Master in Economics: Empirical Applications and Policies

University of the Basque Country UPV/EHU

The sensitivity of estimated DSGE models to alternative data vintages

Author: Óscar Martínez Pérez

Supervisor: Jesús Vázquez Pérez

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Universidad del País Vasco

Euskal Herriko Unibertsitatea

MASTER IN ECONOMICS

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Abstract

This paper considers the estimation of a structural DSGE model with three alternative macroeconomic data vintages corresponding to the first-release (real-time data), the third-release data, and the highly revised data to assess the sensitivity of the estimation arising from the data revision process. The empirical evidence based on a structural econometric approach suggests that some structural and shock process parameters are only identified whenever highly revised data become available. More generally, several parameters are highly sensitive to data vintage in the estimation procedure. Data revisions also affect the estimated properties of the economic agents' expectations that determine their decisions. Its empirical validation is assessed through the corresponding observable counterparts reported in the Survey of Professional Forecasters.

Keywords: data revision, medium-scale DSGE model, real-time data.

1 Introduction

Statistical agencies, and other institutions such as central banks, collect and analyze a vast amount of macroeconomic data. These data may have many different characteristics depending, among other things, on the level of aggregation, the implementation of seasonal adjustments, and the introduction of data revisions when more accurate macroeconomic information becomes available. Certainly, the tasks associated with the collection of good data involves high costs in terms of both effort and resources. This indicates that central banks and policymakers find it highly relevant to their decisions (Bernanke and Boivin, 2003). The availability and timing of data have not only become a crucial issue for central banks but also have great importance for other important activities such as economic research and policy evaluation. In particular, there has been a substantial increase in popularity in the analysis of data revisions, as well as analyses based on real-time data. This popularity is shown by the continuous publications of real-time data reported on the Philadelphia Federal Reserve Bank website, the creation of real-time data sets such as that of Dean Croushore and Tom Stark (Croushore and Stark, 2001),[1] and more generally, the evidence on the importance of revisions provided by many academic papers.[2]

A data revision is a statistical process by which already published data is modified to offer higher quality data. These revisions involve two type of components. On the one hand, there is *noise reduction*, which according to Mankiw and Shapiro (1986) reduces measurement errors, for example by using larger samples or correcting errors. On the other hand, data revisions also involve *adding news*. These occur when statistical agencies correctly use the data they have available to form existing values, and then extra news comes after the data is released.

In many cases, these changes can be quite significant, for instance, the one associated with US investment growth in 1980. In mid-August of the same year published data for the second quarter suggests an almost null growth on investment (0.02 percent). This value was revised just two months later and investment growth for the second quarter of 1980 was recalculated, placing it at more than 3 percent.[3]

[1]There are others examples of real-time data sets creation such as Gerdesmeier and Roffia (Herrmann, Orphanides and Siklos, 2005).

[2]Croushore (2011) provides an excellent source of the literature on real-time data and their revisions.

[3]Croushore (2011) points out a notable example regarding US GDP. In January of 2009, published data suggested that there had been an annualized drop in GDP for the last quarter of 2008 of 3.8 percent,

Until recent times, economists have assumed that data revisions are small and have no real effect on economic modeling, research, and forecasting. In many cases, the data used for these studies are not the revised data, but the unrevised data that was available to economic agents at the time. When considering the transcripts of the 1992 Fed policymakers' meeting, it can be observed that a concern was on deceleration of the economy. When looking at the data, it is possible to realize that the GDP grew by 3.3 percent, which does not precisely transmit a slowdown. However, when looking at the data that was available at the time, growth was observed much lower, which might have led policymakers to worry (Croushore, 2011). This example again shows the importance of data revisions in an area as relevant as economic policymaking, which may lead to severe consequences. For this reason, data revisions have gained increasing attention in recent years. One of the best-known studies on the importance of analysis with real-time and revised data is the one carried out by Orphanides (2001). This study shows that the Taylor principle to avoid the possibility of self-fulfilling equilibria and bubbles (i.e. the short-term interest rate monitored by the central bankers have to react more than proportionally to changes in the rate of inflation) does not hold when real-time data is considered in the estimated policy rule. However, this principle holds if revised data is used instead of real-time data. Moreover, there are many other notable contributions to the topic in monetary policy as Bernanke and Boivin (2001) and Rudebusch (2001), and in forecasting as Amato and Swanson (2001) and Stark and Croushore (2002).

Researchers and policymakers analyze economic contexts, search for solutions, make decisions, and create forecasts through economic models. The contributions to this data revision literature using structural models are still rather limited.[4] Therefore, this paper adds an analysis of the sensitivity of a dynamic stochastic general equilibrium (DSGE) model across alternative data vintages. These models are typically estimated using highly revised data. Moreover, expectations play a central role in modern macroeconomics as emphasized in seminal papers such as Barro (1984) and Friedman (1995). But, in reality, decisions are based on real-time data, that is, highly inaccurate data. We assess the

a large but not alarming drop. However, when the data was revised just a month later, this decline was recalculated at 6.2 percent, which positioned the American economy in the worst recession in the past 25 years.

[4] Among others, a few examples are Vázquez, María-Dolores and Londoño, 2012; Casares and Vázquez, 2016.

importance of data revisions by estimating the standard medium-scale new-Keynesian model suggested by Smets and Wouters (2007) using alternative vintages of aggregate data. This canonical DSGE model includes seven shocks and various sources of nominal rigidities, affecting prices and wages. It also includes a few sources of real rigidities, such as consumption habit formation as well as capital accumulation and capital utilization adjustment costs. More precisely, this model will be estimated using three different data vintages to analyze the sensitivity of parameters estimates to data revisions.

The second part of the analysis focuses on the properties of the expectations generated through the different estimated versions of the DSGE model. By doing so, it will allow us to better assess the impact that different data vintages may have on the expectations that determine economic agents' decisions. Besides, a comparison of the model's expectations with those reported in the Survey of Professional Forecasters will allow us to evaluate the empirical validity of the expectations implied by the DSGE model estimated with alternative data vintages.

Finally, an analysis of the transmission mechanisms of monetary policy shocks is carried out. They are evaluated through the impulse-response functions of inflation and GDP growth. These impulse-response functions will be generated with the alternative model estimations obtained across data vintages. In this way, it is shown how different data vintages affect the transmission of shocks.

The rest of the paper is organized as follows. Section 2 briefly presents the canonical DSGE model. Section 3 describes the alternative data vintages considered, the differences between these data vintages, and describes the estimation methodology. In Sections 4, the results of the model estimates are discussed. Section 5 presents the properties of the expectations implied by the estimated models. Section 6 analyzes the shocks transmission mechanisms. Finally, Section 7 concludes.

