q1
Hungary	2001Q3	2001Q2
India	2016Q3	2015Q1
Ireland	1999Q1	1997Q1
Israel	1997Q2	1994Q3
Italy	1999Q1	1998Q1
Japan	2013Q1	2012Q1
Korea	1999Q1	1998Q2
Mexico	2001Q1	1998Q1
Netherlands	1999Q1	1998Q1
Norway	2001Q1	1999Q2
Paraguay	2011Q2	2004Q2
Peru	2002Q1	1994Q1
Philippines	2002Q1	2001Q4
Poland	1999Q1	1998Q1
Russia	2014Q1	2013Q3
South Africa	2000Q1	1999Q2
Spain	1997Q1	1994Q4
Switzerland	2000Q1	1999Q3
Thailand	2000Q2	2000Q1
Turkey	2002Q1	2001Q2
Ukraine	2016Q1	2015Q3
United States	2012Q1	2008Q4
Uruguay	2007Q3	2004Q4

Source: Central Bank websites and IMF. These are the countries used in this study.

B Inflation Targeting

A country is called an Inflation Targeter (Hammond et al. (2012)) when the following conditions are met.

1. Price stability is recognised as the explicit goal of monetary policy.
2. There is a public announcement of a quantitative target for inflation.
3. Monetary policy is based on a wide set of information, including an inflation forecast.
4. Transparency
5. Accountability mechanisms.

C Country Classification

The following table details three different classifications for each country. First, whether each country is advanced or developing. Second, whether each country has a single or dual mandate. Third, whether the country has experienced an episode of hyperinflation.

The classification of a country as developing or advanced is based on the UN country classification. The distinction between countries who have single mandates and those with dual mandates (or flexible targets) is based on the mandates available on the central bank websites. A country has been classified as one with hyper inflationary episodes if it has ever had inflation greater than 50%, in the sample period.

Note: The final data used for the event study analysis excludes the countries that have had episodes of hyperinflation in the period covered by the data set.

Table C.2: List of IT countries

Name of Country	Development Status	Mandate	Hyper Inflation
Argentina	Developing	No-mandate	Yes
Austria	Advanced	Dual	No
Belgium	Advanced	Dual	No
Brazil	Developing	Single	Yes
Chile	Developing	Single	No
Colombia	Developing	Single	No
Czech Republic	Developing	Single	Yes
Finland	Advanced	Dual	No
Germany	Advanced	Dual	No
Hungary	Advanced	Single	No
India	Developing	Single	No
Ireland	Advanced	Dual	No
Israel	Developing	Single	No
Italy	Advanced	Dual	No
Japan	Advanced	Single	No
Korea	Developing	Single	No
Mexico	Developing	Single	No
Netherlands	Advanced	Dual	No
Norway	Advanced	Single	No
Paraguay	Developing	Single	No
Peru	Developing	Single	Yes
Philippines	Developing	Single	No
Poland	Advanced	Single	Yes
Russia	Developing	Single	Yes
South Africa	Developing	Single	No
Spain	Advanced	Dual	No
Switzerland	Advanced	Dual	No
Thailand	Developing	Single	No
Turkey	Developing	Single	Yes
Ukraine	Developing	Single	Yes
United States	Advanced	Dual	No
Uruguay	Developing	Single	Yes

Source: Central Bank websites, UN classification.

D Barro and Gordon (1983)

Let's assume the following simple model of the central bank with the loss function given by,

$$\mathcal{L}^{CB} = \max_{\pi_t} \frac{1}{2}\Big[(y_t - y^*)^2 + a(\pi_t - \pi_t^*)^2\Big] \tag{38}$$

Where, y_t and π_t are the current output and inflation levels. y^*, π^* are the potential output and inflation target. $\mathcal{L}^{CB}$ represents the loss function of the central bank subject to the following constraint,

$$y_t = b(\pi_t - \pi_t^e) \tag{39}$$

39 is the Phillips Curve, $a, b > 0$ and there is perfect foresight. Given there are rational expectations this would imply that $\pi_t^e = \pi_t$. That is, agents always know the optimal level of inflation from the central bank's loss function. Let us now consider the switch in regimes.

D.1 Pre-Inflation Targeting: No commitment

Let's solve for the optimal inflation when the central bank does not have full commitment which is assumed to be the case before Inflation Targeting. This is not an unreasonable assumption, since many economies faced high inflation prior to the adoption of targeting.

Take first order conditions and solve for optimal inflation with given inflation expectations and $\pi^* = 0$,

$$\pi_t = \frac{b(\pi_t^e + y^*)}{a+b} \tag{40}$$

$$\pi_t^e = \frac{(a+b)\pi_t - by^*}{b} \tag{41}$$

Given the central bank does not have commitment and agents have rational expectations, the inflation will follow (41) which is often referred to as the inflation bias level.

D.2 Post-Inflation Targeting: Full commitment

Let the central bank now announce the new credible policy of inflation targeting. Further, assume that the bank now has full commitment to bring reduce inflation to the target and let $\pi_t^* \geq 0$.

Then, following the same procedure as above we find the following,

$$\pi_t = \pi_t^* = \pi_t^e \tag{42}$$

Therefore, with rational expectations and full commitment by the central bank, inflation expectations will always be equal to the inflation target. Therefore, in accordance with the rational expectations hypothesis (REH) inflation should jump from (41) to (42) once inflation targeting is announced.

E A note on Short-Run Expectations

The primary goal of Inflation Targeting is to anchor medium-long run expectations. Thus, it can be argued that IT should not matter for short run expectations. However, consider the Euler equation based on the Neoclassical Growth Model,

$$u'(c_t) = \beta \mathbb{E}_t \left[u'(c_{t+1}) \frac{(1+i_t)}{1+\pi_{t+1}} \right] \tag{43}$$

Equation (43) explains how consumption today, adjusts to inflation expectations one-period ahead. Thus, adjustment to short run expectations leads to stimulation of consumption which further contributes to a rise in inflation. Moreover, since the objective of Inflation Targeting is respond to deviations in target irrespective of the length of time of deviations. Therefore, the central bank would also want to pay attention to short run expectations. In addition, the long run is derived by taking the sum of (43) to infinity. Therefore, indicating the importance of short run expectations.

The paper now turns to the data to analyse the effect of the introduction of Inflation Targeting on Inflation expectations. Before describing the empirical framework, the next section details the data used in this study along with some of the properties of the forecasts.

F Summary Statistics

Implementation

Table F.3: Inflation Expectations: Full Sample around Implementation

Country Name	$E(\pi^e_{t,pre})$	σ_{pre}	ρ_{pre}	$E(\pi^e_{t,post})$	σ_{post}	ρ_{post}
Argentina	19.27***	21.56	.815	28.23	8.27	.524
Austria	2.77***	.870	.980	1.87	.521	.804
Belgium	2.46***	.692	.963	1.88	.729	.777
Brazil	502.19***	679.26	.906	6.07	1.89	.808
Chile	9.81***	4.59	.944	3.45	1.07	.773
Colombia	22.03***	2.91	.915	5.65	3.05	.976
Czech Republic	14.20***	9.17	.834	3.11	2.15	.944
Finland	3.36***	.95	.793	1.718	.768	.843
Germany	2.79***	.984	.971	1.65	.540	.836
Hungary	19.50***	7.86	.960	4.24	2.00	.938
India	7.25***	2.44	.884	4.89	.501	.659
Ireland	2.66***	.436	.796	2.18	1.67	.920
Israel	10.48***	2.81	-.081	2.82	1.74	.903
Italy	4.46***	1.58	.963	1.875	.761	.914
Japan	.497***	.938	.926	.842	.548	.785
Korea	7.10***	1.78	.772	3.1	.979	.887
Mexico	17.77***	10.82	.864	4.68	.872	.893
Netherlands	2.62***	.513	.886	1.96	.762	.881
Norway	2.54***	.642	.802	2.11	.479	.669
Paraguay	11.15***	4.61	.675	4.79	1.07	.802
Peru	4.34***	1.02	.626	2.88	.695	.742
Philippines	8.84***	2.85	.845	4.43	1.50	.853
Poland	30.31***	19.98	.788	3.19	2.187	.957
Russia	125.09***	296.80	.893	7.75	3.35	.906
South Africa	9.82***	2.75	.942	6.13	1.42	.844
Spain	5.075***	1.21	.724	2.27	1.05	.897
Switzerland	2.10***	1.53	.974	.757	0.635	.896
Thailand	6.00***	1.96	.864	2.63	1.33	.794
Turkey	70.98***	18.64	.747	12.02	8.84	.968
Ukraine	13.69***	7.27	.895	11.23	2.01	.564
United States	2.75***	.701	.839	2.025	.304	.741
Uruguay	25.24***	22.81	.983	7.89	.855	.682

Table F.4: Inflation: Full Sample around Implementation

Country Name	$E(\pi_{t,pre})$	σ_{pre}	ρ_{pre}	$E(\pi_{t,post})$	σ_{post}	ρ_{post}
Argentina	15.30	29.14	.9570	32.19	10.2649	.842
Austria	2.44	1.15	.937	1.87	.8031499	.849
Belgium	2.03	.714	.822	1.92	1.140096	.828
Brazil	715.42	1091.51	.879	6.34	2.663077	.888
Chile	10.03	5.24	.981	3.16	1.945892	.855
Colombia	22.21	3.92	.946	5.14	2.189618	.935
Czech Republic	11.29	4.63	.788	2.51	2.134448	.907
Finland	2.41	1.16	.883	1.39	1.148651	.898
Germany	2.70	1.65	.923	1.43	.6642704	.815
Hungary	19.33	7.75	.957	3.74	2.360664	.921
India	7.68	3.39	.859	4.95	2.304561	.748
Ireland	2.25	.74	.798	1.84	2.486491	.935
Israel	2.81	1.30	.272	.456	1.000285	.209
Italy	4.02	1.53	.969	1.70	1.043962	.927
Japan	.198	1.07	.864	.858	1.019516	.773
Korea	5.71	1.86	.661	2.34	1.242359	.887
Mexico	18.32	10.78	.906	4.27	1.017846	.836
Netherlands	2.43	.602	.853	1.87	.943258	.884
Norway	2.33	.679	.740	2.01	1.059178	.652
Paraguay	10.37	5.43	.864	3.79	1.373676	.734
Peru	91.54	412.78	.879	2.72	1.362741	.852
Philippines	7.76	3.80	.888	3.73	2.016421	.871
Poland	30.84	18.08	.983	2.76	2.55652	.949
Russia	76.71	183.58	.960	6.74	4.509322	.893
South Africa	9.09	3.53	.906	5.32	2.693829	.884
Spain	4.74	.981	.875	2.07	1.46061	.888
Switzerland	2.00	1.91	.973	.490	.8771129	.854
Thailand	4.64	2.42	.873	2.02	1.933139	.823
Turkey	75.04	18.01	.826	11.38	7.448558	.961
Ukraine	293.86	1130.55	.801	10.28	3.593149	.270
United States	2.59	1.08	.747	1.59	.7077859	.797
Uruguay	25.45	25.76	.992	7.95	1.077938	.791

Table F.5: Forecast Errors: Full Sample around Implementation

Country Name	$E(\pi^e_{t,pre})$	σ_{pre}	ρ_{pre}	$E(\pi^e_{t,post})$	σ_{post}	ρ_{post}
Argentina	-3.96**	18.68295	.670***	3.96	8.650262	.707**
Austria	-0.327***	.4679931	.565***	0.001	.6910679	.730***
Belgium	-0.432***	.4195077	.455**	0.041	.9064904	.683***
Brazil	213.23***	499.1188	.622***	0.268	1.722025	.662***
Chile	0.218	1.665489	.403**	-0.285*	1.516027	.741***
Colombia	0.420	2.01485	.476**	-0.504**	1.734053	.855***
Czech Republic	-0.942***	3.760238	.54**	-0.603***	1.589391	.725***
Finland	-0.089	.796839	.598**	-0.320***	.80405	.730***
Germany	-0.170	.8298142	.748***	-0.214***	.51593	.551***
Hungary	0.429	2.878666	.521***	-0.490***	1.29543	.653***
India	-0.417***	2.850399	.738***	0.060	2.654569	.765***
Ireland	-7.938***	.6385225	.662***	-0.340**	1.475234	.823***
Israel	-.0437***	3.297099	.078	-2.36***	1.854971	.590***
Italy	-0.299***	.5861911	.732***	-0.169**	.6230933	.738***
Japan	-1.384***	.6225561	.549***	-0.751***	.7110261	.683***
Korea	0.545	1.839256	-0.453**		1.040202	.8157***
Mexico	-0.188**	3.251321	.392**	-0.085	.7393395	.561 ***
Netherlands	-0.213*	.492692	.673***	-0.095	.5500805	.532***
Norway	-1.18**	.7191434	.630***	-0.998***	1.042371	.517***
Paraguay	-1.751***	3.662622	0.422***	-0.162	1.138949	.426**
Peru	-1.08**	1.207112	0.618**	-0.694***	1.056194	.776***
Philippines	0.530	2.473918	.521***	-0.162**	1.628617	.741***
Poland	-23.43***	9.745684	.236	-694***	1.293753	.686***
Russia	-0.731**	81.00855	.703***	-0.428**	2.575003	.620***
South Africa	-0.327	1.994642	.624***	-1.01*	2.056672	.785***
Spain	-0.106	.7509802	.335	-0.805***	1.023761	.682***
Switzerland	-1.35***	.5722116	.764***	-0.209**	.5019372	.637***
Thailand	4.05**	2.42579	.816***	-0.615***	1.572284	.651***
Turkey	-0.007	12.03262	-.019	-0.640	3.690881	.597***
Ukraine	13.69403***	8.550081	.775***	-0.950	4.020822	.781***
United States	-0.158	.968073	.641***	-0.431***	.6205168	.609***
Uruguay	0.2156	5.417912	.620***	0.063	.9759901	.535***

