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On the Sources of the Great Moderation in Italy

A Time Varying VAR Approach

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Abstract The Great Moderation, a long-lasting period of reduced fluctuations in key macroeconomic variables, has attracted the attention of many scholars because of the positive outcomes associated with low volatility. The aim of these studies has mainly been to identify the ultimate source of this phenomenon. Interestingly, even though the Great Moderation has been documented to be an international phenomenon, the literature has exclusively focused on analyzing the experience of the United States. In this work, we aim at expanding our knowledge of the Great Moderation by analyzing the Italian experience, filling a research gap identified in the literature. To do so, we develop a novel time varying VAR model to implement: (i) a forecast error variance decomposition analysis; (ii) an impulse response function analysis; (iii) a counterfactual experiment. The empirical evidence provided by these exercises highlights that the Great Moderation in Italy was mostly the consequence of good luck, with better monetary policy playing a secondary role. Accordingly, we conclude that low volatility will not necessarily be the norm in the future, since an increase in the size of exogenous shocks could rapidly overturn this state.

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1 Introduction

Starting from the 1980's, advanced economies have experienced a reduction in the volatility of their major macroeconomic variables. This long-lasting period of mild volatility has come to be known as the Great Moderation, and several studies have assessed its economic consequences. Overall, the consensus has settled on the idea that low volatility positively affects an economy, which implies that the Great Moderation is desirable and should be preserved.

Despite the recent financial crisis, studies on whether the Great Moderation is ongoing have been, so far, inconclusive (see, e.g., Clark, 2009; Canarella et al., 2010). Nonetheless, to understand whether it will last, it is crucial to identify what caused it in the first place. The literature analyzing the sources of this phenomenon has proposed three main hypotheses on its origin. These are the better monetary policy hypothesis, arguing that a more responsive monetary policy could account for the reduction in volatility; the better structure of the economy hypothesis, emphasizing the role that a more efficient and robust economy could have played; and the good luck hypothesis, suggesting that lower volatility was merely the consequence of a reduction in the magnitude of the exogenous shocks hitting the economy. Although the literature investigating these hypotheses is abundant, consensus on the ultimate source of the phenomenon is yet to be achieved.

One peculiarity of these studies is that, despite the Great Moderation being an international phenomenon, evidence on countries other than the United States is still lacking. Accordingly, some authors (see, e.g., Cabanillas and Ruscher, 2008) have highlighted the importance of expanding the analysis to contexts where the Great Moderation has taken place, but its sources have never been investigated. Embracing this challenge, the goal of this work is to expand our understanding of the Great Moderation by investigating its sources in Italy, starting to fill this research gap.

Making use of a time varying parameter VAR, we implement: (i) a forecast error variance decomposition analysis; (ii) an impulse response function analysis; (iii) a counterfactual experiment. We find that the Great Moderation in Italy was mainly determined by good luck, while monetary policy played a secondary role. Therefore, this study supports the hypothesis that low volatility will not necessarily be the norm in the future, since an increase in the size of exogenous shocks could rapidly overturn this state.

The remainder of this thesis is organized as follows. Section 2 presents a review of the state of knowledge on the Great Moderation. This way, it will be clear how our contribution places itself within the literature. Section 3 displays a series of break tests to provide evidence on the presence of the Great Moderation in Italy. These findings will inform us on the features that a framework aiming at describing Italy will need to display, guiding the choice of our model. Section 4 presents our model and its estimation procedure. After having detailed our analysis and discussed our results in Section 5, Section 6 concludes this work.

2 The Great Moderation

This section will provide an overview of the current state of knowledge on the Great Moderation. Specifically, we will begin by highlighting the relevant positive economic outcomes associated with the Great Moderation to shed light on the reasons behind its desirability. Having emphasized the advantages coming from this phenomenon, we will move to the presentation of the empirical evidence on its timing and, later, we will explore the main hypotheses that have been put forward to explain its sources. Building on the need to expand our knowledge of this long-lasting period of reduced volatility, we will lastly present our research question and explain why this work focuses on the Italian experience.