2 Model

This section describes the canonical medium-scale new-Keynesian model suggested by Smets and Wouters (2007). This DSGE model builds on the basic new-Keynesian model, thus sharing part of the structural components as the New Keynesian Philips curve, a dynamic IS curve, and a standard monetary policy rule.[5] In addition, the model has different building blocks that incorporate various nominal and real frictions affecting firms' and households' decisions.[6] As a micro-founded model, households maximize a utility function that extends infinitely over time and includes two arguments: the consumption of a composite good and hours worked. In order to introduce some monopolistic power in the labor market, it is assumed that household members supply units of labor, and an intermediate labor union differentiates labor units. This labor union sets wages following Calvo's (1983) model. Moreover, consumption has an external habit formation component. Households also rent capital services to firms, hold riskless bonds, and decide the amount of capital they accumulate, given the capital adjustment cost.

The composite consumption good is obtained as a combination of intermediate differentiated goods. The intermediate good producers set prices and decide the amount of inputs (capital and labor) they need by maximizing their profits, given a production function. As the labor union, this building block is considered to create monopolistic power to introduce the nominal sticky prices à la Calvo (1983). The intermediate goods are then bought by the final good producers, who resell the final composite good in a perfectly competitive market to consumers, investors, and the government.

It should be noted that prices and wages that do not adjust due to the parameter introduced by Calvo are indexed to past inflation. Therefore prices, similarly to wages, are adjusted with the present and expected marginal costs that depend on wages and on the rental rate of capital, but also on lagged inflation.[7]

The last sector to be considered in the model is the central bank. It follows a Taylor-type rule (Taylor 1993) that adjusts the interest rate in response to the output gap, the inflation, and the output gap growth.[8]

The model also incorporates five structural shocks following an AR(1) process and

[5] Worth mentioning that this model corresponds to a closed economy and it does not include a government sector.

[6] The log-linearized equations around the steady-state balance growth path are presented in the Appendix. For a more in-depth explanation of the model and their components, see Smets and Wouters (2007), and its Model Appendix with the full derivations.

[7] Wages depend on past and expected wages and inflation.

[8] The output gap is defined as the difference between the current and potential level of output, that is, the one that would be achieved in an economy with flexible prices and wages.

two shocks following an ARMA(1,1) process (in particular the wage and price mark-up shocks). These are the productivity shock (ε_t^a), the risk premium shock (ε_t^b), and the investment-specific technology shock (ε_t^i), the last two affecting the intertemporal margin. The wages and price mark-up shocks ($\varepsilon_t^w, \varepsilon_t^p$), affecting the intratemporal margin. Further, by including the moving average processes, this mark-up shocks capture the high-frequency fluctuations. Finally, the monetary policy shock and exogenous spending shocks ($\varepsilon_t^r, \varepsilon_t^g$), capturing policy shocks. The last mentioned shock (i.e., the exogenous spending shock) is also affected by the productivity shock to capture the effect of the net exports.

3 Data and estimation methodology

The data used to estimate the model consists of three sets of seven variables, all comprised between the first quarter of 1966 until the first quarter of 2009. First, we have the highly revised data series, the same that Smets and Wouters (2007) used in their study, but now including a more recent sample. These data sets include variables that must have been revised for at least three years to be considered highly revised data.

Second, two different vintages are used. The first is the real-time data or first-release data. These data are the initial announcements of macroeconomic variables published by the US statistical agencies and are released around 45 days after the end of the quarter. The second vintage used is the third release; this is published approximately two months after the first release. For example, the data for the last quarter of 2000 was published for the first time approximately in 2001 mid-February. The second release (not used in this study) was published in 2001 mid-March. A month later, mid-April, another revision was made corresponding to the third release. After these publications, the data undergoes an annual revision by the end of July for the following three years. Moreover, benchmark revisions are applied to them every five years, which involve changes in the base year to compute real (deflated) values as well as other statistical adjustments.[9]

To ensure that the chosen revised observations were not to experience sizable revisions

[9] A more detailed information of the data vintage can be obtained from the "General Notes on the Philadelphia Fed's Real-Time Data Set for Macroeconomists (RTDSM) – Variables from the National Income and Product Accounts" published in the Real-Time Data Research Center of the Fed of Philadelphia website. See also Croushore (2011).

in future releases, it has been decided to consider data up to the first quarter of 2009. All the revised data is retrieved from the Bureau of Economic Analysis and, the two other data vintages are collected from the Federal Reserve Bank of Philadelphia real-time database.

The seven observable time series variables are the same as the ones considered in Smets and Wouters (2007). That is, the log differences of real consumption, real gross domestic product (GPD), real investment and real wage, the log of hours worked, the inflation rate obtained from the first difference of the log of the implicit GDP deflator, and the federal funds rate. For the estimations using the first and third releases, not all the variables are considered in their vintage. For these two estimates, only real consumption, real GDP, real investment, and inflation are taken into account; for the remaining three variables, the revised data is used. The reason is the lack of the first and third releases of the real wage data and hours worked. Likewise, the first and third releases of the population series used to calculate the per capita values were also not available. Moreover, it is important to notice that the federal funds rate is not revised. As is standard in the related literature, the seven observable variables used in the estimation procedure are considered covariance stationary.

3.1 Second-moment statistics

The plots of the real-time and revised time series used in the empirical analysis are shown in the Appendix. In these plots, it is observed how the volatility of the series changes when the revisions are applied. The reduction in the size of investment fluctuations is noteworthy. This fact is confirmed by the standard deviation statistic shown in Table 1.[10] In this table, it is shown that the investment's volatility is approximately three times lower in the revised series than in the real-time series. It is also remarkable that the volatility of all the revised series is lower than the volatility of the real-time series, except for the output. Croushore (2011) explains that GDP growth is underestimated in times of economic expansion and overestimated in times of recession. Therefore, GDP volatility is greater when the series is revised. Nonetheless, it can be seen in all series

[10]The second-moment statistics for the first and third release of real wage, hours worked, and the short term interest rate are not calculated since the series used for the first two variables are only the strong revised data, while the third variable (the federal funds rate) is not revised at all.

Table 1: Second-moment Statistics

	ΔGDP	ΔCons.	ΔInv.	Inf.	ΔWage	H. Worked	Int. rate
Std. dev.							
First release	0.8056	0.7664	6.0418	0.6367	-	-	-
Third release	0.8609	0.8134	6.2772	0.6578	-	-	-
Revised	0.8617	0.7310	2.2111	0.5885	0.6593	2.8214	0.8310
First Order Autocorrelation							
First release	0.4818	0.0213	0.5690	0.8189	-	-	-
Third release	0.4267	0.0775	0.6045	0.8078	-	-	-
Revised	0.2944	0.2693	0.5941	0.8824	0.0287	0.9714	0.9512
Correlations							
First-Revised	0.8071	0.7729	0.7932	0.9265	-	-	-
Third-Revised	0.8159	0.7675	0.7949	0.9218	-	-	-
First-Third	0.9770	0.9829	0.9789	0.9876	-	-	-

Note: The second-moment statistics for the first and third releases of real wage, hours worked, and the short term interest rate, are not calculated since we only considered revised data for these variables.

that the standard deviation of output is higher than the consumption standard deviation. And at the same time, the standard deviation of investment is greater than the standard deviations of both output and consumption.