Table F.6: Inflation Expectations: 5 years around Implementation

Country Name	$E(\pi^e_{t,pre})$	σ_{pre}	ρ_{pre}	$E(\pi^e_{t,post})$	σ_{post}	ρ_{post}
Argentina	28.58***	4.80	.841***	32.14***	9.96	.665**
Austria	2.23***	.649	.965***	1.69***	.475	.772***
Belgium	2.06***	.446	.940***	1.80***	.366	.725***
Brazil	302.38**	632.32	.952***	7.71***	1.94	.511**
Chile	7.43***	2.16	.946***	3.41***	.791	.792***
Colombia	20.16***	1.04	.370***	9.24***	3.42	.963***
Czech Republic	11.18***	2.89***	.737	6.3***	2.94	.931***
Finland	1.80***	.552***	.592	1.79***	.673	.832***
Germany	2.13***	.550	.914***	1.57***	.448	.825***
Hungary	18.50***	6.40	.937***	6.704***	1.82	.912***
India	7.52***	.644	.537**	5.08***	.522	.683***
Ireland	2.49***	.359	.725***	3.60***	1.18	.847***
Israel	10.15***	2.14	-.069	4.833***	2.55	.879***
Italy	3.6***	1.31	.939***	2.366***	.376	.831***
Japan	.125	.724	.760***	.845***	.594	.787***
Korea	5.55***	1.87	.794***	3.53***	.353	.472**
Mexico	18.00***	6.74	.930***	4.941***	1.16	.966***
Netherlands	2.34***	.160	.398*	2.66***	.825	.778***
Norway	2.4***	.410	.544**	2.02***	.641	.800***
Paraguay	8.26***	2.02	.585**	5.27***	1.15	0.674***
Peru	4.34***	1.02	.626**	2.57***	.521	.630***
Philippines	7.28***	1.62	.349	5.32***	1.32	.858***
Poland	24.71***	7.12	.868***	6.60***	3.38	.969***
Russia	8.07***	.899	.714***	7.77***	3.68	.912***
South Africa	8.16***	1.45	.806***	6.26***	1.599	.893***
Spain	3.42***	1.04	.967***	2.91***	.505	.856***
Switzerland	1.07***	.539	.873***	1.12***	.353	.809***
Thailand	6.49***	2.25	.835***	2.53***	.763	.768***
Turkey	64.95***	18.81	.857***	17.25***	13.26	.977***
Ukraine	13.62***	9.83	.918***	11.23***	2.01	.564**
United States	2.39***	.807	.657***	1.97***	.323	.723***
Uruguay	11.95***	7.69	.840***	7.42***	.752	.378*

Table F.7: Inflation: 5 years around Implementation

Country Name	$E(\pi^e_{t,pre})$	σ_{pre}	ρ_{pre}	$E(\pi^e_{t,post})$	σ_{post}	ρ_{post}
Argentina	14.22***	5.27	.836***	37.72***	12.30	.916***
Austria	1.72***	.801	.870***	1.90***	.765	.892***
Belgium	1.63***	.571	.686***	1.97***	.649	.694***
Brazil	462.15*	1165.37	.878***	8.30***	3.33	.823***
Chile	7.19***	2.19	.943***	2.78***	1.15	.819***
Colombia	19.96***	2.07	.824***	7.50***	1.45	.840***
Czech Republic	11.53***	4.95	.790***	4.99***	3.77	.900***
Finland	1.04***	.581	.679***	1.56***	1.07	.906***
Germany	1.60***	.678	.869***	1.41***	.495	.705***
Hungary	18.15***	7.08	.963***	6.22***	2.47	.933***
India	9.07***	2.07	.771***	5.17***	1.96	.718***
Ireland	2.09***	.515	.574***	3.76***	1.56	.876***
Israel	2.60***	.934	.045	.980***	1.35	.063
Italy	3.31***	1.44	.953***	2.41***	.382	.876***
Japan	-.28	1.01	.781***	.913***	1.09	.776***
Korea	3.94***	2.44	.771***	3.08***	.785	.684***
Mexico	17.58***	7.36	.964***	4.57***	.882	.863***
Netherlands	2.10***	.367	.774***	2.53***	.995	.926***
Norway	2.43***	.632	.804***	1.74***	1.15	.503**
Paraguay	7.44***	3.28	.775***	4.64***	2.12	.758***
Peru	4.46***	2.76	.959***	2.16***	1.24	.753***
Philippines	5.90***	2.19	.851***	4.22***	1.80	.894***
Poland	25.24***	8.51	.982***	5.62***	3.97	.957***
Russia	7.43***	2.59	.672***	6.04***	4.34	.954***
South Africa	7.00***	2.34	.762***	4.59***	4.12	.872***
Spain	3.19***	1.29	.951***	3.13***	.582	.512**
Switzerland	.791***	.646	.824***	.967***	.446	.639***
Thailand	4.91***	3.12	.874***	2.36***	1.56	.903***
Turkey	68.81***	16.84	.890***	14.80***	11.15	.982***
Ukraine	14.93***	19.48	.916***	10.28***	3.59	.270
United States	2.25***	1.78	.707***	1.42***	.708	.768***
Uruguay	10.94***	7.56	.836***	7.894	7.72***	.635***

Table F.8: Forecast Errors: 5 years around Implementation

Country Name	$E(\pi^e_{t,pre})$	σ_{pre}	ρ_{pre}	$E(\pi^e_{t,post})$	σ_{post}	ρ_{post}
Argentina	-14.35***	4.12	.466**	5.58**	9.34	.616**
Austria	-.507***	.429	.383*	.208	.651	.782***
Belgium	-.426***	.445	.418*	.172	.621	.538**
Brazil	159.77	598.42	.611**	.592	2.95	.651***
Chile	-.236	1.14	.609**	-.626**	1.00	.572**
Colombia	-.194	2.00	.459**	-1.73***	2.33	.846***
Czech Republic	.351	4.04	.546**	-1.30**	2.39	.696***
Finland	-.763***	.826	.628**	-.232	.810	.697***
Germany	-.528***	.469	.683***	-.156*	.417	.425**
Hungary	-.353	2.66	.538**	-.477*	1.27	.647***
India	1.55**	2.25	.721***	.091	2.22	.733***
Ireland	-.398**	.515	.398*	.158	1.20	.709***
Israel	-7.54***	2.59	.091	-3.85***	2.76	.573**
Italy	-.288**	.624	.729***	.043	.352	.599***
Japan	-.409**	.789	.511**	.067	.753	.693***
Korea	-1.61**	2.16	.609**	-.451**	.767	.608***
Mexico	-.416	1.89	.568**	-.369**	.684	.651***
Netherlands	-.236**	.327	.693***	-.130	.583	.551**
Norway	.037	.698	.651***	-.281	1.26	.406**
Paraguay	-.818	2.88	.480**	-.623	1.90	.602***
Peru	-1.75***	1.20	.618**	-.406	1259	.748***
Philippines	-1.37**	1.84	.394*	-1.10**	1.59	.779***
Poland	.538	3.57	.360	-.988**	1.89	.683***
Russia	-.631	2.59	.729***	-1.72***	1.74	.670***
South Africa	-1.15**	2.13	.636**	-1.66**	3.18	.820***
Spain	-.228*	.538	.670***	.224	.595	.407**
Switzerland	-.278**	.375	.596**	-.161**	.351	.287
Thailand	-1.57**	3.15	.819***	-.166	1.12	.691***
Turkey	3.86**	7.85	.192	-2.45**	4.52	.579**
Ukraine	1.31	13.64	.769***	-.950	4.02	.781***
United States	-.139	1.63	.602**	-.550***	.633	.551**
Uruguay	-1.00	4.37	.438**	.299	0.902	.314

Announcement

Table F.9: Inflation Expectations: Full Sample around Announcement

Country Name	$E(\pi^e_{t,pre})$	σ_{pre}	ρ_{pre}	$E(\pi^e_{t,post})$	σ_{post}	ρ_{post}
Argentina	18.95***	21.79	.813***	28.66***	7.30	.530**
Austria	2.91***	.783	.975***	1.85***	.520	.807***
Belgium	2.85***	.563	.925***	1.87***	.686	.777***
Brazil	864.80***	702.20	.836***	6.65***	3.37	.936***
Chile	26.52***	-	-	-	3.91	-
Colombia	14.36***	.937	.626	8.96***	6.80	.991***
Czech Republic	14.20357***	9.31	.832***	3.19***	2.25	.949***
Finland	3.92***	.734	.382	1.79***	.819	.869***
Germany	2.95***	.937	.969***	1.65***	.531	.831***
Hungary	19.76***	7.78	.958***	4.30***	2.06	.942***
India	7.36***	2.48	.883***	5.08***	.522	.683***
Ireland	2.74***	.394	.811***	2.20***	1.60	.918***
Israel	10.70***	3.37	-.303	3.62***	2.93	.918***
Italy	4.82***	1.34	.941***	1.87***	.744	.914***
Japan	.516***	.956	.925***	.75***	.570	.824***
Korea	6.93***	1.76	.754***	3.29***	1.42	.938***
Mexico	19.53***	12.49	.857***	5.90***	3.32	.981***
Netherlands	2.67***	.538	.881***	1.98***	.748	.882***
Norway	2.56***	.695	.828***	2.14***	.477	.665***
Paraguay	13.31***	4.38	.405**	6.04***	2.14	.859***
Peru	8.9***	-	-	-	.891	-
Philippines	33.01***	2.85	.842***	4.46***	1.51	.856***
Poland	127.74***	19.95	.752***	3.56***	2.74	.972***
Russia	10.13***	299.62	.892***	7.72***	3.22	.905***
South Africa	5.6***	2.66	.935***	6.14***	1.39	.842***
Spain	2.19***	1.22	.572**	2.45***	1.15	.920***
Switzerland	2.108333***	1.53	.973***	.756***	.627	.895***
Thailand	6.13***	1.83	.838***	2.62***	1.33	.795***
Turkey	71.50***	19.19	.761***	14.09***	13.43	.939***
Ukraine	12.94***	5.95	.890***	14.21***	8.87	.707***
United States	2.88***	.613	.899***	2.03***	.468	.593***
Uruguay	28.94***	23.29	.981***	7.68***	.996	.735***

Table F.10: Inflation: Full Sample around Announcement

Country Name	$E(\pi^e_{t,pre})$	σ_{pre}	ρ_{pre}	$E(\pi^e_{t,post})$	σ_{post}	ρ_{post}
Argentina	14.84***	29.43	.961***	31.89***	9.24	.809***
Austria	2.62***	1.04	.917***	1.83***	.818	.857***
Belgium	2.36***	.574	.818***	1.87***	1.09	.823***
Brazil	1236.78***	1200.72	.816***	6.56***	3.37	.931***
Chile	-	-	-	3.45122	4.51	-
Colombia	27.86***	2.27	.843**	8.52***	6.69	.990***
Czech Republic	11.21***	4.71	.795***	2.63***	2.40	.909***
Finland	3.33***	.676	.898**	1.40***	1.12	.888***
Germany	2.99***	1.54	.904***	1.40***	.675	.817***
Hungary	19.59***	7.66	.956***	3.81***	2.41	.924***
India	7.80***	3.46	.859***	5.17***	1.96	.718***
Ireland	2.34***	.779	.830***	1.85***	2.38	.933***
Israel	3.13***	1.51	.252	.667***	1.16	.428***
Italy	4.34***	1.36	.956***	1.70***	1.02	.926***
Japan	.222**	1.09	.865***	.714***	1.03	.791***
Korea	5.83***	1.69	.773***	2.42***	1.38	.841***
Mexico	20.44***	12.07	.896***	5.51***	3.57	.977***
Netherlands	2.50***	.612	.852***	1.88***	.922	.882***
Norway	2.20***	.646	.705***	2.09***	1.05	.668***
Paraguay	12.15***	5.58	.842***	5.22***	2.79	.810***
Peru	-	769.01	-	-	4.15	-
Philippines	7.86***	3.77	.886***	3.73***	2.00	.869***
Poland	33.86***	17.29	.980***	3.08***	2.94	.957***
Russia	78.42***	185.49	.959***	6.71***	4.32	.893***
South Africa	9.67***	3.07	.897***	5.23***	2.69	.872***
Spain	5.23***	.741	.775***	2.23***	1.51	.901***
Switzerland	2.04***	1.96	.975***	.507***	.873	.853***
Thailand	4.73***	2.39	.868***	2.01***	1.92	.823***
Turkey	75.74***	18.42	.823***	13.54***	12.96	.959***
Ukraine	299.49**	1142.39	.800***	13.37***	9.93	.884***
United States	2.78***	.822	.665***	1.59***	1.06	.751***
Uruguay	29.30***	26.60	.991***	7.63***	1.33	.823***

Table F.11: Forecast Errors: Full Sample around Announcement

Country Name	$E(\pi^e_{t,pre})$	σ_{pre}	ρ_{pre}	$E(\pi^e_{t,post})$	σ_{post}	ρ_{post}
Argentina	-4.10**	18.93	.672***	3.22	7.74	.713**
Austria	-.288**	.474	.539**	-.023	.691	.738***
Belgium	-.492***	.413	.530**	-.005	.868	.677***
Brazil	371.98**	616.58	.554**	-.089	1.87	.706***
Chile	-	-	-	-	1.57	-
Colombia	1.34**	1.74	.582	-.439**	1.78	.744***
Czech Republic	.288	3.78	.549**	-.557***	1.63	.714***
Finland	-.585**	.458	-.222	-.393***	.848	.753***
Germany	.040	.801	.699***	-.249***	.532	.588***
Hungary	-.169	2.91	.523***	-.486***	1.28	.648***
India	.446	2.93	.741***	.091	2.22	.733***
Ireland	-.396**	.631	.733***	-.353**	1.42	.817***
Israel	-8.03***	3.86	-.154	-2.95***	2.59	.727***
Italy	-.478***	.608	.722***	-.168**	.611	.737***
Japan	-.294***	.632	.550***	-.035	.687	.681***
Korea	-1.093***	1.56	.414**	-.870***	1.24	.766***
Mexico	.906	3.59	.320	-.388***	1.03	.645***
Netherlands	-.165	.516	.688***	-.097*	.542	.532***
Norway	-.359**	.673	.537***	-.047	1.01	.529***
Paraguay	-1.540**	4.057	.379**	-.820**	2.08	.500
Peru	-	-	-	-	1.19	-
Philippines	-1.03**	2.47	.519***	-.730***	1.64	.741***
Poland	.844	10.37	.230	-.484***	1.36	.668***
Russia	-23.98**	81.92	.702***	-1.00**	2.47	.618***
South Africa	-.460	1.85	.585***	-.910***	2.09	.782***
Spain	-.369	.872	.298	-.213**	.988	.677***
Switzerland	-.141	.569	.780***	-.249***	.509	.640***
Thailand	-1.40***	2.44	.817***	-.606***	1.56	.649***
Turkey	4.24**	12.44	-.010	-.553	3.65	.498***
Ukraine	-.009	8.57	.837***	-.837	4.61	.607**
United States	-.103	.773	.552***	-.438**	1.02	.694***
Uruguay	.366	5.87	.616***	-.046	1.22	.656***