2.1 Economic Benefits of Lower Volatility

The former chairman of the Federal Reserve Board, Ben Bernanke, defined the Great Moderation as a "substantial decline in macroeconomic volatility" that has represented "one of the most striking features of the economic landscape over the past twenty years" (Bernanke, 2012). Given the relevance of this phenomenon, it is important to highlight the favourable economic consequences brought by such a decline in volatility, which have made it the epicentre of a flourishing literature that investigates its timing and sources.

Historically, economic stability has been considered a desirable property for an economy. Looking at the United States, well before empirical studies could confirm the truthfulness of such a belief, the Employment Act of 1946, later reinforced by the Full Employment and Balanced Growth Act of 1978, mandated by law the need to introduce policies that would foster economic growth within a stable macroeconomic framework (Barlevy, 2004). The pivotal contribution of Lucas (1987), however, challenged this view that emphasized the importance of macroeconomic stability. In his influential monograph *Models of Business Cycles*, Lucas made use of the preferences of a representative agent to estimate the gains associated with a reduction in the fluctuations over the business cycle: contrary to common belief, he found that the agent was willing to sacrifice a very limited portion of his lifetime consumption to avoid macroeconomic instability. This evidence led the author to conclude that the welfare gains of low volatility had been overestimated.

The thought-provoking analysis carried out by Lucas stimulated a vast literature assessing the economic consequences of a stable macroeconomic environment. Dolmas (1998) extended the work of Lucas by modelling the risk preferences of a representative agent to plausible alternative specifications other than the ones formerly considered. He found that the costs associated with a highly volatile business cycle were much larger than in previous estimates. A similar finding was portrayed by Barlevy (2004), who concluded that had economic stability not been pursued, the society would have faced large welfare costs, which led the author to claim that avoiding high volatility should have a primary role in the policy making process.

Yellen and Akerlof (2006), by looking at the labour market, also made a case for the relevance of assuring macroeconomic stability: according to their empirical evidence, unemployment levels are lower and output levels are higher as a consequence of stabilization policies. Moreover, using data at the firm level, Davis and Kahn (2008) found evidence of lower risk for workers of losing their jobs and lower production costs for firms as a consequence of reduced volatility.

Moving away from the direct critique of Lucas' contribution, Storesletten et al. (2001) developed an overlapping generations model calibrated to the United States to show that, as a consequence of the counter-cyclicality of individual specific shocks, lower volatility does result in welfare gains: their estimates suggest that agents would devote as much as 2.5% of their lifetime consumption to avoid macroeconomic instability. Following a similar line of thought, Krusell et al. (2009) evaluated the welfare gains of low volatility in a model with heterogeneous agents with respect to their wealth. Not only did the authors find a higher cost associated with instability than the one estimated by Lucas, but they were also able to show that households at the extremes of the wealth distribution (either very rich or very poor) enjoyed very large welfare gains from low volatility. According to their estimates, the individuals placed at the bottom of the income distribution would experience a welfare gain equal to a 4% increase in their average consumption as a consequence of lower volatility over the business cycle.

Finally, taking into account a broader perspective, Chatterjee and Corbae (2000) analyzed the role of macroeconomic stability in reducing the likelihood of deep crises that result in the collapse of the overall economic activity (events such as the Great Depression). The authors found that, because of the long-lasting negative effects of deep recessions on the labour market, economic agents would be willing to sacrifice between 1.05% and 6.59% of their annual consumption to reduce their risk of facing these crises. Accordingly, they concluded that the welfare gains from macroeconomic stability are non-negligible when the risk of unlikely, yet destructive events is taken into account.

Overall, the contributions that followed the work of Lucas highlighted the existence of positive outcomes coming from a stable macroeconomic environment.

2.2 Empirical Evidence on the Great Moderation

Having established that low volatility is a desirable property of an economy, as a consequence of the welfare gains associated with it, we can move to the evidence on the existence of the Great Moderation and to a review of its possible explanations.