In addition to the standard deviation statistics, Table 1 shows other second moments obtained across data vintages. Thus, the first-order autocorrelation of each variable is also affected by the revision process. Take the example of GDP, for which the autocorrelation statistic is approximately 35% lower in the revised series than in the other two vintages. In contrast, the autocorrelation of consumption is roughly zero for the first and third releases, whereas for the revised data it is roughly 0.27. Note also that (revised) real wages show low persistence while (revised) hours worked, and the interest rate are highly persistent.

The correlation between vintages is very high in all cases. By looking at the correlation of the first or third release with the revised series, it can be seen that they are approximately 0.8, while the correlation of inflation across vintages exceeds 0.9. Nonetheless, the correlation between first and third releases of all variables have a coefficient around 0.98. This value reflects that the time proximity between these two vintages may not allow the second and third release revisions to greatly modify or affect the data.

3.2 Estimation methodology

The methodology used to carry out model estimation is the same two-step Bayesian econometrics procedure used in Smets and Wouters (2007) and in the related literature. The first step maximizes a log posterior function, which combines the empirical likelihood of the data with the prior distributions information of the parameters. The prior distributions of the parameters have also been set as in Smets and Wouters (2007).[11] Then, in the second step, the posterior distributions of the parameters are computed through the Metropolis-Hastings algorithm.[12]

Five parameters are not likely identified with the set of observables used in the estimation procedure. Following Smets and Wouters (2007), the quarterly depreciation rate (δ) and the exogenous spending-GDP ratio (g_y) are set at 0.025 and 0.18, respectively. Moreover, the curvature parameters of the Kimball aggregators of labor and goods markets (ε_w and ε_p) are both set at 10, and the mark-up in the labor market (λ_w) is set at 1.5.

4 Estimation results

The posterior distributions resulting from the estimation process are shown in Tables 2 and 3. They include the estimations using the three alternative data vintages. Comparing the estimations, it is shown that most structural and shock parameters are fairly robust.[13] This result is in line with the findings of Casares and Vázquez (2016). Among these almost unaffected parameters, the estimations of the monetary policy rule can be highlighted. The parameter that suffers the most change in this Taylor-type is the monetary policy shock persistence (ρ_r) that, as Vázquez, Maria-Dolores, and Londoño (2012) found, is larger than in previous studies. This result is in stark contrast to the findings of Orphanides (2001). This discrepancy could be due to differences in the methodology. Orphanides' analysis estimates the Taylor rule using regression methods, whereas in Vázquez et al. (2012), Casares and Vázquez (2016), as well as this paper estimate the

[11]The description of these parameters and their prior distributions are specified in Tables 2 and 3.

[12]The estimation is carried out entirely with the Dynare software. We consider an acceptance ratio of approximately 30% on the two Metropolis-Hastings blocks used, a sample of 250,000 draws, and ignoring the first 20% of these draws.

[13]It has been taken as a change in the estimated parameter if the estimation values do not fit into the credible sets estimated for the other data vintages.

Table 2: Prior and Posterior Distributions of Structural Parameters

		Prior distribution			Posterior distributions: First-release		Third-release		Revised Data	
	Description	Distr.	Mean	St. Dev.	Mean	5% - 95%	Mean	5% - 95%	Mean	5% - 95%
φ	Elast. cap. adj. cost	N	4.00	1.50	5.17	[4.69 - 5.63]	3.86	[2.02 - 5.26]	5.10	[3.42 - 6.87]
σ_c	Elast. consumption	N	1.50	0.37	1.28	[1.20 - 1.36]	1.58	[1.23 - 0.93]	1.40	[1.13 - 1.69]
h	Habit formation	B	0.70	0.10	0.73	[0.70 - 0.75]	0.63	[0.52 - 0.73]	0.64	[0.54 - 0.73]
ξ_w	Wage stickiness	B	0.50	0.10	0.79	[0.77 - 0.81]	0.79	[0.72 - 0.86]	0.72	[0.62 - 0.82]
σ_l	Lab. supply elast.	N	2.00	0.75	1.88	[1.47 - 2.20]	2.70	[2.02 - 3.45]	1.88	[0.93 - 2.79]
ξ_p	Price stickiness	B	0.50	0.10	0.77	[0.74 - 0.80]	0.69	[0.61 - 0.77]	0.72	[0.65 - 0.80]
ι_w	Wage index. to past inf.	B	0.50	0.15	0.45	[0.39 - 0.49]	0.44	[0.27 - 0.63]	0.59	[0.38 - 0.80]
ι_p	Price index. to past inf.	B	0.50	0.15	0.27	[0.23 - 0.30]	0.14	[0.05 - 0.23]	0.26	[0.10 - 0.41]
ψ	Elas. cap. util. adj. cost	B	0.50	0.15	0.25	[0.22 - 0.29]	0.03	[0.01 - 0.04]	0.76	[0.64 - 0.89]
ϕ_p	1 + fix. cost in prod.	N	1.25	0.12	1.39	[1.35 - 1.44]	1.56	[1.44 - 1.67]	1.61	[1.49 - 1.74]
r_π	Reaction on inf.	N	1.50	0.25	1.60	[1.54 - 1.60]	1.93	[1.62 - 2.23]	1.89	[1.59 - 2.19]
ρ	Int. rate smoothing	B	0.75	0.10	0.80	[0.78 - 0.83]	0.85	[0.82 - 0.88]	0.80	[0.76 - 0.85]
r_y	React. output gap	N	0.12	0.05	0.08	[0.06 - 0.09]	0.13	[0.08 - 0.17]	0.07	[0.03 - 0.10]
$r_{\Delta y}$	React. change out. gap	N	0.12	0.05	0.20	[0.19 - 0.21]	0.2	[0.16 - 0.24]	0.23	[0.19 - 0.28]
$\bar{\pi}$	SS inflation	G	0.62	0.10	0.83	[0.80 - 0.87]	0.81	[0.60 - 1.00]	0.77	[0.60 - 0.93]
$\bar{\beta}$	Func. of disc. fact.	G	0.25	0.10	0.54	[0.52 - 0.56]	0.19	[0.09 - 0.28]	0.16	[0.06 - 0.25]
$\bar{l}$	SS hous worked	N	0.00	2.00	3.63	[2.87 - 4.37]	3.61	[2.15 - 5.09]	2.02	[0.32 - 3.71]
$\bar{\gamma}$	SS growth rate	N	0.40	0.10	0.27	[0.24 - 0.30]	0.34	[0.30 - 0.37]	0.40	[0.38 - 0.43]
α	Cap. share in tot. income	N	0.30	0.05	0.05	[0.03 - 0.06]	0.05	[0.04 - 0.06]	0.20	[0.17 - 0.23]

Note 1: The posterior distributions are obtained using the Metropolis-Hastings algorithm.

Note 2: N: Normal; B: Beta; G: Gamma.