Table F.12: Inflation Expectations: 5 years around Announcement

Country Name	$E(\pi^e_{t,pre})$	σ_{pre}	ρ_{pre}	$E(\pi^e_{t,post})$	σ_{post}	ρ_{post}
Argentina	27.12***	5.07	.861***	31.78***	9.01	.647**
Austria	2.68***	.710	.967***	1.62***	.469	.791***
Belgium	2.85***	.563	.925***	1.81***	.374	.761***
Brazil	1019.68***	655.4	.841***	13.12***	11.53	.659***
Chile	-	-	-	-	-	-
Colombia	26.52***	.937	.626	20.53***	1.36	.644***
Czech Republic	11.18***	2.89	.737***	6.3***	2.94	.931***
Finland	3.92***	.734	.382	2.07***	.824	.830***
Germany	2.54***	.769	.958***	1.58***	.457	.823***
Hungary	14.89***	5.51	.965***	5.88***	1.78	.913***
India	7.52***	.644	.537**	5.08***	.522	.683***
Ireland	2.67***	.388	.823***	3.32***	1.21	.881***
Israel	11.16***	3.53	-.400	8.25***	2.99	.737***
Italy	4.27***	1.167	.918***	2.29***	.404	.880***
Japan	.195	.736	.769***	.704***	.653	.823***
Korea	5.87***	.625	.400**	4.62***	2.00	.852***
Mexico	21.25***	14.37	.853***	9.67***	4.50	.974***
Netherlands	2.41***	.235	.746***	2.75***	.739	.742***
Norway	2.27***	.481	.634**	2.31***	.587	.736***
Paraguay	11.81***	2.95	.542**	8.18***	1.87	.590**
Peru	-	-	-	-	-	-
Philippines	7.75***	1.61	.326	5.70***	1.20	.861***
Poland	24.71***	7.12	.868***	6.60***	3.38	.969***
Russia	10.18***	2.40	.910***	8.04***	3.21	.901***
South Africa	8.55***	1.24	.732***	6.66***	1.37	.835***
Spain	5.95***	1.11	.341	3.19***	1.08	.972***
Switzerland	1.22***	.563	.835***	1.05***	.383	.858***
Thailand	6.49***	2.25	.835***	2.53***	.763	.768***
Turkey	70.52***	18.82	.804***	25.20***	19.68	.915***
Ukraine	10.21***	3.89	.778***	14.92***	8.71	.706***
United States	2.67***	.384	.758***	2.27***	.723	.656***
Uruguay	10.97***	8.30	.867***	7.36***	1.14	.531**

Table F.13: Inflation: 5 years around Announcement

Country Name	$E(\pi^e_{t,pre})$	σ_{pre}	ρ_{pre}	$E(\pi^e_{t,post})$	σ_{post}	ρ_{post}
Argentina	12.87***	4.80	.892***	33.67***	13.84	.937***
Austria	2.25***	.877	.892***	1.62***	.809	.914***
Belgium	2.36***	.574	.818***	1.83***	.735	.753***
Brazil	1460.50***	1179.76	.770***	12.06***	16.22	.960***
Chile	-	-	-	-	-	-
Colombia	27.86***	2.27	.843**	20.32***	2.07	.814***
Czech Republic	11.53***	4.95	.790***	4.99***	3.77	.900***
Finland	3.33***	.676	.898**	1.12***	.657	.732***
Germany	2.28***	1.04	.931***	1.21***	.553	.746***
Hungary	14.32***	4.90	.982***	5.47***	2.03	.847***
India	9.07***	2.07	.771***	5.17***	1.96	.718***
Ireland	2.11***	.628	.756***	3.58***	1.71	.913***
Israel	2.99***	1.59	.285	1.92***	1.52	.209
Italy	3.86***	1.26	.937***	2.35***	.448	.881***
Japan	-.158	1.06	.784***	.742**	1.18	.811***
Korea	5.19***	1.17	.422*	3.25***	1.88	.805***
Mexico	21.72***	13.93	.895***	9.21***	5.11	.977***
Netherlands	2.25***	.430	.810***	2.63***	.893	.906***
Norway	2.03***	.611	.641**	2.06***	1.29	.597**
Paraguay	9.23***	4.20	.646**	6.91***	3.29	.749***
Peru	-	769.01	-	2.884722	-	-
Philippines	6.30***	2.11	.853***	4.43***	1.78	.898***
Poland	25.24***	8.51	.982***	5.62***	3.97	.957***
Russia	8.948***	3.49	.915***	7.20***	4.29	.885***
South Africa	8.036***	1.58	.582**	4.88***	4.07	.848***
Spain	5.38***	.752	.741**	3.09***	1.20	.947***
Switzerland	.800***	.660	.798***	.906***	.470	.656***
Thailand	4.91***	3.12	.874***	2.367***	1.56	.903***
Turkey	72.38***	16.65	.932***	23.76***	20.79	.940***
Ukraine	7.21**	9.17	.905***	17.64***	16.19	.866***
United States	2.94***	.766	.593**	1.86***	1.53	.703***
Uruguay	9.83***	8.17	.861***	7.11***	1.49	.793***

Table F.14: Forecast Errors: 5 years around Announcement

Country Name	$E(\pi^e_{t,pre})$	σ_{pre}	ρ_{pre}	$E(\pi^e_{t,post})$	σ_{post}	ρ_{post}
Argentina	-14.25***	3.20	.439**	1.89	11.59	.806***
Austria	-.425***	.442	.435**	-.003	.688	.810***
Belgium	-.492***	.413	.530**	.013	.621	.519**
Brazil	440.82**	651.23	.512**	-1.06	8.31	-.941***
Chile	-	-	-	3.45122	2.05	-
Colombia	1.34*	1.740	.582	-.212	1.97	.402**
Czech Republic	.351	4.04	.546**	-1.30**	2.39	.696***
Finland	-.585**	.458	-.222	-.952***	.879	.661***
Germany	-.262**	.568	.711***	-.369***	.462	.524**
Hungary	-.562	1.95	.590**	-.403	1.48	.659***
India	1.55**	2.25	.721***	.091	2.22	.733***
Ireland	-.551***	.567	.655***	.255	1.06	.687***
Israel	-8.77***	3.87	-.390	-6.33***	3.05	.500**
Italy	-.402**	.666	.762***	.061	.343	.588**
Japan	-.353*	.819	.518**	.038	.770	.732***
Korea	-.671**	1.40	.372	-1.36***	1.91	.716***
Mexico	.477	4.01	.343	-.459	1.57	.723***
Netherlands	-.157*	.392	.678***	-.121	.571	.520**
Norway	-.235	.746	.522**	-.247	1.28	.435**
Paraguay	-2.57**	3.82	.506**	-1.26**	2.91	.482**
Peru	-	-	-	-	.888	-
Philippines	-1.45**	1.83	.392**	-1.27***	1.51	.811***
Poland	.538	3.57	.360	-.988**	1.89	.683***
Russia	-1.23**	2.41	.820***	-.831	2.55	.619***
South Africa	-.518	1.91	.598**	-1.77**	3.26	.805***
Spain	-.569**	.857	.041	-.103	.568	.723***
Switzerland	-.424***	.302	.394**	-.151*	.396	.324
Thailand	-1.57**	3.15	.819***	-.166	1.12	.691***
Turkey	1.86	9.01	.206	-1.44	6.80	.304
Ukraine	-2.99*	6.76	.769***	2.72	11.93	.765***
United States	.276	.672	.309	-.413	1.42	.613***
Uruguay	-1.14	4.23	.440**	-.250	1.55	.508**

G Rational Expectation Hypothesis

Table G.15: Rational Expectations Test

Country Name	Pre-IT	Post-IT
Argentina	.431***	.529***
	(.099)	(0.069)
Austria	.296***	.659***
	(.048)	(0.059)
Belgium	.202	.611***
	(.128)	(0.511)
Brazil	.410***	.455***
	(.046)	(0.077)
Chile	.167***	.650***
	(.041)	(0.055)
Colombia	.355***	-.162
	(.062)	(0.221)
Czech Republic	.654***	.269**
	(.134)	(.142)
Finland	.401**	.521***
	(.147)	(.057)
Germany	.448***	.470***
	(.038)	(0.070)
Hungary	.054	.290***
	(.072)	(0.080)
India	.592***	1.139***
	(.150)	(0.042)
Ireland	.695***	.449***
	(.095)	(0.082)
Israel	2.22**	0.693***
	(.0672)	(0.207)
Italy	.038	0.411***
	(.089)	(0.054)
Japan	.288**	.598***
	(.094)	(.081)
Korea	.526**	.539***
	(.211)	(.114)
Mexico	.041	.396**
	(.058)	(.135)
Netherlands	.467***	.343***
	(.130)	(.083)

Table G.15: Rational Expectations Test

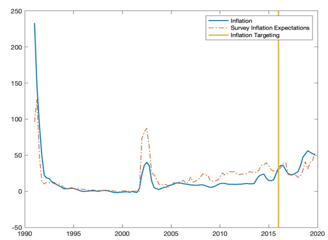
Country Name	Pre-IT	Post-IT
Norway	.612**	.881***
	(.221)	(.059)
Paraguay	.343***	.535**
	(.086)	(.224)
Peru	.572***	.669***
	(.074)	(.067)
Philippines	.430***	.547***
	(.064)	(.107)
Poland	.034	.262***
	(.122)	(.059)
Russia	-.367***	.385***
	(.019)	(.102)
South Africa	.355***	.652***
	(.070)	(.098)
Spain	.025	.487***
	(.141)	(.052)
Switzerland	.225***	.401***
	(.049)	(.077)
Thailand	.673***	.592***
	(.145)	(.081)
Turkey	.187	-.082
	(.130)	(.080)
Ukraine	.564***	.968***
	(.089)	(.171)
United States	.689***	.791***
	(.094)	(.070)
Uruguay	.130**	.588***
	(.041)	(.105)

Note: Newey West standard errors in parenthesis.

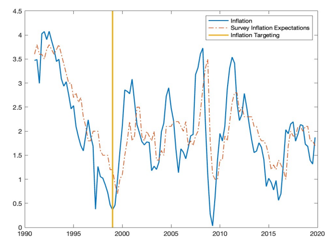
H Time Series Graphs for all IT countries