2.2.1 Existence

Kim and Nelson (1999) and McConnell and Perez-Quiros (2000) are among the very first empirical studies finding proof of the Great Moderation in the Unites States: in both cases, focusing on the output growth rate, the authors found a break in the volatility of the series during the first quarter of 1984. Starting from these contributions, the literature detailing the existence of the Great Moderation has moved in two directions.

One the one hand, researchers have extended the bulk of evidence on the Great Moderation in the United States by documenting lower volatility in a multitude of variables. Besides the studies by Kim et al. (2004), where a break in the volatility of inflation and of the interest rate is found, and by Warnock and Warnock (2000), where a statistically significant reduction in employment volatility is assessed, the most important work in this field is that of Stock and Watson (2002). In their paper, the authors tested 168 variables, including GDP and its main components, monetary aggregates, multiple interest rates, stock prices and employment, for a break at an unknown date. Strikingly, from their analysis emerged that around 40% of those variables experienced a significant reduction in volatility between 1983 and 1985, which they identified as the most plausible candidate period where the beginning of the Great Moderation could be dated.

On the other hand, the literature has investigated the extent to which countries other than the United States were also subject to the Great Moderation. Given the problems associated with data availability, most of the literature has focused on analyzing advanced economies. Smith and Summers (2009) found a break in the series of output volatility of Australia, Canada and the United Kingdom between the early 1980's and the early 1990's, while a break for the Japanese series is found already in 1974. Mills and Wang (2003) expanded this evidence by considering all G7 countries, and concluded that each of them faced a reduction in output volatility within a two-decade period starting in the mid-1970's; this finding was later confirmed by the analysis in Stock and Watson (2003a).

The study by Cecchetti et al. (2006) increased the number of countries considered to 25, where less developed countries were analyzed as well: their estimates show that, for 16 of these economies, volatility experienced a statistically significant reduction over time. Building on this contribution, Corić (2012) further extended the sample, bringing it to a total of 98 countries. The author found breaks in the volatility of output for the majority of the countries examined, and his study highlighted that the Great Moderation began later in developing economies.

One crucial characteristic of studies aiming at dating the Great Moderation is that they either extended the analysis to multiple variables for the United States economy exclusively (and, occasionally, to the United Kingdom; see, e.g., Benati, 2004), or they increased the amount of countries analyzed, but only tested output volatility. In this respect, the analysis by van Dijk et al. (2002) was the first one to combine these two aspects, since it investigated the presence of breaks in 19 series covering all G7 countries. Finding a widespread reduction in volatility across economies, this study represents the most important piece of evidence indicating that the Great Moderation has been an international phenomenon.

2.2.2 Possible Sources of the Great Moderation

So far, we have discussed the importance of the Great Moderation and the evidence on its timing. As emphasized by Summers (2005), however, the possibility to keep enjoying the positive outcomes associated with this phenomenon crucially relies on its sources. Accordingly, this section will review the literature on the determinants of the Great Moderation. Overall, three hypotheses can be identified: the good monetary policy hypothesis, the good luck hypothesis, and the better structure of the economy hypothesis, which we will now present.

The Good Monetary Policy Hypothesis One of the peculiarities of the 1980's has been the change in the conduct of monetary policy in the United States, generally associated with the appointment of Volcker as the chairman of the Federal Reserve Board in 1979. According to the study by Judd and Trehan (1995), in fact, where a reaction function accounting for the response of the FED to changes in inflation was estimated for various points in time, monetary policy became more aggressive against inflationary pressures from the early 1980's. This finding was later confirmed by DeLong (1997), who concluded that, indeed, it was only from the early 1980's that the FED started to take the need of mitigating inflation as a priority matter.