Table 3: Prior and Posterior Distributions of Shock Processes Parameters

		Prior distribution			Posterior distributions: First-release		Posterior distributions: Third-release		Posterior distributions: Revised Data	
	Description	Distr.	Mean	St. Dev.	Mean	5% - 95%	Mean	5% - 95%	Mean	5% - 95%
σ_a	Prod. shock error	IG	0.10	2.00	0.48	[0.44 - 0.52]	0.48	[0.43 - 0.52]	0.44	[0.40 - 0.49]
σ_b	Risk prem. shock error	IG	0.10	2.00	0.25	[0.22 - 0.28]	0.22	[0.16 - 0.28]	0.20	[0.14 - 0.25]
σ_g	Exo. spend. shock error	IG	0.10	2.00	0.58	[0.53 - 0.63]	0.61	[0.56 - 0.67]	0.50	[0.45 - 0.55]
σ_I	Inv. shock error	IG	0.10	2.00	0.59	[0.53 - 0.64]	1.07	[0.80 - 1.37]	0.39	[0.33 - 0.46]
σ_r	Mon. pol. shock error	IG	0.10	2.00	0.25	[0.23 - 0.27]	0.24	[0.21 - 0.26]	0.24	[0.22 - 0.27]
σ_p	Price mark-up shock error	IG	0.10	2.00	0.18	[0.15 - 0.22]	0.18	[0.14 - 0.21]	0.13	[0.10 - 0.16]
σ_w	Wage mark-up shock error	IG	0.10	2.00	0.28	[0.25 - 0.30]	0.30	[0.25 - 0.34]	0.30	[0.26 - 0.34]
ρ_a	Prod. shock persist.	B	0.50	0.20	0.98	[0.98 - 0.99]	0.99	[0.98 - 1.00]	0.95	[0.93 - 0.97]
ρ_b	Risk prem. shock persist.	B	0.50	0.20	0.40	[0.34 - 0.47]	0.55	[0.37 - 0.74]	0.44	[0.22 - 0.68]
ρ_g	Exo. spend. shock persist.	B	0.50	0.20	0.99	[0.99 - 1.00]	0.99	[0.98 - 0.99]	0.98	[0.96 - 0.99]
ρ_I	Inv. shock persist.	B	0.50	0.20	0.95	[0.92 - 0.98]	0.66	[0.53 - 0.78]	0.76	[0.68 - 0.85]
ρ_r	Mon. pol. shock persist.	B	0.50	0.20	0.27	[0.21 - 0.31]	0.12	[0.03 - 0.20]	0.18	[0.07 - 0.29]
ρ_p	Price mark-up shock persist.	B	0.50	0.20	0.96	[0.93 - 0.98]	0.94	[0.90 - 0.99]	0.85	[0.77 - 0.94]
ρ_w	Wage mark-up shock persist.	B	0.50	0.20	0.88	[0.86 - 0.90]	0.90	[0.79 - 1.00]	0.97	[0.95 - 0.99]
μ_p	Price mark-up shock MA coef.	B	0.50	0.20	0.86	[0.79 - 0.90]	0.78	[0.67 - 0.89]	0.66	[0.50 - 0.83]
μ_w	Wage mark-up shock MA coef.	B	0.50	0.20	0.78	[0.73 - 0.82]	0.80	[0.66 - 0.96]	0.89	[0.82 - 0.96]
ρ_{ga}	Interaction parameter	B	0.50	0.20	0.02	[0.01 - 0.04]	0.09	[0.01 - 0.17]	0.53	[0.39 - 0.67]

Note 1: The posterior distributions are obtained using the Metropolis-Hastings algorithm.

Note 2: IG: Inversgamma; B: Beta.

Taylor rule as a building block of a complete DSGE model. Furthermore, Orphanides (2001) does not impose the Taylor principle, whereas the principle is in general imposed in DSGE model specifications.

The nominal rigidities parameters that shoe a high sensitivity to the data vintage used are the degree of indexation to past inflation in prices (ι_p in the New Keynesian Philips curve) and wages (ι_w). A much lower indexation degree is obtained when both are estimated with the third release. This estimation makes the New Keynesian Philips curve closer to the standard forward-looking Philips curve if the revised data is not used. Likewise, as previous findings indicate (Casares and Vázquez, 2016), the same situation applies with the wage-setting curve.

Regarding the real rigidities parameters, the steady-state price mark-up (ϕ_p), and the elasticity of capital utilization adjustment cost (ψ) are clearly affected by the vintage. Both estimates obtained using real-time data reflect a weaker rigidity, in particular the cost of capital utilization. This friction, when estimated with the first or third release, is genuinely low. If we extend this to the extreme where $\psi = 0$, the rental rate of capital would be constant. However, the estimation with the revised data suggests just the opposite: the estimate is closer to 1, making it more expensive to change the use of capital, and therefore its use will not change much. With the higher value of ϕ_p when using the revised data, we extract that real-time data does not give us an accurate image of the role that fixed costs play in aggregate production.

The difference in the estimates of price and wage mark-up autoregressive coefficients move in opposite directions if we switch from real-time to revised data. The estimate corresponding to the wage mark-up autoregressive component (ρ_w) is higher using revised data. Meanwhile the corresponding to the price mark-up shock autoregressive component (ρ_p) is higher when using real-time data. The same pattern as in the price mark-up process is also seen in the parameter associated with the persistence of the productivity shock (ρ_a). As a consequence of their high value, they are the primary source of the forecast error variance decomposition of the real variables at long horizons (Smets and Wouters, 2007). Hence, by using real-time data, these shocks explain a larger proportion of the aggregate fluctuations of real variables. Furthermore, the moving-average coefficients (μ_p, μ_w) associated with these same two processes, also exhibit the same pattern. Thereby, using real-time data provides a scenario in which the wage mark-up shock has much less presence in the wage-setting equation. In the same way, the price mark-up shock is more important in the New Keynesian Philips curve than the revised data suggest.

Other structural and shock parameters are sensitive to the data vintage used in the estimation procedure. For instance, the steady-state hours worked, the steady-state growth rate, and the discount factor.[14] Both, the discount factor function, and the steady-state hours worked parameters estimation are lower using the revised data. Nonetheless, the growth rate estimate is higher using revised data. This may likely affect the estimates of many structural parameters, since the estimated DSGE model is expressed in terms of log-deviations around the (estimated) balanced growth path.

As for the other shock processes parameters, the three that have suffered the most variation ($\sigma_g, \sigma_I, \rho_I$) have been estimated at a lower value. More precisely, if we use data available in real-time, whether it is the first or the third release, the size of the investment shocks is larger and they further exhibit higher persistence.

Surprisingly, some unexpected results have been found. In particular, three patterns can be highlighted. The first is found in estimates of parameters such as the capital share in total income (α) or the interaction parameter of the productivity shock with the expending or net exports shock (ρ_{ga}). Their estimates obtained with the vintages that have not been highly revised are close to zero. On the contrary, the estimates obtained using revised data, are far from zero showing that revisions play an important role in improving the estimates of certain parameters since the values of these parameters do not correspond to the estimates obtained using the first and the third releases.

The second pattern is the difference in the size of the credible sets of the estimates when using revised data. For instance, it is found for the estimates of the level of wage stickiness (ξ_w), the elasticity of the capital utilization adjustment cost (ψ), and the persistence of the production shock (ρ_a) that their respective credible sets are much larger when using highly revised data. Moreover, this effect is observed in more than half of the parameters.