Figure H.1: Inflation and Inflation expectations

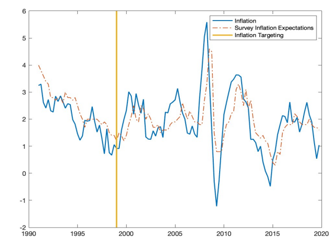
(a) Argentina



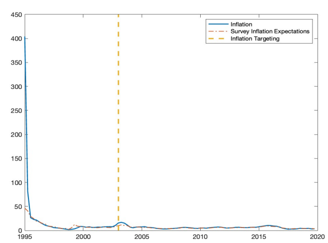
(b) Austria



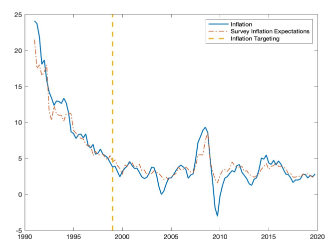
(c) Belgium



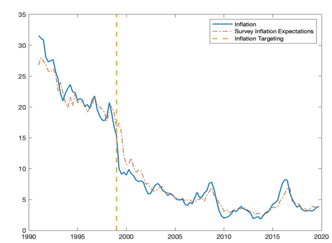
(d) Brazil



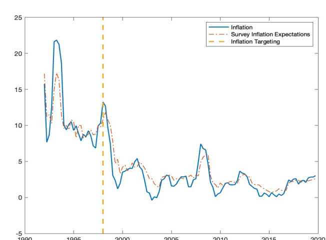
(e) Chile



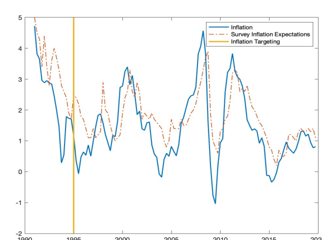
(f) Colombia



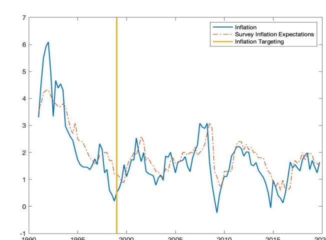
(g) Czech Republic



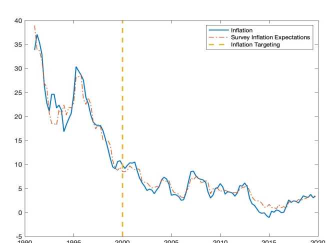
(h) Finland



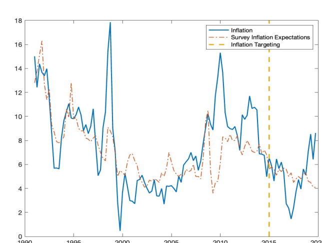
(i) Germany



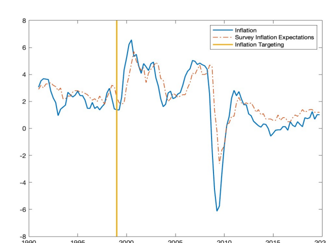
(j) Hungary



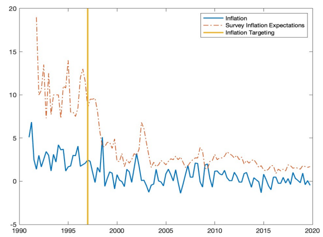
(k) India



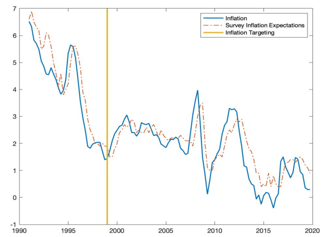
(l) Ireland



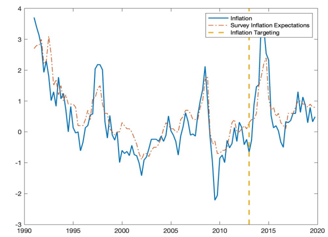
(m) Israel



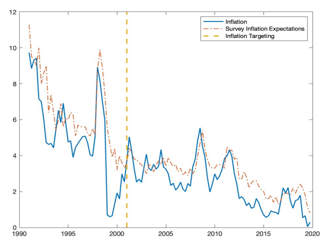
(n) Italy



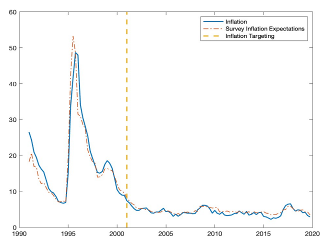
(o) Japan



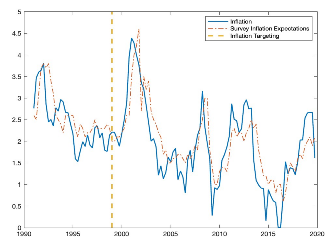
(p) Korea



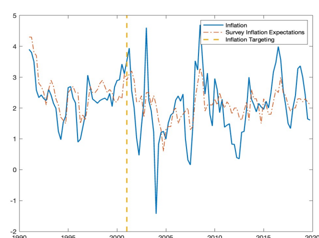
(q) Mexico



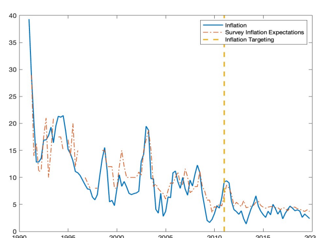
(r) Netherlands



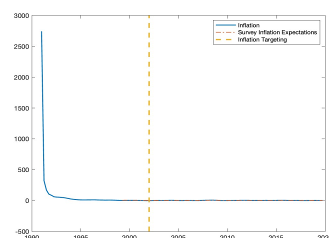
(s) Norway



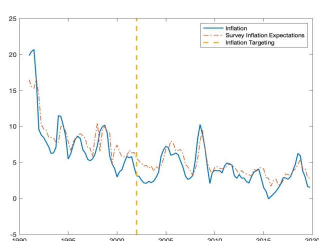
(t) Paraguay



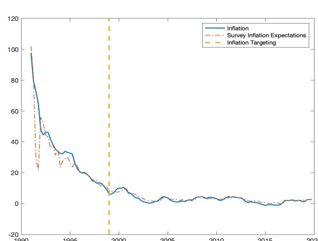
(u) Peru



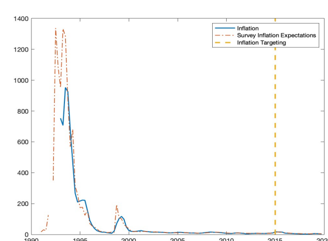
(v) Philippines



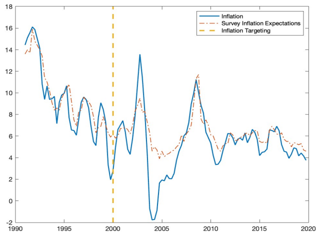
(w) Poland



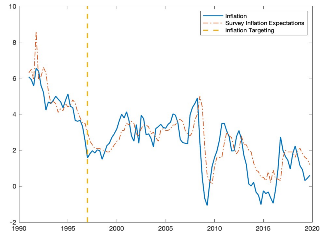
(x) Russia



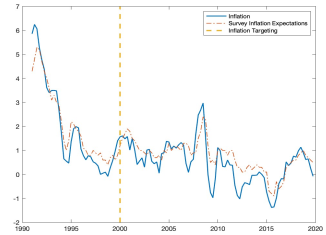
(y) South Africa



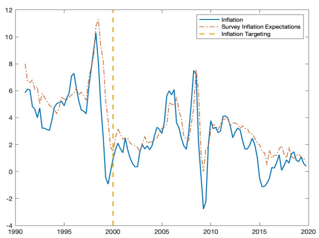
(z) Spain



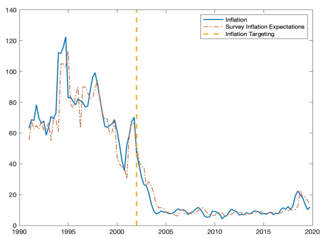
(aa) Switzerland



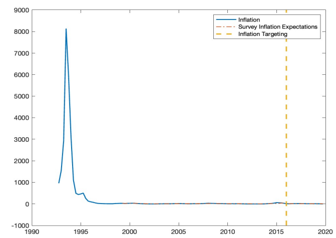
(ab) Thailand



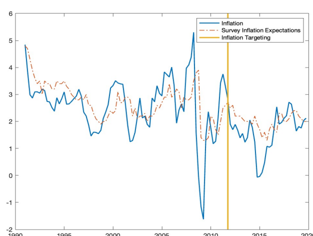
(ac) Turkey



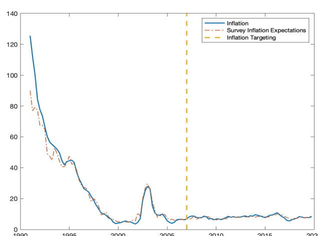
(ad) Ukraine



(ae) United States



(af) Uruguay



I Structural Break Tests

I.1 Inflation

Table I.16: Argentina

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.737***	0.635***
	(0.0733)	(0.0408)
Cons$*\mathbb{1}_{t\geq t^*}$		-5.030**
		(1.948)
Lag$*\mathbb{1}_{t\geq t^*}$		0.434***
		(0.0636)
Constant	2.990***	3.062***
	(0.834)	(0.476)
Observations	114	114
R-squared	0.853	0.910

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.737***	0.618***
	(0.0733)	(0.0350)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.708
		(2.243)
Lag$*\mathbb{1}_{t\geq t^*}$		0.412***
		(0.0658)
Constant	2.990***	2.865***
	(0.834)	(0.431)
Observations	114	114
R-squared	0.853	0.925

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.17: Austria

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.881***	0.679***
	(0.0423)	(0.0772)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.854***
		(0.222)
Lag$*\mathbb{1}_{t\geq t^*}$		0.412***
		(0.0769)
Constant	0.226**	0.693***
	(0.0923)	(0.221)
Observations	114	114
R-squared	0.794	0.847

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.881***	0.605***
	(0.0423)	(0.0831)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.105***
		(0.248)
Lag$*\mathbb{1}_{t\geq t^*}$		0.479***
		(0.0780)
Constant	0.226**	0.958***
	(0.0923)	(0.256)
Observations	114	114
R-squared	0.794	0.861

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.18: Belgium

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.822***	0.220***
	(0.0767)	(0.0605)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.575***
		(0.159)
Lag$*\mathbb{1}_{t\geq t^*}$		0.818***
		(0.0499)
Constant	0.328**	1.502***
	(0.150)	(0.173)
Observations	114	114
R-squared	0.681	0.915

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.822***	0.0917**
	(0.0767)	(0.0382)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.079***
		(0.162)
Lag$*\mathbb{1}_{t\geq t^*}$		0.925***
		(0.0311)
Constant	0.328**	2.047***
	(0.150)	(0.173)
Observations	114	114
R-squared	0.681	0.966

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.19: Brazil

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.909***	0.884***
	(0.166)	(0.180)
Cons$*\mathbb{1}_{t\geq t^*}$		-75.37
		(63.90)
Lag$*\mathbb{1}_{t\geq t^*}$		0.212
		(0.179)
Constant	15.69	74.76
	(13.64)	(63.99)
Observations	114	114
R-squared	0.826	0.828

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.909***	0.824***
	(0.166)	(0.211)
Cons$*\mathbb{1}_{t\geq t^*}$		-218.7
		(176.2)
Lag$*\mathbb{1}_{t\geq t^*}$		0.146
		(0.226)
Constant	15.69	218.7
	(13.64)	(176.2)
Observations	114	114
R-squared	0.826	0.832

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.20: Chile

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.896***	0.793***
	(0.0302)	(0.0487)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.808***
		(0.496)
Lag$*\mathbb{1}_{t\geq t^*}$		0.322***
		(0.0747)
Constant	0.365**	1.449***
	(0.164)	(0.453)
Observations	114	114
R-squared	0.936	0.950

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.896***	1.91e-08
	(0.0302)	(1.48e-08)
Cons$*\mathbb{1}_{t\geq t^*}$ = o,		-
Lag$*\mathbb{1}_{t\geq t^*}$		1.000***
		(1.70e-08)
Constant	0.365**	6.94e-09
	(0.164)	(2.33e-08)
Observations	114	114
R-squared	0.936	1.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.21: Colombia

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.963***	0.749***
	(0.0127)	(0.0774)
Cons$*\mathbb{1}_{t\geq t^*}$		-4.958***
		(1.676)
Lag$*\mathbb{1}_{t\geq t^*}$		0.216***
		(0.0721)
Constant	0.122	5.034***
	(0.103)	(1.757)
Observations	114	114
R-squared	0.985	0.988

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.963***	0.0740
	(0.0127)	(0.0539)
Cons$*\mathbb{1}_{t\geq t^*}$		-24.76***
		(1.751)
Lag$*\mathbb{1}_{t\geq t^*}$		0.925***
		(0.0546)
Constant	0.122	24.75***
	(0.103)	(1.754)
Observations	114	114
R-squared	0.985	0.999

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.22: Czech Republic

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.934***	0.660***
	(0.0627)	(0.126)
Cons$*\mathbb{1}_{t\geq t^*}$		-4.081***
		(1.203)
Lag$*\mathbb{1}_{t\geq t^*}$		0.321**
		(0.138)
Constant	0.252	4.057***
	(0.183)	(1.198)
Observations	111	111
R-squared	0.877	0.903

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.934***	0.654***
	(0.0627)	(0.126)
Cons$*\mathbb{1}_{t\geq t^*}$		-4.135***
		(1.181)
Lag$*\mathbb{1}_{t\geq t^*}$		0.373***
		(0.132)
Constant	0.252	4.015***
	(0.183)	(1.189)
Observations	111	111
R-squared	0.877	0.903

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.23: Finland

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.886***	0.289***
	(0.0470)	(0.0927)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.532***
		(0.303)
Lag$*\mathbb{1}_{t\geq t^*}$		0.740***
		(0.0842)
Constant	0.147*	1.488***
	(0.0779)	(0.312)
Observations	114	114
R-squared	0.810	0.940

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.886***	0.0174
	(0.0470)	(0.0142)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.977***
		(0.0866)
Lag$*\mathbb{1}_{t\geq t^*}$		0.984***
		(0.0128)
Constant	0.147*	2.974***
	(0.0779)	(0.0853)
Observations	114	114
R-squared	0.810	0.997

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.24: Germany

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.895***	0.815***
	(0.0577)	(0.0759)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.550***
		(0.181)
Lag$*\mathbb{1}_{t\geq t^*}$		0.322***
		(0.0779)
Constant	0.161*	0.367**
	(0.0919)	(0.179)
Observations	114	114
R-squared	0.842	0.862

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.895***	0.758***
	(0.0577)	(0.0822)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.804***
		(0.203)
Lag$*\mathbb{1}_{t\geq t^*}$		0.381***
		(0.0776)
Constant	0.161*	0.613***
	(0.0919)	(0.211)
Observations	114	114
R-squared	0.842	0.871

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.25: Hungary

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.947***	0.882***
	(0.0243)	(0.0421)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.869***
		(0.708)
Lag$*\mathbb{1}_{t\geq t^*}$		0.169***
		(0.0570)
Constant	0.190	1.589**
	(0.163)	(0.697)
Observations	114	114
R-squared	0.969	0.971

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.947***	0.871***
	(0.0243)	(0.0418)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.086***
		(0.713)
Lag$*\mathbb{1}_{t\geq t^*}$		0.160***
		(0.0587)
Constant	0.190	1.862***
	(0.163)	(0.700)
Observations	114	114
R-squared	0.969	0.971

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.26: India

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.845***	0.821***
	(0.0741)	(0.0791)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.286***
		(0.766)
Lag$*\mathbb{1}_{t\geq t^*}$		0.398***
		(0.133)
Constant	1.067**	1.280**
	(0.488)	(0.546)
Observations	114	114
R-squared	0.742	0.751

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.845***	0.815***
	(0.0741)	(0.0791)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.543***
		(0.761)
Lag$*\mathbb{1}_{t\geq t^*}$		0.415***
		(0.129)
Constant	1.067**	1.355**
	(0.488)	(0.553)
Observations	114	114
R-squared	0.742	0.754

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.27: Ireland

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.930***	0.152***
	(0.0510)	(0.0571)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.857***
		(0.147)
Lag$*\mathbb{1}_{t\geq t^*}$		0.857***
		(0.0556)
Constant	0.114	1.838***
	(0.142)	(0.144)
Observations	114	114
R-squared	0.868	0.976

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.930***	0.130**
	(0.0510)	(0.0519)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.971***
		(0.162)
Lag$*\mathbb{1}_{t\geq t^*}$		0.879***
		(0.0502)
Constant	0.114	1.954***
	(0.142)	(0.160)
Observations	114	114
R-squared	0.868	0.980

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.28: Israel

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.514***	0.0125
	(0.110)	(0.0344)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.550***
		(0.196)
Lag$*\mathbb{1}_{t\geq t^*}$		0.997***
		(0.00748)
Constant	0.392***	2.546***
	(0.115)	(0.198)
Observations	111	111
R-squared	0.268	0.909

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.514***	-0.00492
	(0.110)	(0.0140)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.790***
		(0.303)
Lag$*\mathbb{1}_{t\geq t^*}$		1.002***
		(0.00621)
Constant	0.392***	2.792***
	(0.115)	(0.303)
Observations	111	111
R-squared	0.268	0.959

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.29: Italy

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.944***	0.806***
	(0.0235)	(0.0544)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.743***
		(0.238)
Lag$*\mathbb{1}_{t\geq t^*}$		0.261***
		(0.0541)
Constant	0.0771	0.618**
	(0.0639)	(0.241)
Observations	114	114
R-squared	0.934	0.946