The reasons underlying such a change were examined by Romer and Romer (2002). The authors analyzed the beliefs governing monetary policy over time by making use of the Federal Reserve's internal forecasts and discussions on monetary and fiscal issues. The analysis of this material led them to conclude that, despite the use of fairly sophisticated models already in the 1970's, the understanding of the functioning of the economy during that period was generally flawed, and increased in the following decades. This view was supported by Bernanke (2012) as well. According to the author, in the pre-Volcker era monetary policy was poorly performed as a consequence of two misconceptions held by policymakers. On the one hand, there was an "output optimism": the long-run rate of unemployment that the economy could sustain was estimated at an unrealistically low level that, combined with the belief of a permanent trade-off between inflation and unemployment, created an incentive to increase inflation to reach unrealistically low unemployment targets. On the other hand, there was an "inflation pessimism": policymakers believed monetary policy to be an ineffective tool to control inflation which, on the contrary, was assumed to be an exclusively supply-driven phenomenon. Thus, Bernanke (2012) concluded that it was only from the early 1980's that monetary policy began to be optimally implemented, prioritizing the reduction of inflation and of volatility during the business cycle.

Overall, there is large consensus that monetary policy experienced important developments during the 1980's that made it more prone to mitigate fluctuations. However, this is not enough to conclude that it represents the ultimate source of the Great Moderation. Accordingly, several authors carried out empirical analyses to test this hypothesis. Clarida et al. (2000) are among the first ones to provide evidence that the change in monetary policy led to the Great Moderation. In their study, the authors develop a New-Keynesian model with monopolistic competition and sticky prices where the central bank is allowed to follow two alternative policy rules: in the first case, describing the pre-Volcker era, monetary policy responds to inflation in an accommodating manner; in the second case, describing the post-Volcker era, an aggressive anti-inflationary response is modelled. Crucially, their findings highlight the possibility that this change in the monetary policy conduct could account for the macroeconomic stabilization experienced by the Unites States.

Similar investigations were implemented by Lubik and Schorfheide (2004) and Benati and Surico (2009). In the former study, the authors rely on a New-Keynesian framework to show that monetary policy before the late 1970's strengthened the propagation of exogenous shocks hitting the economy, having an anti-stabilization role that is not found in later periods. Benati and Surico (2009) also developed a New-Keynesian model. In their framework, the monetary policy block is allowed to switch from following a passive anti-inflationary behavior to following an active one. Their results point to the possibility that such a switch determined a large reduction in output volatility, suggesting that the Great Moderation was led by monetary policy (analogous conclusions were reached by Boivin and Giannoni (2006) through a counterfactual experiment). In a slightly different manner, the New-Keynesian model developed by Canova (2009) confirms these results, although it also finds that exogenous shocks hitting the economy were relevant contributors in this respect. Finally, despite tackling the issue from a different perspective, the study of Blanchard and Simon (2001) agrees on the relevant role of monetary policy to explain the Great Moderation. According to their estimates, inflation and output volatility are highly correlated and, given the reduction in the latter coming from more efficient monetary practices from the early 1980's, their study suggests that monetary policy enhanced macroeconomic stability after the 1970's.

The Good Luck Hypothesis Despite the timing of the Great Moderation matches that of the switch in the conduct of monetary policy, some studies fail to find empirical evidence that causally links the two phenomena (see, e.g., Hanson, 2006). As a consequence, the literature has evolved to provide alternative explanations for the Great Moderation. The good luck hypothesis represents the second theory that has been proposed, and it supports the idea that the Great Moderation was mainly the consequence of a reduction in the magnitude of the exogenous shocks hitting the economy. Starting from the study by Hamilton (1983), this reduction in exogenous shocks has mostly been associated with oil price fluctuations, which were particularly pronounced during the 1970's and decreased in the following decades.

In their seminal contribution, Stock and Watson (2002) presented the estimates of a VAR analysis where they included four equations: the IS curve, the Phillips curve, the Taylor rule and a process describing commodity prices. Their estimates, finding that between 60% and 90% of the reduction in volatility was a consequence of the reduction of exogenous shocks, strongly support the good luck hypothesis. These results were later confirmed by the study by Primiceri (2005), who developed a time varying parameter VAR with three variables: inflation, unemployment and the short-term interest rate. Computing impulse response functions and finding a large reduction in the magnitude of exogenous shocks over time, the author claimed that good luck was the ultimate source of the Great Moderation.