The third and last pattern observed is found in variables such as the reaction of the central bank to the output gap (r_y), the price indexation to past inflation included in the New Keynesian Philips curve (ι_p), the elasticity of the capital adjustment cost (φ), the

[14]The parameter that appears in Table 2 ($\bar{\beta}$) is a function of the discount factor β. Formally, $\bar{\beta} = 100(\beta^{-1} - 1)$.

labor supply elasticity (σ_l) and the risk premium shock persistence (ρ_b). The estimates of these parameters using the first release and the revised data are very close. But somewhat surprisingly, they are not when using the third release data. These changes in the estimated parameters could be due to the fact that the information incorporated in the revision associated with the third release still contains a lot of noise, which is subsequently eliminated in the following revisions.

5 An assessment of model's expectations

The behavior of economic agents is largely determined by their expectations about the future evolution of the aggregate economy. This conditional decision making is therefore of great importance (Barro, 1984). In order to assess the model's expectations of the different estimates, the root mean square error (RMSE) has been calculated.[15] Following Slobodyan and Wouters (2012), this analysis will help us to assess the empirical validity -internal and external- of the estimated expectations using alternative data vintages.

Table 4 shows the RMSE statistics of the expectations resulting from the different model estimates. These comparisons are calculated for the following forward-looking variables: consumption, inflation, investment, hours worked and real wages. There are two other forward-looking variables: the value of capital (q_t) and the rental rate of capital (r_t^k). But since they are not observable, it is not possible to calculate the fit of these generated expectations. The first panel of the table corresponds to the comparison with the revised data observable counterparts. In the first column of this panel the RMSE is shown corresponding to the comparison with the expectations offered by the Survey of Professional Forecasters (SPF).[16] Among other forecasts, the SPF reports the one-step-ahead quarterly forecasts of variables considered in the DSGE model. These SPF forecasts are based on real-time data, and are closer to the implied estimated expectations obtained from the estimation of the DSGE model using first-release vintage data. Moreover, the SPF forecasts can be viewed as a benchmark to assess the estimated expectations across alternative data vintages. The following three columns of the first

[15] The calculations are made based on the following formula: $RMSE = \sqrt{(\sum_{t=1}^{T}(x_{1,t} - x_{2,t})^2)/T}$, where $x_{1,t}$ and $x_{2,t}$ are the two variables that are compared.

[16] The corresponding SPF data have been retrieved from the Federal Reserve Bank of Philadelphia.

Table 4: Assessment of model's expectations: RMSE

	Observed counterpart in the Revised Vintage				Observed counterpart in its Vintage	
	SPF	First	Third	Revised	First	Third
Inflation	0.3592	0.3081	0.3038	0.2713	0.3605	0.3790
Consumption	0.6635	0.7284	0.7025	0.6059	0.7977	0.8253
Investment	2.6167	3.5003	2.5763	1.5176	5.1893	4.9236
Hours Worked	-	0.6230	0.6008	0.6024	-	-
Real Wage	-	0.7043	0.6893	0.6827	-	-

panel show the expectations' RMSE obtained using the different model estimations compared with the revised observable counterparts.[17] The SPF does not report all the data corresponding to the years considered in the model estimates. Therefore, the corresponding RMSE's calculation of the investment and the consumption is from the last quarter of 1981 until the second quarter of 2009. The period for calculating the GDP deflator inflation RMSE of the SPF corresponds between the first quarter 1969 and the second quarter of 2009. The rest of RMSE shown in Table 4 are calculated with the whole sample period (i.e., from the second quarter of 1966 to the second quarter of 2009).

The RMSE performance using the expectations of the model estimated with revised data is better than that of professional forecasters. It is also possible to appreciate how the data reported in the third release form expectations as accurate as those offered in the SPF. Nevertheless, the performance of the first-release data model expectations is worse than those in the SPF. An unexpected scenario since both are formulated using real-time data. This result suggests that the model may not be the best way to generate expectations when using non-revised data. Thus suggesting that the macroeconomic data revision procedures provide helpful information to identify agents' expectations.

The second panel of Table 4 shows the RMSE of models expectations compared with the same vintage observable data. In this case, the RMSE statistics are worse than when the expectations are compared with the revised observables. In particular, the high

[17] The values corresponding to the RMSE of hours worked and real wages are not calculated since these data are not available in the SPF.

Table 5: Assessment of the models' expectations with the SPF: RMSE

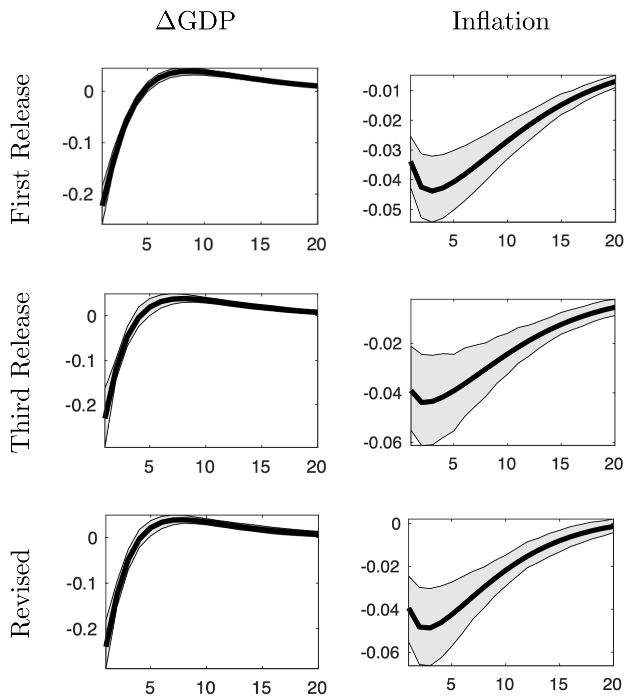
	Forecasts reported by the SPF		
	First	Third	Revised
Inflation	0.3490	0.3619	0.3547
Consumption	0.4880	0.5261	0.4136
Investment	5.0366	3.9989	2.0576

value of the investment's RMSEs stand out. Also, the RMSE value of the investment expectations using the revised data is higher. These high values could be caused by the large volatility that this variable exhibits. Returning to Table 1 where the second-moment statistics are shown, the first and the third releases of investment standard deviation takes values greater than 6. This high volatility associated with the first and thirs releases of investment data makes difficult the identification of the expectations' processes when these vintages are used, thus causing higher RMSE values. Although the RMSE of investment expectations from the revised data is also high, it is still lower than the value obtained with the other vintages. This difference is also originated from the difference in the volatility. Hence, this result shows again the importance of time series volatility in the expectations assessment.

The rest of the values in the second panel are slightly higher, but are of a similar order. This result shows that the model does not perform extremely inaccurate in formulating expectations, despite using real-time data.