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.944***	0.730***
	(0.0235)	(0.0755)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.130***
		(0.357)
Lag$*\mathbb{1}_{t\geq t^*}$		0.332***
		(0.0708)
Constant	0.0771	1.011***
	(0.0639)	(0.368)
Observations	114	114
R-squared	0.934	0.950

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.30: Japan

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.816***	0.713***
	(0.0523)	(0.0614)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.0961
		(0.122)
Lag$*\mathbb{1}_{t\geq t^*}$		0.428***
		(0.148)
Constant	0.0376	0.00499
	(0.0499)	(0.0566)
Observations	114	114
R-squared	0.710	0.754

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.816***	0.709***
	(0.0523)	(0.0613)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.119
		(0.101)
Lag$*\mathbb{1}_{t\geq t^*}$		0.438***
		(0.133)
Constant	0.0376	0.0184
	(0.0499)	(0.0588)
Observations	114	114
R-squared	0.710	0.757

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.31: Korea

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.866***	0.476***
	(0.0457)	(0.102)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.862***
		(0.577)
Lag$*\mathbb{1}_{t\geq t^*}$		0.576***
		(0.0941)
Constant	0.365***	2.744***
	(0.114)	(0.597)
Observations	114	114
R-squared	0.807	0.860

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.866***	0.365***
	(0.0457)	(0.121)
Cons$*\mathbb{1}_{t\geq t^*}$		-3.641***
		(0.690)
Lag$*\mathbb{1}_{t\geq t^*}$		0.665***
		(0.126)
Constant	0.365***	3.538***
	(0.114)	(0.676)
Observations	114	114
R-squared	0.807	0.905

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.32: Mexico

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.949***	0.913***
	(0.0647)	(0.102)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.750
		(1.673)
Lag$*\mathbb{1}_{t\geq t^*}$		0.193*
		(0.108)
Constant	0.305	1.250
	(0.437)	(1.705)
Observations	114	114
R-squared	0.912	0.913

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.949***	0.888***
	(0.0647)	(0.107)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.114
		(2.102)
Lag$*\mathbb{1}_{t\geq t^*}$		0.0977
		(0.114)
Constant	0.305	2.071
	(0.437)	(2.100)
Observations	114	114
R-squared	0.912	0.914

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.33: Netherlands

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.881***	0.338***
	(0.0435)	(0.0838)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.645***
		(0.178)
Lag$*\mathbb{1}_{t\geq t^*}$		0.701***
		(0.0781)
Constant	0.225**	1.570***
	(0.0959)	(0.186)
Observations	114	114
R-squared	0.793	0.923

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.881***	0.315***
	(0.0435)	(0.0823)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.738***
		(0.186)
Lag$*\mathbb{1}_{t\geq t^*}$		0.722***
		(0.0763)
Constant	0.225**	1.667***
	(0.0959)	(0.195)
Observations	114	114
R-squared	0.793	0.928

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.34: Norway

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.662***	0.160***
	(0.0804)	(0.0531)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.018***
		(0.137)
Lag$*\mathbb{1}_{t\geq t^*}$		0.895***
		(0.0379)
Constant	0.696***	1.903***
	(0.188)	(0.164)
Observations	114	114
R-squared	0.443	0.873

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.662***	0.102**
	(0.0804)	(0.0392)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.965***
		(0.128)
Lag$*\mathbb{1}_{t\geq t^*}$		0.932***
		(0.0276)
Constant	0.696***	1.892***
	(0.188)	(0.149)
Observations	114	114
R-squared	0.443	0.917

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.35: Paraguay

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.895***	0.825***
	(0.0609)	(0.0751)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.127***
		(0.720)
Lag$*\mathbb{1}_{t\geq t^*}$		0.273*
		(0.138)
Constant	0.680*	1.592**
	(0.379)	(0.649)
Observations	97	97
R-squared	0.790	0.800

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.895***	0.715***
	(0.0609)	(0.0900)
Cons$*\mathbb{1}_{t\geq t^*}$		-3.735***
		(0.955)
Lag$*\mathbb{1}_{t\geq t^*}$		0.423***
		(0.0936)
Constant	0.680*	3.006***
	(0.379)	(0.974)
Observations	97	97
R-squared	0.790	0.824

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.36: Peru

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.851***	0.345**
	(0.0644)	(0.156)
Cons$*\mathbb{1}_{t \geq t^*}$		-1.504*
		(0.773)
Lag$*\mathbb{1}_{t \geq t^*}$		0.692***
		(0.141)
Constant	0.382**	1.418*
	(0.192)	(0.804)
Observations	81	81
R-squared	0.726	0.873

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.851***	1.50e-08
	(0.0644)	(9.43e-09)
Cons$*\mathbb{1}_{t \geq t^*}$ = o,		-
Lag$*\mathbb{1}_{t \geq t^*}$		1.000***
		(1.18e-08)
Constant	0.382**	-4.97e-09
	(0.192)	(1.63e-08)
Observations	81	81
R-squared	0.726	1.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.37: Philippines

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.802***	0.583***
	(0.0534)	(0.0728)
Cons$*\mathbb{1}_{t \geq t^*}$		-3.023***
		(0.544)
Lag$*\mathbb{1}_{t \geq t^*}$		0.492***
		(0.0780)
Constant	0.864***	2.738***
	(0.244)	(0.550)
Observations	114	114
R-squared	0.817	0.878

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.802***	0.568***
	(0.0534)	(0.0743)
Cons$*\mathbb{1}_{t \geq t^*}$		-3.201***
		(0.551)
Lag$*\mathbb{1}_{t \geq t^*}$		0.507***
		(0.0783)
Constant	0.864***	2.909***
	(0.244)	(0.561)
Observations	114	114
R-squared	0.817	0.883

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.38: Poland

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.907***	0.871***
	(0.0296)	(0.0561)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.781
		(1.368)
Lag$*\mathbb{1}_{t\geq t^*}$		0.168***
		(0.0640)
Constant	0.325*	1.659
	(0.191)	(1.373)
Observations	114	114
R-squared	0.985	0.986

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.907***	0.836***
	(0.0296)	(0.0605)
Cons$*\mathbb{1}_{t\geq t^*}$		-3.135*
		(1.644)
Lag$*\mathbb{1}_{t\geq t^*}$		0.144**
		(0.0700)
Constant	0.325*	3.110*
	(0.191)	(1.643)
Observations	114	114
R-squared	0.985	0.987

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.39: Russia

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.889***	0.889***
	(0.0958)	(0.0976)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.050
		(3.036)
Lag$*\mathbb{1}_{t\geq t^*}$		0.222
		(0.143)
Constant	0.264	0.153
	(2.411)	(3.063)
Observations	107	107
R-squared	0.924	0.924

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.889***	0.889***
	(0.0958)	(0.0977)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.016
		(3.112)
Lag$*\mathbb{1}_{t\geq t^*}$		0.222
		(0.143)
Constant	0.264	0.136
	(2.411)	(3.137)
Observations	107	107
R-squared	0.924	0.924

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.40: South Africa

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.886***	0.658***
	(0.0366)	(0.0937)
Cons$*\mathbb{1}_{t\geq t^*}$		-3.117***
		(0.921)
Lag$*\mathbb{1}_{t\geq t^*}$		0.416***
		(0.103)
Constant	0.633***	2.738***
	(0.239)	(0.879)
Observations	114	114
R-squared	0.838	0.881

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.886***	0.540***
	(0.0366)	(0.103)
Cons$*\mathbb{1}_{t\geq t^*}$		-4.508***
		(0.919)
Lag$*\mathbb{1}_{t\geq t^*}$		0.527***
		(0.103)
Constant	0.633***	4.136***
	(0.239)	(0.919)
Observations	114	114
R-squared	0.838	0.905

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.41: Spain

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.918***	0.264***
	(0.0349)	(0.0878)
Cons$*\mathbb{1}_{t\geq t^*}$		-3.441***
		(0.436)
Lag$*\mathbb{1}_{t\geq t^*}$		0.767***
		(0.0787)
Constant	0.168	3.372***
	(0.112)	(0.455)
Observations	114	114
R-squared	0.861	0.955

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.918***	0.0964**
	(0.0349)	(0.0413)
Cons$*\mathbb{1}_{t\geq t^*}$		-4.632***
		(0.208)
Lag$*\mathbb{1}_{t\geq t^*}$		0.913***
		(0.0377)
Constant	0.168	4.608***
	(0.112)	(0.214)
Observations	114	114
R-squared	0.861	0.982

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.42: Switzerland

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.882***	0.773***
	(0.0269)	(0.0487)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.357***
		(0.112)
Lag$*\mathbb{1}_{t\geq t^*}$		0.336***
		(0.0592)
Constant	0.0539	0.289***
	(0.0460)	(0.103)
Observations	114	114
R-squared	0.889	0.915

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.882***	0.777***
	(0.0269)	(0.0492)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.328***
		(0.116)
Lag$*\mathbb{1}_{t\geq t^*}$		0.338***
		(0.0588)
Constant	0.0539	0.263**
	(0.0460)	(0.107)
Observations	114	114
R-squared	0.889	0.916

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.43: Thailand

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.879***	0.606***
	(0.0618)	(0.109)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.953***
		(0.534)
Lag$*\mathbb{1}_{t\geq t^*}$		0.503***
		(0.0979)
Constant	0.294*	1.723***
	(0.177)	(0.550)
Observations	114	114
R-squared	0.779	0.849

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.879***	0.595***
	(0.0618)	(0.115)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.011***
		(0.578)
Lag$*\mathbb{1}_{t\geq t^*}$		0.511***
		(0.102)
Constant	0.294*	1.793***
	(0.177)	(0.596)
Observations	114	114
R-squared	0.779	0.849

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.44: Turkey

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.975***	0.794***
	(0.0318)	(0.127)
Cons$*\mathbb{1}_{t\geq t^*}$		-13.35
		(9.489)
Lag$*\mathbb{1}_{t\geq t^*}$		-0.0445
		(0.186)
Constant	0.385	15.55*
	(0.692)	(9.139)
Observations	114	114
R-squared	0.955	0.963

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.975***	0.774***
	(0.0318)	(0.130)
Cons$*\mathbb{1}_{t\geq t^*}$		-17.17*
		(9.538)
Lag$*\mathbb{1}_{t\geq t^*}$		0.214
		(0.140)
Constant	0.385	16.91*
	(0.692)	(9.628)
Observations	114	114
R-squared	0.955	0.960

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.45: Ukraine

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.893***	0.885***
	(0.0816)	(0.0814)
Cons$*\mathbb{1}_{t\geq t^*}$		-8.383**
		(3.906)
Lag$*\mathbb{1}_{t\geq t^*}$		0.613**
		(0.273)
Constant	1.187*	1.703**
	(0.707)	(0.810)
Observations	81	81
R-squared	0.793	0.805

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.893***	0.930***
	(0.0816)	(0.102)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.705
		(2.833)
Lag$*\mathbb{1}_{t\geq t^*}$		-0.103
		(0.182)
Constant	1.187*	1.395
	(0.707)	(0.980)
Observations	81	81
R-squared	0.793	0.806

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.46: United States

(a) Implementation

VARIABLES	1	2
Lag Inflation	0.784***	0.690***
	(0.115)	(0.146)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.988**
		(0.397)
Lag$*\mathbb{1}_{t\geq t^*}$		0.429***
		(0.159)
Constant	0.482*	0.783**
	(0.271)	(0.391)
Observations	114	114
R-squared	0.626	0.656

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.784***	0.432***
	(0.115)	(0.136)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.708***
		(0.299)
Lag$*\mathbb{1}_{t\geq t^*}$		0.676***
		(0.108)
Constant	0.482*	1.541***
	(0.271)	(0.356)
Observations	114	114
R-squared	0.626	0.764

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.47: Uruguay

(a) Implementation

VARIABLES	(1)	(2)
Lag Inflation	0.773***	0.746***
	(0.155)	(0.162)
Cons$*\mathbb{1}_{t\geq t^*}$		-14.32***
		(3.685)
Lag$*\mathbb{1}_{t\geq t^*}$		0.611***
		(0.122)
Constant	4.127	3.995
	(2.591)	(2.447)
Observations	115	115
R-squared	0.659	0.679

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Inflation	0.909***	0.906***
	(0.0172)	(0.0213)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.147**
		(0.909)
Lag$*\mathbb{1}_{t\geq t^*}$		0.256***
		(0.0767)
Constant	0.762***	0.916
	(0.284)	(0.702)
Observations	113	113
R-squared	0.985	0.985

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

I.2 Inflation Expectations

Table I.48: Argentina

(a) Implementation

VARIABLES	(1)	(2)
Lag Expectations	0.773***	0.746***
	(0.155)	(0.162)
Cons$*\mathbb{1}_{t\geq t^*}$		-14.32***
		(3.685)
Lag$*\mathbb{1}_{t\geq t^*}$		0.611***
		(0.122)
Constant	4.127	3.995
	(2.591)	(2.447)
Observations	115	115
R-squared	0.659	0.679

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	(1)	(2)
Lag Expectations	0.773***	0.743***
	(0.155)	(0.163)
Cons$*\mathbb{1}_{t\geq t^*}$		-14.01***
		(3.366)
Lag$*\mathbb{1}_{t\geq t^*}$		0.611***
		(0.119)
Constant	4.127	3.909
	(2.591)	(2.406)
Observations	115	115
R-squared	0.659	0.681

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.49: Austria

(a) Implementation

VARIABLES	(1)	(2)
Lag Expectations	0.907***	0.738***
	(0.0440)	(0.0944)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.918***
		(0.270)
interactPi_e		0.401***
		(0.0879)
Constant	0.180**	0.663**
	(0.0890)	(0.275)
Observations	115	115
R-squared	0.850	0.888

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.907***	0.666***
	(0.0440)	(0.108)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.148***
		(0.315)
Lag$*\mathbb{1}_{t\geq t^*}$		0.461***
		(0.0951)
Constant	0.180**	0.914***
	(0.0890)	(0.332)
Observations	115	115
R-squared	0.850	0.898

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.50: Belgium

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.816***	0.403***
	(0.105)	(0.132)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.574***
		(0.309)
Lag$*\mathbb{1}_{t\geq t^*}$		0.686***
		(0.115)
Constant	0.357*	1.407***
	(0.194)	(0.330)
Observations	115	115
R-squared	0.704	0.883

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.816***	0.192*
	(0.105)	(0.102)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.315***
		(0.281)
Lag$*\mathbb{1}_{t\geq t^*}$		0.850***
		(0.0837)
Constant	0.357*	2.234***
	(0.194)	(0.311)
Observations	115	115
R-squared	0.704	0.939

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.51: Brazil

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.934***	0.913***
	(0.105)	(0.114)
Cons$*\mathbb{1}_{t\geq t^*}$		-36.87
		(35.47)
Lag$*\mathbb{1}_{t\geq t^*}$		0.269*
		(0.157)
Constant	7.300	35.74
	(7.147)	(35.53)
Observations	115	115
R-squared	0.872	0.873

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.934***	0.857***
	(0.105)	(0.141)
Cons$*\mathbb{1}_{t\geq t^*}$		-114.9
		(106.7)
Lag$*\mathbb{1}_{t\geq t^*}$		0.0335
		(0.172)
Constant	7.300	115.4
	(7.147)	(106.6)
Observations	115	115
R-squared	0.872	0.875

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.52: Chile

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.893***	0.814***
	(0.0499)	(0.0764)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.993***
		(0.559)
Lag$*\mathbb{1}_{t\geq t^*}$		0.367***
		(0.0833)
Constant	0.410*	1.349**
	(0.212)	(0.610)
Observations	115	115
R-squared	0.933	0.942

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.893***	1.70e-08
	(0.0499)	(1.12e-08)
Cons$*\mathbb{1}_{t\geq t^*}$		-
Lag$*\mathbb{1}_{t\geq t^*}$		1.000***
		(1.19e-08)
Constant	0.410*	-1.43e-08
	(0.212)	(1.32e-08)
Observations	115	115
R-squared	0.933	1.000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.53: Colombia

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.977***	0.759***
	(0.0119)	(0.0751)
Cons$*\mathbb{1}_{t\geq t^*}$		-4.884***
		(1.650)
Lag$*\mathbb{1}_{t\geq t^*}$		0.180**
		(0.0865)
Constant	0.0332	5.093***
	(0.0898)	(1.630)
Observations	115	115
R-squared	0.987	0.990

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.977***	0.0359*
	(0.0119)	(0.0196)
Cons$*\mathbb{1}_{t\geq t^*}$		-25.53***
		(0.602)
Lag$*\mathbb{1}_{t\geq t^*}$		0.964***
		(0.0200)
Constant	0.0332	25.53***
	(0.0898)	(0.602)
Observations	115	115
R-squared	0.987	0.999

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.54: Czech Republic

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.910***	0.446***
	(0.0534)	(0.151)
Cons$*\mathbb{1}_{t\geq t^*}$		-5.769***
		(1.455)
Lag$*\mathbb{1}_{t\geq t^*}$		0.556***
		(0.151)
Constant	0.299	5.725***
	(0.184)	(1.467)
Observations	111	111
R-squared	0.909	0.944

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.910***	0.445***
	(0.0534)	(0.151)
Cons$*\mathbb{1}_{t\geq t^*}$		-5.803***
		(1.455)
Lag$*\mathbb{1}_{t\geq t^*}$		0.557***
		(0.151)
Constant	0.299	5.762***
	(0.184)	(1.466)
Observations	111	111
R-squared	0.909	0.944

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.55: Finland

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.853***	0.309***
	(0.0500)	(0.111)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.265***
		(0.439)
Lag$*\mathbb{1}_{t\geq t^*}$		0.740***
		(0.0956)
Constant	0.253***	2.179***
	(0.0889)	(0.465)
Observations	115	115
R-squared	0.791	0.919

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.853***	0.0523
	(0.0500)	(0.0491)
Cons$*\mathbb{1}_{t\geq t^*}$		-3.576***
		(0.293)
Lag$*\mathbb{1}_{t\geq t^*}$		0.954***
		(0.0436)
Constant	0.253***	3.564***
	(0.0889)	(0.301)
Observations	115	115
R-squared	0.791	0.976

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.56: Germany

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.929***	0.795***
	(0.0342)	(0.0780)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.717***
		(0.238)
Lag$*\mathbb{1}_{t\geq t^*}$		0.333***
		(0.0842)
Constant	0.122*	0.510**
	(0.0675)	(0.224)
Observations	115	115
R-squared	0.886	0.908

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.929***	0.736***
	(0.0342)	(0.0822)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.941***
		(0.256)
Lag$*\mathbb{1}_{t\geq t^*}$		0.387***
		(0.0848)
Constant	0.122*	0.734***
	(0.0675)	(0.248)
Observations	115	115
R-squared	0.886	0.916

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.57: Hungary

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.941***	0.890***
	(0.0222)	(0.0356)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.609**
		(0.637)
Lag$*\mathbb{1}_{t\geq t^*}$		0.136***
		(0.0503)
Constant	0.266*	1.431**
	(0.146)	(0.625)
Observations	115	115
R-squared	0.975	0.976

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.941***	0.887***
	(0.0222)	(0.0366)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.679**
		(0.673)
Lag$*\mathbb{1}_{t\geq t^*}$		0.134***
		(0.0493)
Constant	0.266*	1.517**
	(0.146)	(0.662)
Observations	115	115
R-squared	0.975	0.976

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.58: India

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.878***	0.862***
	(0.0672)	(0.0718)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.662***
		(0.755)
Lag$*\mathbb{1}_{t\geq t^*}$		0.476***
		(0.140)
Constant	0.780*	0.930*
	(0.422)	(0.471)
Observations	115	115
R-squared	0.801	0.804

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.878***	0.855***
	(0.0672)	(0.0725)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.062**
		(0.841)
Lag$*\mathbb{1}_{t\geq t^*}$		0.330**
		(0.161)
Constant	0.780*	1.004**
	(0.422)	(0.482)
Observations	115	115
R-squared	0.801	0.805

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.59: Ireland

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.921***	0.111***
	(0.0528)	(0.0414)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.388***
		(0.129)
Lag$*\mathbb{1}_{t\geq t^*}$		0.898***
		(0.0400)
Constant	0.170	2.366***
	(0.130)	(0.129)
Observations	115	115
R-squared	0.844	0.978

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.921***	0.0694**
	(0.0528)	(0.0293)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.556***
		(0.109)
Lag$*\mathbb{1}_{t\geq t^*}$		0.936***
		(0.0279)
Constant	0.170	2.543***
	(0.130)	(0.110)
Observations	115	115
R-squared	0.844	0.986

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.60: Israel

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.736***	0.156
	(0.137)	(0.203)
Cons$*\mathbb{1}_{t\geq t^*}$		-8.273***
		(2.575)
Lag$*\mathbb{1}_{t\geq t^*}$		0.852***
		(0.194)
Constant	1.112*	8.241***
	(0.664)	(2.616)
Observations	115	115
R-squared	0.539	0.716

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.736***	0.122
	(0.137)	(0.177)
Cons$*\mathbb{1}_{t\geq t^*}$		-8.220***
		(2.852)
Lag$*\mathbb{1}_{t\geq t^*}$		0.888***
		(0.164)
Constant	1.112*	8.180***
	(0.664)	(2.905)
Observations	115	115
R-squared	0.539	0.747

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.61: Italy

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.951***	0.882***
	(0.0223)	(0.0453)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.551**
		(0.226)
Lag$*\mathbb{1}_{t\geq t^*}$		0.201***
		(0.0528)
Constant	0.0775	0.385*
	(0.0550)	(0.215)
Observations	115	115
R-squared	0.950	0.955

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.951***	0.839***
	(0.0223)	(0.0764)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.784*
		(0.402)
Lag$*\mathbb{1}_{t\geq t^*}$		0.241***
		(0.0755)
Constant	0.0775	0.624
	(0.0550)	(0.406)
Observations	115	115
R-squared	0.950	0.956

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.62: Japan

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.885***	0.853***
	(0.0531)	(0.0578)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.159**
		(0.0683)
Lag$*\mathbb{1}_{t\geq t^*}$		0.308***
		(0.0851)
Constant	0.0502*	0.0438
	(0.0281)	(0.0323)
Observations	115	115
R-squared	0.826	0.837

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.885***	0.852***
	(0.0531)	(0.0579)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.122**
		(0.0572)
Lag$*\mathbb{1}_{t\geq t^*}$		0.279***
		(0.0816)
Constant	0.0502*	0.0446
	(0.0281)	(0.0342)
Observations	115	115
R-squared	0.826	0.836

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.63: Korea

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.906***	0.582***
	(0.0409)	(0.0893)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.957***
		(0.638)
Lag$*\mathbb{1}_{t\geq t^*}$		0.441***
		(0.0923)
Constant	0.305**	2.839***
	(0.143)	(0.658)
Observations	115	115
R-squared	0.886	0.918

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.906***	0.527***
	(0.0409)	(0.0955)
Cons$*\mathbb{1}_{t\geq t^*}$		-3.210***
		(0.668)
Lag$*\mathbb{1}_{t\geq t^*}$		0.474***
		(0.101)
Constant	0.305**	3.159***
	(0.143)	(0.672)
Observations	115	115
R-squared	0.886	0.925

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.64: Mexico

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.929***	0.868***
	(0.0848)	(0.123)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.996
		(1.975)
Lag$*\mathbb{1}_{t\geq t^*}$		0.0850
		(0.154)
Constant	0.529	2.145
	(0.587)	(1.920)
Observations	115	115
R-squared	0.868	0.871

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.929***	0.850***
	(0.0848)	(0.124)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.829
		(2.209)
Lag$*\mathbb{1}_{t\geq t^*}$		0.109
		(0.135)
Constant	0.529	2.934
	(0.587)	(2.190)
Observations	115	115
R-squared	0.868	0.873

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.65: Netherlands

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.899***	0.385***
	(0.0738)	(0.121)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.702***
		(0.266)
Lag$*\mathbb{1}_{t\geq t^*}$		0.660***
		(0.102)
Constant	0.213	1.613***
	(0.142)	(0.298)
Observations	115	115
R-squared	0.811	0.918

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.899***	0.371***
	(0.0738)	(0.118)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.765***
		(0.267)
Lag$*\mathbb{1}_{t\geq t^*}$		0.672***
		(0.100)
Constant	0.213	1.679***
	(0.142)	(0.298)
Observations	115	115
R-squared	0.811	0.920

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.66: Norway

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.717***	0.445***
	(0.0657)	(0.103)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.675***
		(0.205)
Lag$*\mathbb{1}_{t\geq t^*}$		0.694***
		(0.0808)
Constant	0.621***	1.376***
	(0.156)	(0.254)
Observations	115	115
R-squared	0.577	0.770

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.717***	0.442***
	(0.0657)	(0.102)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.693***
		(0.202)
Lag$*\mathbb{1}_{t\geq t^*}$		0.705***
		(0.0779)
Constant	0.621***	1.376***
	(0.156)	(0.255)
Observations	115	115
R-squared	0.577	0.786

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.67: Paraguay

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.796***	0.669***
	(0.107)	(0.132)
Cons$*\mathbb{1}_{t\geq t^*}$		-4.248***
		(1.296)
Lag$*\mathbb{1}_{t\geq t^*}$		0.449***
		(0.161)
Constant	1.793**	3.625***
	(0.823)	(1.301)
Observations	115	115
R-squared	0.642	0.669

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.796***	0.442***
	(0.107)	(0.139)
Cons$*\mathbb{1}_{t\geq t^*}$		-7.679***
		(1.543)
Lag$*\mathbb{1}_{t\geq t^*}$		0.619***
		(0.125)
Constant	1.793**	7.274***
	(0.823)	(1.651)
Observations	115	115
R-squared	0.642	0.721

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.68: Peru

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.123***	0.118***
	(0.0102)	(0.00878)
Cons$*\mathbb{1}_{t\geq t^*}$		-47.70***
		(11.81)
Lag$*\mathbb{1}_{t\geq t^*}$		0.913***
		(0.0152)
Constant	18.91***	47.61***
	(4.625)	(11.81)
Observations	115	115
R-squared	0.766	0.804

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.123***	0.0989***
	(0.0102)	(0.00425)
Cons$*\mathbb{1}_{t\geq t^*}$		-172.0***
		(29.04)
Lag$*\mathbb{1}_{t\geq t^*}$		0.870***
		(0.00718)
Constant	18.91***	172.1***
	(4.625)	(29.04)
Observations	115	115
R-squared	0.766	0.938

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.69: Philippines

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.881***	0.688***
	(0.0435)	(0.0918)
Cons$*\mathbb{1}_{t\geq t^*}$		-3.014***
		(0.731)
Lag$*\mathbb{1}_{t\geq t^*}$		0.411***
		(0.0955)
Constant	0.613***	2.541***
	(0.233)	(0.764)
Observations	115	115
R-squared	0.857	0.886

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.881***	0.685***
	(0.0435)	(0.0931)
Cons$*\mathbb{1}_{t\geq t^*}$		-3.050***
		(0.747)
Lag$*\mathbb{1}_{t\geq t^*}$		0.413***
		(0.0955)
Constant	0.613***	2.583***
	(0.233)	(0.781)
Observations	115	115
R-squared	0.857	0.886

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.70: Poland

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.780***	0.604***
	(0.0902)	(0.149)
Cons$*\mathbb{1}_{t\geq t^*}$		-9.322**
		(4.098)
Lag$*\mathbb{1}_{t\geq t^*}$		0.381**
		(0.155)
Constant	1.500**	9.308**
	(0.661)	(4.101)
Observations	115	115
R-squared	0.845	0.874

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.780***	0.560***
	(0.0902)	(0.166)
Cons$*\mathbb{1}_{t\geq t^*}$		-11.54**
		(5.086)
Lag$*\mathbb{1}_{t\geq t^*}$		0.408**
		(0.177)
Constant	1.500**	11.58**
	(0.661)	(5.076)
Observations	115	115
R-squared	0.845	0.881

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.71: Russia

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.876***	0.876***
	(0.110)	(0.111)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.981
		(4.624)
Lag$*\mathbb{1}_{t\geq t^*}$		0.218
		(0.147)
Constant	1.099	1.172
	(3.599)	(4.643)
Observations	107	107
R-squared	0.890	0.890