The expectations implied by alternative data vintages are also compared to those provided in the SPF as shown in Table 5. The RMSE statistics suggest that the vintage used to identify inflation and consumption expectations does not matter since they all show approximately similar values when compared to the SPF. Regarding investment expectations, the RMSE statistics are similar to those obtained when expectations are compared with the observable counterpart of the same vintage. An exception occurs for consumption expectations, which are closer to the forecasts in the SPF than to any of the other observed vintages.

Figure 1: Impulse Response to a Monetary Policy Shock



6 Impulse response analysis

This section analyzes the differences of structural shocks transmission mechanisms to see the vintage implication in the business cycles. For this purpose, the impulse-response functions (IRF) are generated and evaluated using the three model estimations.

Figure 1 shows a comparison of the impulse-response functions to a monetary policy shock on inflation and output growth.[18] The comparison is made using the first-release data, third-release data, and the strongly revised data model estimations. Generally speaking, no significant differences in the IRF behavior are detected. This is in line with the findings of Casares and Vázquez (2016). They found that the Smets and Wouters (2007) model using strongly revised data and the extended model incorporating the revision processes provide similar responses of output growth, consumption growth, and inflation. In the case of this study, it is shown that the response of GDP growth to a monetary policy shock has almost identical square root shapes when using the three

[18]Given that the impulse response functions exhibit a roughly identical behavior across data vintages, this figure only includes the IRF of inflation and GDP growth to a monetary policy shock.

model estimates. A similar scenario takes place when observing the inflation response. The three model estimations using alternative data vintages show very similar effects. The results extracted from this IRF analysis have contrasted our conviction that the differences in the model estimation among alternative data vintage would affect the transmission mechanism of shocks. Actually, the only difference that emerges is the slightly larger persistence in the response of both GDP growth and inflation when the model is estimated using real-time data.

7 Conclusions

This paper considers the estimation of a structural DSGE model with alternative vintage data sets. In particular, the Smets and Wouters (2007) model is estimated with real-time data, the revision corresponding to the third release, and the highly revised data. The main objective of this empirical analysis is to assess how non-highly revised data could affect the estimation of parameters that are key in the characterization of expectations and decision-making of economic agents.

Estimation results based on a structural econometric approach suggest that most of the parameters are fairly robust. The robustness of the estimated parameters associated with monetary policy rule across alternative data vintages is remarkable. Consequently, the effects of using alternative data vintages in monetary policy decision-making seem not to have an economic impact. However, many other parameters are sensitive to the data vintage used. Among them are some of the real and nominal rigidities, and structural shocks.

Regarding the expectations assessment results, the model identifies expectation processes in a more accurate way when is estimated using highly revised data, than when using real-time data. Moreover, these expectations are close to the one-step-ahead forecasts provided in the Survey of Professional Forecasters. This empirical validity provides evidence that their identification using the model estimations is not remarkably inaccurate.

Likewise, the most striking result to emerge from the impulse-response functions analysis is that the use of alternative data vintages do not have a noteworthy effect on the transmission mechanism of structural shocks.

Without doubt, the results suggest that revised data helps to provide a more accurate view of the model estimates and the economic agents' expectations identification. Further, this finding could cause problems in economic analysis and policy evaluations that consider until the last available years since they use both highly revised and real-time data. To avoid this problem, one may think ignoring the three-year most recent observations. Alternatively, other methodologies like the one proposed by Galvão (2017) can be used.

The literature on data vintage implications in the estimation of macrodynamic models is still small. Certainly, it deserves further attention in future research.

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Appendix

The log-linearized equations around their steady state balanced growth path that characterize the equilibrium of the model are shown below:[19]

- Aggregate resource constrain:

$$y_t = c_y c_t + i_y i_t + z_y z_t + \varepsilon_t^g \tag{A1}$$

Where $c_y = 1 - g_y - i_i$, $i_y = (\gamma - 1 + \delta)k_y$, $z_y = R^k k_y$, $\varepsilon_t^g = \rho_g \varepsilon_{t-1}^g + \eta_t^g + \rho_{ga}\eta_t^a$.

- Consumption equation:

$$c_t = c_1 c_{t-1} + (1 - c_1)E_t c_{t+1} + c_2(l_t - E_t l_{t+1}) - c_3(r_t - E_t \pi_{t+1} + \varepsilon_t^b) \tag{A2}$$

Where $c_1 = (\lambda/\gamma)/(1 + \lambda/\gamma)$, $c_2 = [(\sigma_c - 1)(W^h L/C)]/[\sigma_c(1 + \lambda/\gamma)]$, $c_3 = (1 - \lambda/\gamma)/[(1 + \lambda/\gamma)\sigma_c]$, $\varepsilon_t^b = \rho_b \varepsilon_{t-1}^b + \eta_t^b$.

- Investment equation:

$$i_t = i_1 i_{t-1} + (1 - i_1)E_t i_{t+1} + i_2 q_t + \varepsilon_t^i \tag{A3}$$

Where $i_1 = 1/(1 + \beta\gamma^{(1-\sigma_c)})$, $i_2 = [1/(1 + \beta\gamma^{(1-\sigma_c)})\gamma^2\varphi]$, $\varepsilon_t^i = \rho_i \varepsilon_{t-1}^i + \eta_t^i$.

- Arbitrage condition:

$$q_t = q_1 E_t q_{t+1} + (1 - q_1)E_t r_{t+1}^k - (r_t - E_t \pi_{t+1} + \varepsilon_t^b) \tag{A4}$$

Where $q_1 = \beta\gamma^{-\sigma_c}(1 - \delta)$.

- Aggregate production function:

$$y_t = \phi_p(\alpha k_t^s + (1 - \alpha)l_t + \varepsilon_t^a) \tag{A5}$$

Where $\varepsilon_t^a = \rho_a \varepsilon_{t-1}^a + \eta_t^a$

[19] For a deeper explanation of the model and their components see Smets and Wouters (2007) and its Model Appendix with the full derivations.

- Effective capital:

$$k_t^s = k_{t-1} + z_t \tag{A6}$$

- Capital utilization:

$$z_t = z_1 r_t^k \tag{A7}$$

Where $z_1 = (1-\psi)/\psi$.

- Capital accumulation equation:

$$k_t = k_1 k_{t-1} + (1-k_1) i_t + k_2 \varepsilon_t^i \tag{A8}$$

Where $k_1 = (1-\delta)/\gamma,\ k_2 = (1-(1-\delta)/\gamma)(1+\beta\gamma^{(1-\sigma_c)})\gamma^2\varphi$.

- Price mark-up equation:

$$\mu_t^p = mpl_t - w_t = \alpha(k_t^s - l_t) + \varepsilon_t^a - w_t \tag{A9}$$

- New-Keynesian Philips curve:

$$\pi_t = \pi_1 \pi_{t-1} + \pi_2 E_t \pi_{t+1} - \pi_3 \mu_t^p + \varepsilon_t^p \tag{A10}$$

Where $\pi_1 = \iota_p/(1+\beta\gamma^{1-\sigma_c}\iota_p),\ \pi_2 = \beta\gamma^{1-\sigma_c}/(1+\beta\gamma^{1-\sigma_c}\iota_p),\ \pi_3 = 1/(1+\beta\gamma^{1-\sigma_c}\iota_p)[(1-\beta\gamma^{1-\sigma_c}\xi_p)(1-\xi_p/\xi_p((\phi_p-1)\varepsilon_p+1)],\ \varepsilon_t^p = \rho_p\varepsilon_{t-1}^p + \eta_t^p - \mu_p\eta_{t-1}^p$.