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.876***	0.876***
	(0.110)	(0.112)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.983
		(4.741)
Lag$*\mathbb{1}_{t\geq t^*}$		0.218
		(0.148)
Constant	1.099	1.179
	(3.599)	(4.759)
Observations	107	107
R-squared	0.890	0.890

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.72: South Africa

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.926***	0.801***
	(0.0388)	(0.0796)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.567***
		(0.705)
Lag$*\mathbb{1}_{t\geq t^*}$		0.329***
		(0.0795)
Constant	0.463*	1.761**
	(0.248)	(0.769)
Observations	115	115
R-squared	0.897	0.914

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.926***	0.761***
	(0.0388)	(0.0831)
Cons$*\mathbb{1}_{t\geq t^*}$		-3.016***
		(0.746)
Lag$*\mathbb{1}_{t\geq t^*}$		0.358***
		(0.0809)
Constant	0.463*	2.255***
	(0.248)	(0.818)
Observations	115	115
R-squared	0.897	0.918

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.73: Spain

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.915***	0.454***
	(0.0625)	(0.104)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.801***
		(0.467)
Lag$*\mathbb{1}_{t\geq t^*}$		0.592***
		(0.0963)
Constant	0.199	2.685***
	(0.158)	(0.484)
Observations	115	115
R-squared	0.866	0.919

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.915***	0.286***
	(0.0625)	(0.0880)
Cons$*\mathbb{1}_{t\geq t^*}$		-3.980***
		(0.586)
Lag$*\mathbb{1}_{t\geq t^*}$		0.735***
		(0.0828)
Constant	0.199	3.919***
	(0.158)	(0.599)
Observations	115	115
R-squared	0.866	0.936

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.74: Switzerland

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.936***	0.886***
	(0.0303)	(0.0449)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.217**
		(0.101)
Lag$*\mathbb{1}_{t\geq t^*}$		0.206***
		(0.0637)
Constant	0.0423	0.144
	(0.0387)	(0.0915)
Observations	115	115
R-squared	0.932	0.939

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.936***	0.884***
	(0.0303)	(0.0463)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.227**
		(0.108)
Lag$*\mathbb{1}_{t\geq t^*}$		0.209***
		(0.0641)
Constant	0.0423	0.154
	(0.0387)	(0.0993)
Observations	115	115
R-squared	0.932	0.939

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.75: Thailand

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.907***	0.646***
	(0.0502)	(0.131)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.349***
		(0.777)
Lag$*\mathbb{1}_{t\geq t^*}$		0.489***
		(0.133)
Constant	0.286*	1.988**
	(0.159)	(0.781)
Observations	115	115
R-squared	0.840	0.882

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.907***	0.597***
	(0.0502)	(0.138)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.678***
		(0.809)
iLag$*\mathbb{1}_{t\geq t^*}$		0.528***
		(0.134)
Constant	0.286*	2.344***
	(0.159)	(0.826)
Observations	115	115
R-squared	0.840	0.888

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.76: Turkey

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.964***	0.715***
	(0.0323)	(0.116)
Cons$*\mathbb{1}_{t\geq t^*}$		-19.37**
		(8.739)
Lag$*\mathbb{1}_{t\geq t^*}$		0.147
		(0.148)
Constant	0.879	20.49**
	(0.696)	(8.547)
Observations	115	115
R-squared	0.929	0.941

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.964***	0.714***
	(0.0323)	(0.119)
Cons$*\mathbb{1}_{t\geq t^*}$		-20.82**
		(8.938)
Lag$*\mathbb{1}_{t\geq t^*}$		0.324**
		(0.146)
Constant	0.879	20.13**
	(0.696)	(8.883)
Observations	115	115
R-squared	0.929	0.939

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.77: Ukraine

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.798***	0.796***
	(0.165)	(0.166)
Cons$*\mathbb{1}_{t\geq t^*}$		43.52
		(32.55)
Lag$*\mathbb{1}_{t\geq t^*}$		-0.570
		(1.014)
Constant	-30.52	-36.28
	(25.32)	(30.00)
Observations	108	108
R-squared	0.638	0.639

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.798***	0.796***
	(0.165)	(0.165)
Cons$*\mathbb{1}_{t\geq t^*}$		33.66
		(30.15)
Lag$*\mathbb{1}_{t\geq t^*}$		0.426**
		(0.185)
Constant	-30.52	-37.46
	(25.32)	(30.63)
Observations	108	108
R-squared	0.638	0.639

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.78: United States

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.831***	0.767***
	(0.0642)	(0.0746)
Cons$*\mathbb{1}_{t\geq t^*}$		-0.950***
		(0.251)
Lag$*\mathbb{1}_{t\geq t^*}$		0.389***
		(0.114)
Constant	0.409***	0.616***
	(0.151)	(0.189)
Observations	115	115
R-squared	0.755	0.771

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

VARIABLES	1	2
Lag Expectations	0.831***	0.641***
	(0.0642)	(0.112)
Cons$*\mathbb{1}_{t\geq t^*}$		-1.457***
		(0.475)
Lag$*\mathbb{1}_{t\geq t^*}$		0.563***
		(0.180)
Constant	0.409***	1.017***
	(0.151)	(0.321)
Observations	115	115
R-squared	0.755	0.828

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table I.79: Uruguay

(a) Implementation

VARIABLES	1	2
Lag Expectations	0.925***	0.924***
	(0.0250)	(0.0277)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.816**
		(1.154)
Lag$*\mathbb{1}_{t\geq t^*}$		0.353***
		(0.124)
Constant	0.627*	0.652
	(0.345)	(0.629)
Observations	114	114
R-squared	0.974	0.974

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Announcement

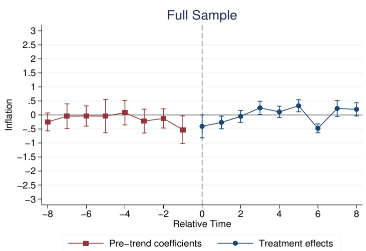
VARIABLES	1	2
Lag Expectations	0.925***	0.921***
	(0.0250)	(0.0300)
Cons$*\mathbb{1}_{t\geq t^*}$		-2.549**
		(1.022)
Lag$*\mathbb{1}_{t\geq t^*}$		0.297***
		(0.0825)
Constant	0.627*	0.842
	(0.345)	(0.838)
Observations	114	114
R-squared	0.974	0.974

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

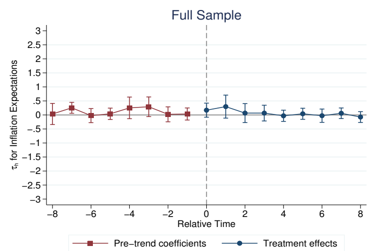
J Additional Results

Figure J.2: Treatment Effects Around Implementation: Full Sample

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

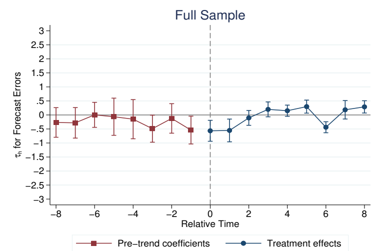
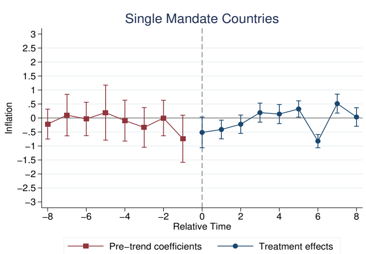
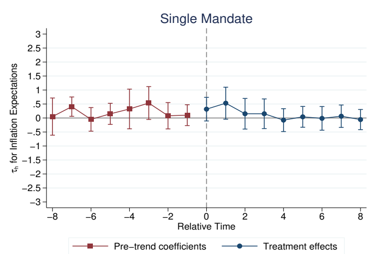


Figure J.3: Treatment Effects Around Implementation: Single Mandate Economies

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

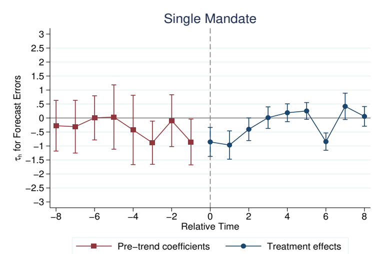
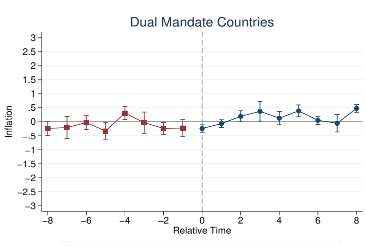
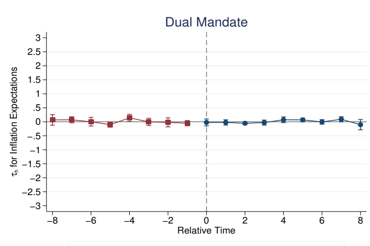


Figure J.4: Treatment Effects Around Implementation: Dual Mandate Economies

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

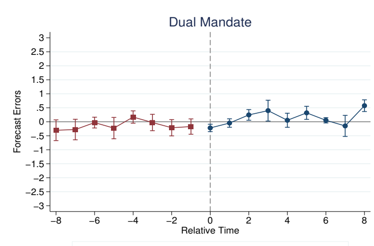
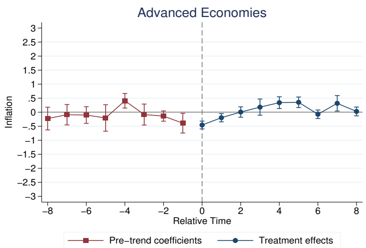
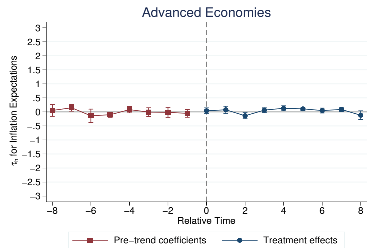


Figure J.5: Treatment Effects Around Implementation: Advanced Economies

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

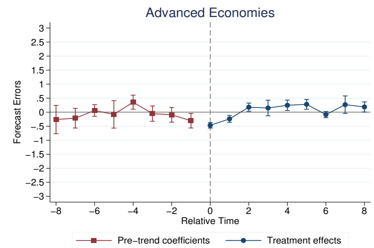
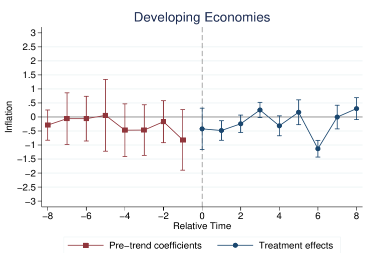
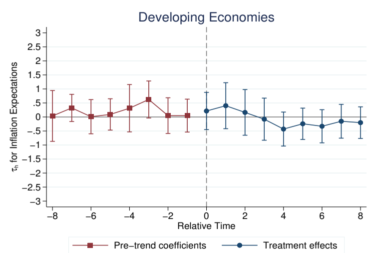


Figure J.6: Treatment Effects Around Implementation: Developing Economies

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

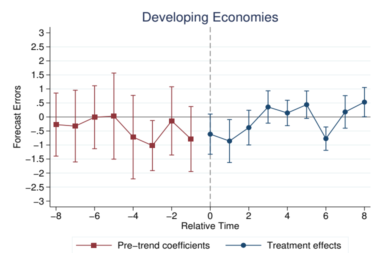
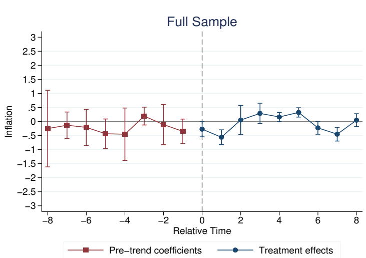
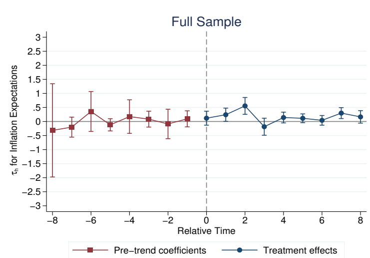


Figure J.7: Treatment Effects Around Announcement: Full Sample

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

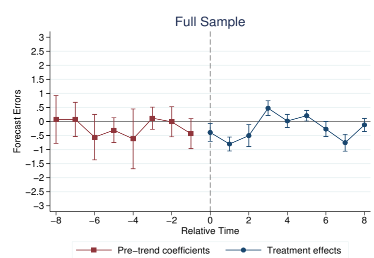
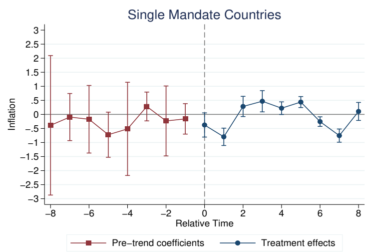
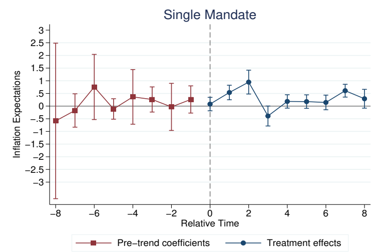


Figure J.8: Treatment Effects Around Announcement: Single Mandate Economies

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

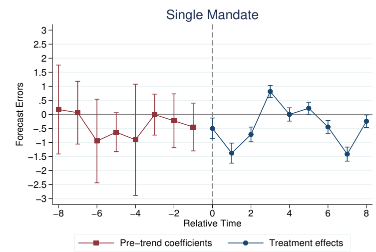
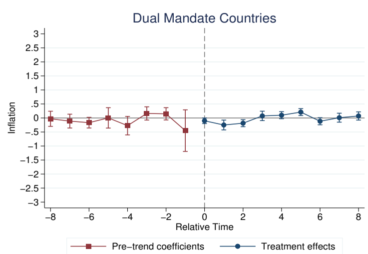
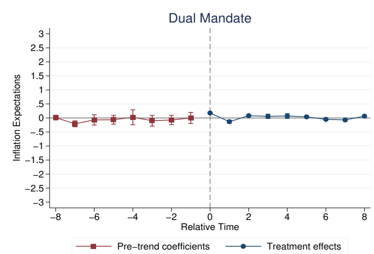