- Optimal demand for capital by firms:

$$r_t = -(k_t^s - l_t) + w_t \tag{A11}$$

- Wage mark-up equation:

$$\mu_t^w = w_t - mrs_t = w_t - \left(\sigma_l l_t + \frac{1}{1-\lambda/\gamma}(c_t - \lambda/\gamma c_{t-1})\right) \tag{A12}$$

- Wage dynamic equation:

$$w_t = w_1 w_{t-1} + (1-w_1)(E_t w_{t+1} + E_t \pi_{t+1}) - w_2 \pi_t + w_3 \pi_{t-1} - w_4 \mu_t^w + \varepsilon_t^w \tag{A13}$$

Where $w_1 = 1/(1+\beta\gamma^{1-\sigma_c})$, $w_2 = (1+\beta\gamma^{1-\sigma_c}\iota_w)/(1+\beta\gamma^{1-\sigma_c})$, $w_3 = \iota_w/(1+\beta\gamma^{1-\sigma_c})$, $w_4 = 1/(1+\beta\gamma^{1-\sigma_c})[(1-\beta\gamma^{1-\sigma_c}\xi_w)(1-\xi_w)/(\xi_w((\phi_w-1)\varepsilon_w+1))]$, $\varepsilon_t^w = \rho_w\varepsilon_{t-1}^w + \eta_t^w - \mu_w\eta_{t-1}^w$.

- Monetary policy rule:

$$r_t = \rho r_{t-1} + (1-\rho)[r_\pi \pi_t + r_y(y_t - y_t^p)] + r_{\Delta y}[(y_t - y_t^p) - (y_{t-1} - y_{t-1}^p)] + \varepsilon_t^r \quad \text{(A14)}$$

Where $\varepsilon_t^r = \rho_r\varepsilon_{t-1}^r + \eta_t^r$.

Figure A 2: GDP Time Series Realization

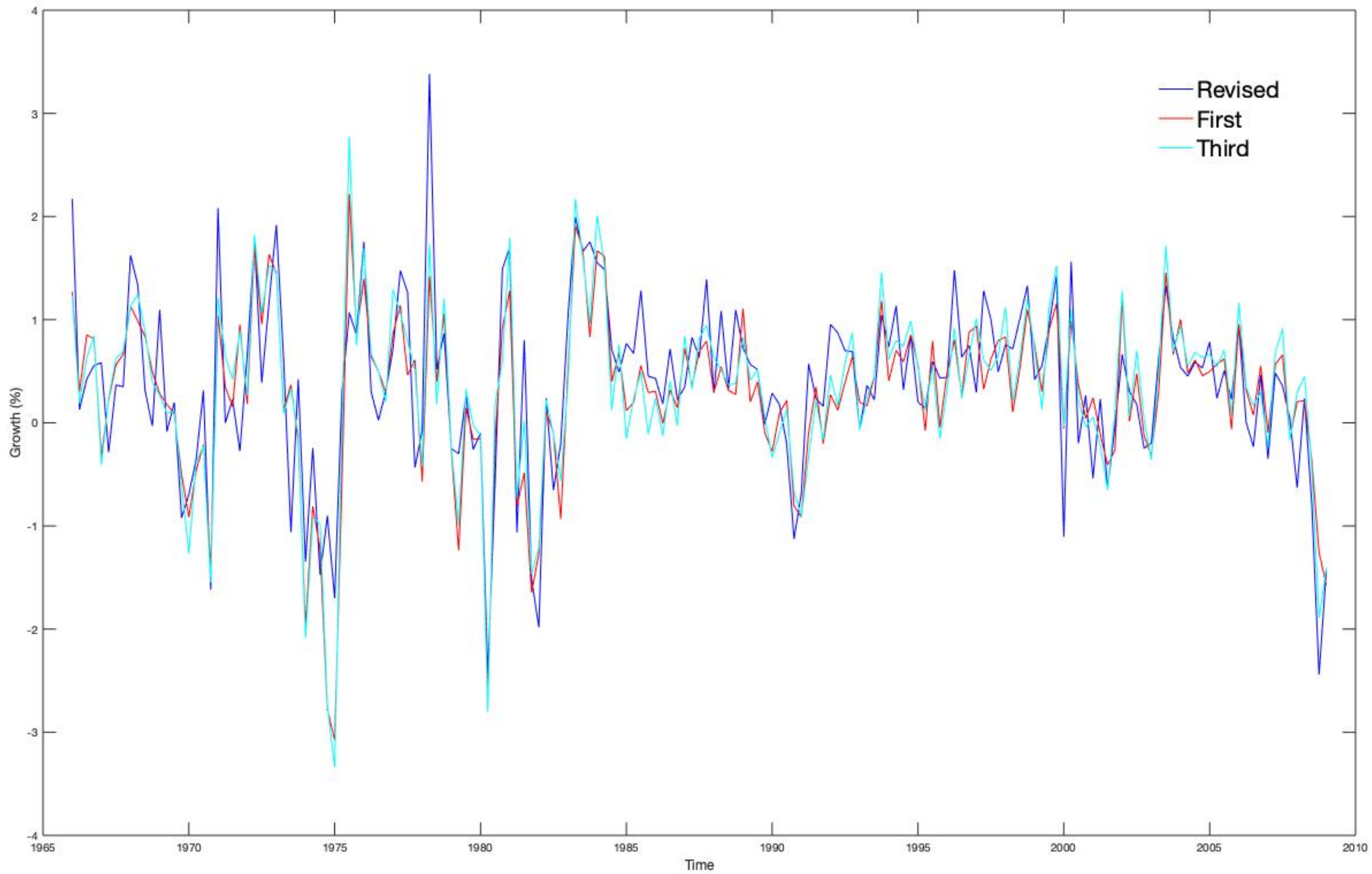

Figure A 3: Consumption Time Series Realization

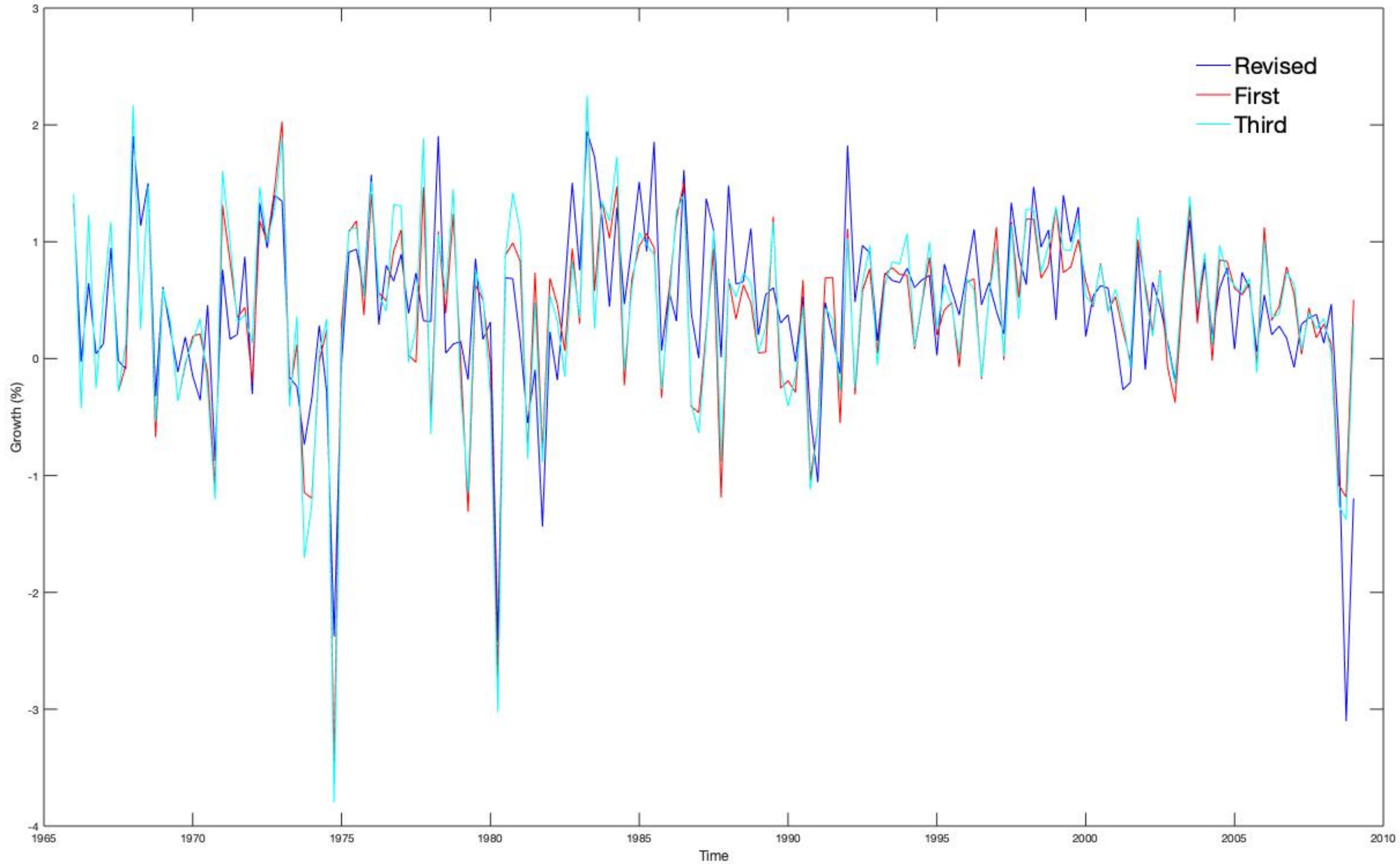

Figure A 4: Inflation Time Series Realization

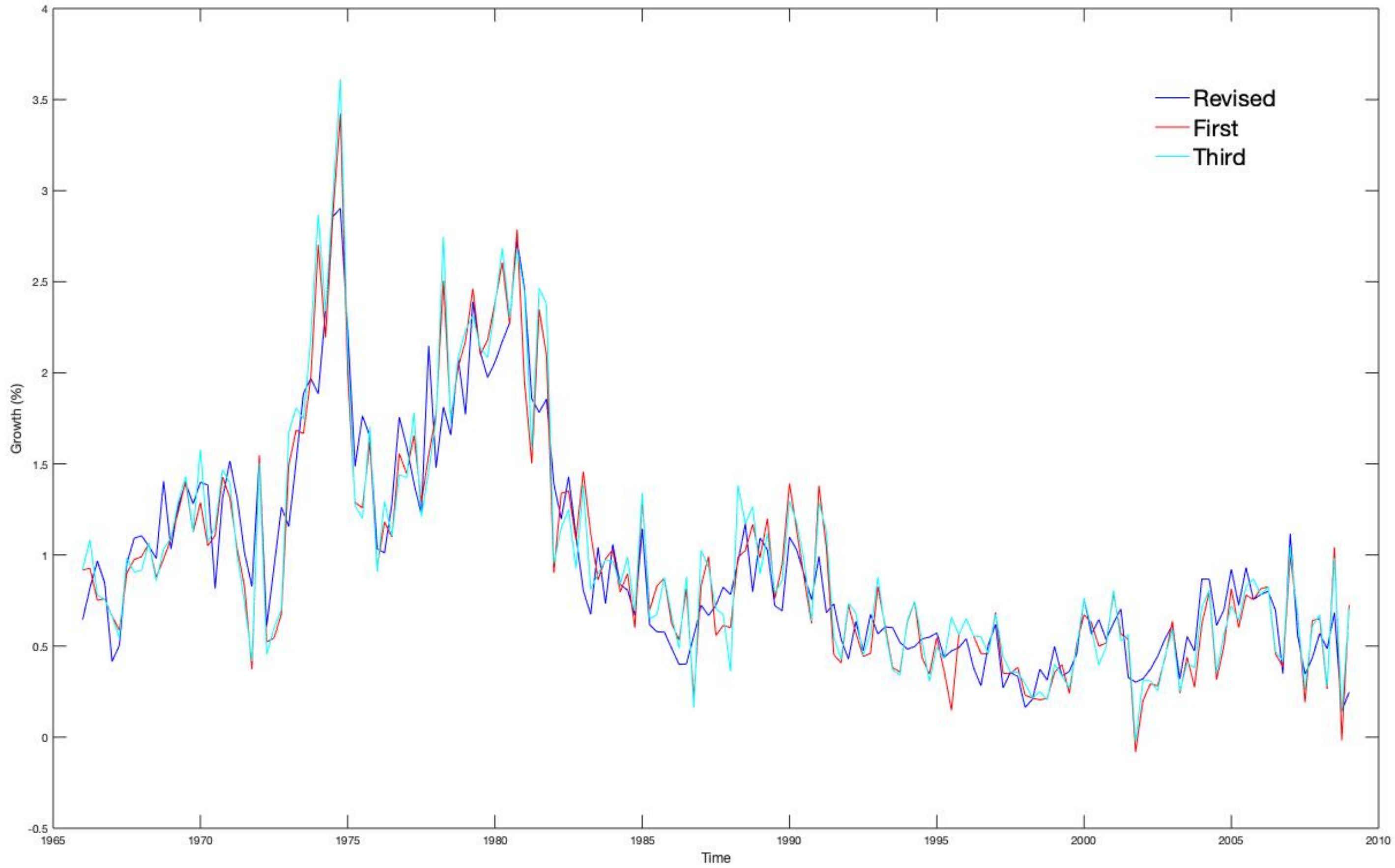

Figure A 5: Investment Time Series Realization