Figure J.9: Treatment Effects Around Announcement: Dual Mandate Economies

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

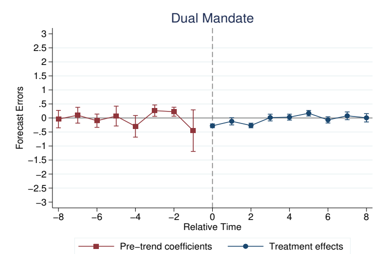
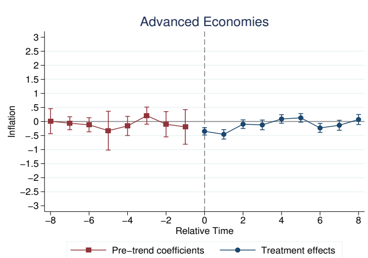
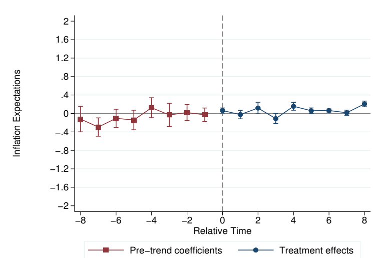


Figure J.10: Treatment Effects Around Announcement: Advanced Economies

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

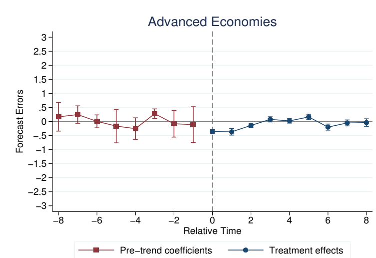
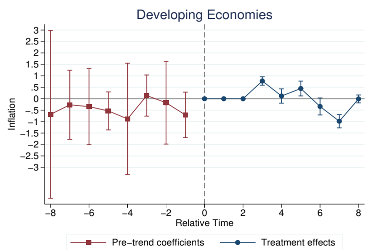
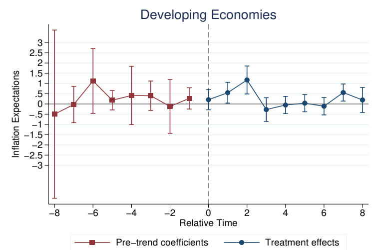


Figure J.11: Treatment Effects Around Announcement: Developing Economies

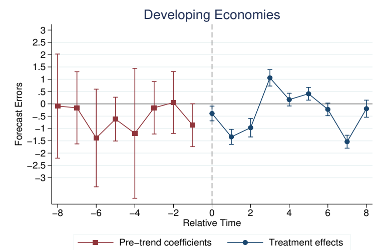
(a) Inflation



(b) Inflation Expectations



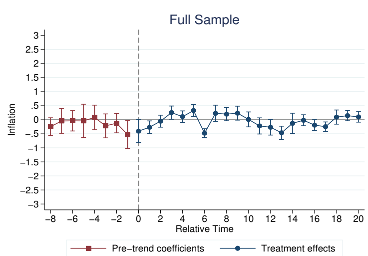
(c) Forecast Errors



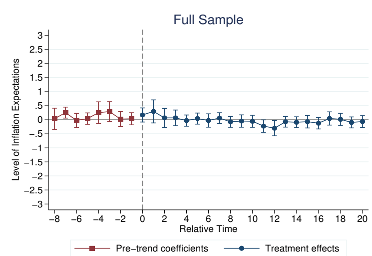
K Treatment effect after Five Years

Figure K.12: Treatment Effects Around Implementation: Full Sample

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

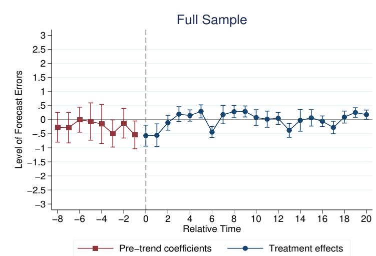
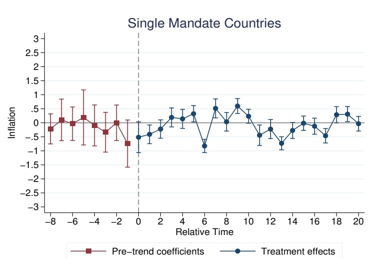
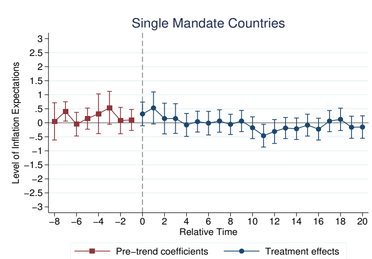


Figure K.13: Treatment Effects Around Implementation: Single Mandate Economies

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

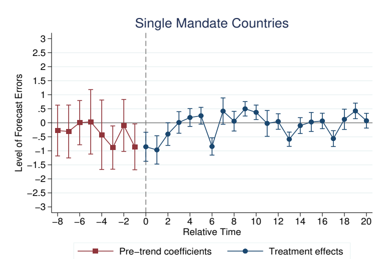
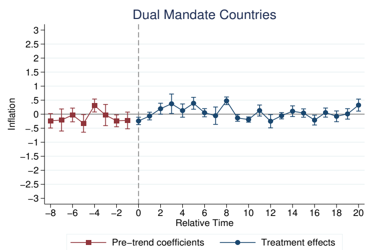
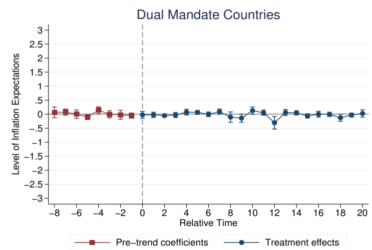


Figure K.14: Treatment Effects Around Implementation: Dual Mandate Economies

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

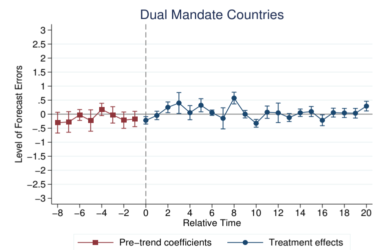
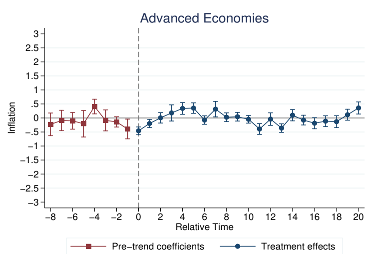
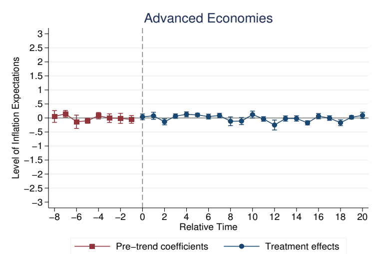


Figure K.15: Treatment Effects Around Implementation: Advanced Economies

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

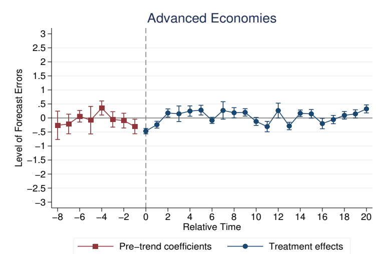
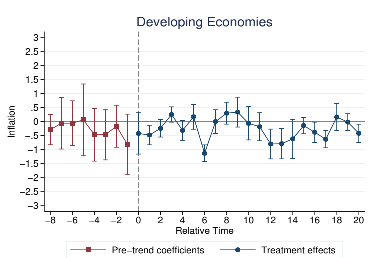
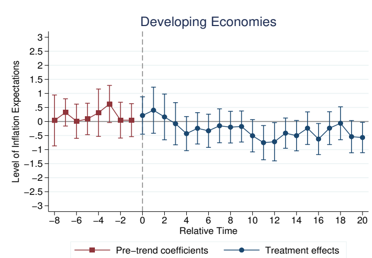


Figure K.16: Treatment Effects Around Implementation: Developing Economies

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

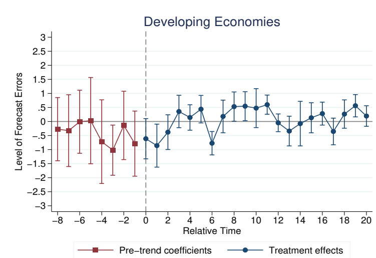
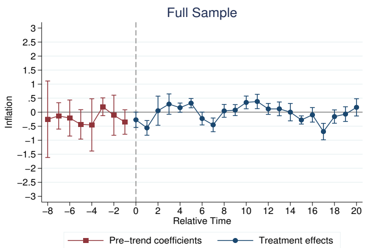
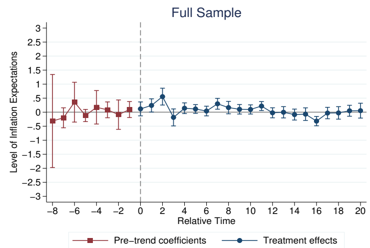


Figure K.17: Treatment Effects Around Announcement: Full Sample

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

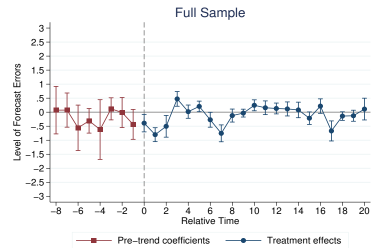
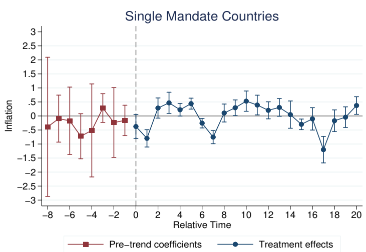
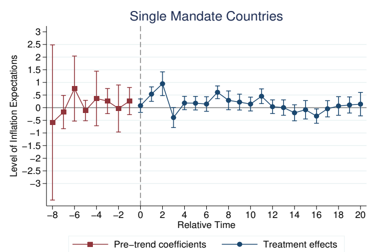


Figure K.18: Treatment Effects Around Announcement: Single Mandate Economies

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

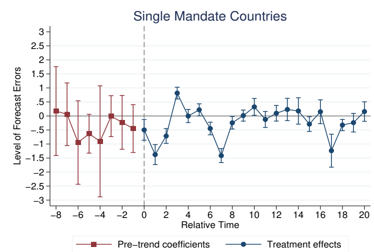
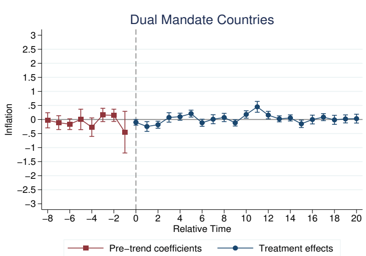
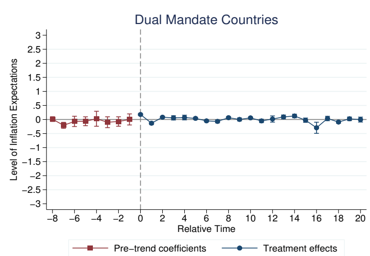


Figure K.19: Treatment Effects Around Announcement: Dual Mandate Economies

(a) Inflation



(b) Inflation Expectations



(c) Forecast Errors

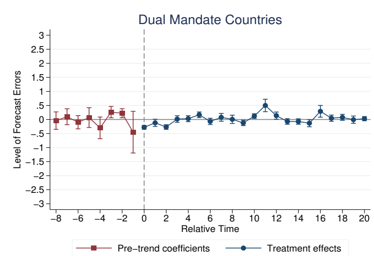


Figure K.20: Treatment Effects Around Announcement: Advanced Economies

(a) Inflation (b) Inflation Expectations (c) Forecast Errors

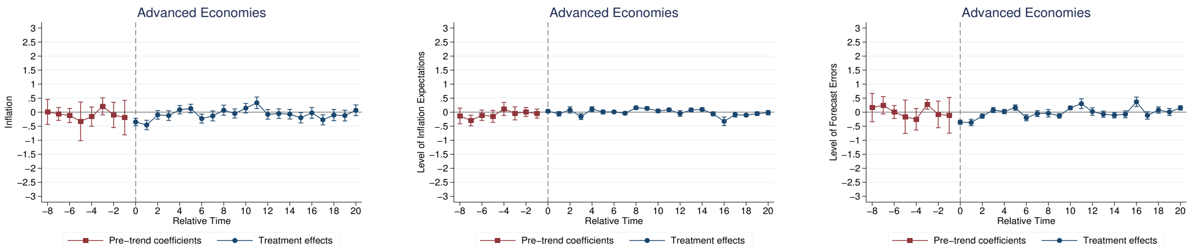
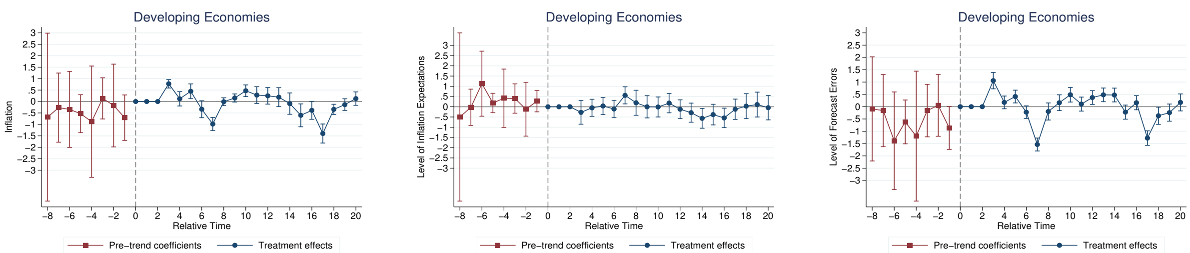


Figure K.21: Treatment Effects Around Announcement: Developing Economies

(a) Inflation (b) Inflation Expectations (c) Forecast Errors



L Arellano-Bond for Announcement Dates

Table L.80: Arellano-Bond Estimation results for equation (13)

VARIABLES	Pre-IT	Post-IT		
	(1)	(2)	(3)	(4)
	π_t^e	π_t^e (1 year)	π_t^e (2 years)	π_t^e (Full Sample)
π_{t-1}^e	0.890***	0.937***	0.935***	0.929***
	(0.0935)	(0.066)	(0.078)	(0.081)
$\pi_{t,fe}$	0.473**	0.119	0.180*	0.299***
	(0.229)	(0.088)	(0.108)	(0.070)
Constant	0.542	0.228	0.261	0.301
	(0.645)	(0.251)	(0.268)	(0.253)
Observations	764	112	204	1,884
Number of countries	23	23	23	23

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1