Benati and Mumtaz (2007) estimated a time varying parameter VAR as well and, using counterfactual experiments, they could simulate what would have happened if the monetary policy implemented by Volcker had prevailed during the 1970's. They were able to show that nothing significant would have changed, which signals a minor role of better monetary policy and a greater role of good luck. Similar conclusions were reached by Benati (2008), who used an analogous methodology but focused on the United Kingdom experience. A time varying coefficients VAR is also the framework that Canova and Gambetti (2009) decided to rely upon in their analysis. In their study, the authors disproved both alternative theories to the good luck hypothesis, and concluded that the Great Moderation owed its existence to the reduced size of exogenous shocks solely.

In addition to these studies, Leduc and Sill (2007) developed a New-Keynesian model to distinguish between the sources of the reduction in output and inflation volatility. According to their analysis, monetary policy could only explain around 17% of the reduction in output volatility, while it could explain as much as 30% of the reduction of inflation volatility. They also found that most of the remaining reduction in output volatility was a consequence of the decline in the volatility of technological and oil shocks. Similarly, Justiniano and Primiceri (2008) built a DSGE model that allowed them to directly identify the shocks leading to the Great Moderation: according to their estimates, exogenous shocks influencing investment decisions were the major source of greater stability.

The Better Structure of the Economy Hypothesis The third hypothesis that has been put forward in the literature emphasizes the changes that led to a stronger structure of the economy, during the 1980's, as the main source of the Great Moderation. This view proposes the idea that, as a consequence of a more robust economy, the shocks hitting it were more smoothly absorbed, which led to smaller fluctuations over the business cycle.

The study by McConnell and Perez-Quiros (2000) represents one of the first contributions validating this hypothesis. Their analysis documents a break in the volatility of a series describing the production of durable goods that could account for the reduction in output volatility. Accordingly, the authors supported the idea that firms reduced their inventories thanks to the introduction of new technologies that led to better inventory management (such as "just in time"). Such inventories, accounting for a large fraction of output volatility, determined its decline (this study is followed by Kahn et al., 2002, who provided evidence of the relevance of changes in inventories on output volatility). Using a heterogeneous-agent VAR model with two sectors, manufacturing and trade, Irvine and Schuh (2007) also suggested that inventory management was crucial. In fact, their estimates found that output was less affected by exogenous shocks as a consequence of the reduction in inventory investment. Similar conclusions were reached by Ramey and Vine (2004), who focused on the United States automobile industry exclusively.

Apart from changes at the firm-level management, studies have also emphasized the importance of additional developments during the 1980's that increased the robustness of the economy. Stiroh (2009) deems the increased flexibility in the labour market the fundamental element leading to lower volatility: in his work, the author shows that this flexibility allowed firms to better react to technology shocks, which in turn led to greater stability in the economy. This finding is confirmed by the analysis of Willis (2003) who, however, also stresses the importance of financial developments. Specifically, the author underlines the relevance of expanded borrowing opportunities for banks, which resulted in their ability to be less exposed to inter-bank lending fluctuations over the business cycle. Financial innovation was also emphasized by Dynan et al. (2006). The authors stressed the idea that the greater ability of households and firms to borrow made them less sensitive to income and cash flow downturns, which eventually had the effect of reducing output volatility. Lastly, McCarthy and Zakrajsek (2007) found that the macroeconomic environment, identified as the deregulation of financial and product markets, trade liberalization, and an increased transparency in the monetary policy conduct, was the key factor determining the Great Moderation.

2.3 How Does Italy Enter the Picture?

The literature review carried out so far has detailed the relevant positive outcomes associated with the Great Moderation, its timing, and the hypotheses on its sources. Admittedly, understanding the determinants of the Great Moderation has attracted the greatest attention, mostly because of its policy relevance. As emphasized by Summers (2005), if better monetary policy led to the reduction in volatility, then it is important to keep implementing it; if it was the better structure of the economy instead, then supporting its main features should be highly prioritized; if, on the contrary, it was good luck to be decisive, then the possibility of an increase in exogenous shocks that may lead to a pre-Great Moderation state needs to be acknowledged. Moreover, answering this question is of great importance because of its implications for the future of the economic landscape. In fact, the better monetary policy hypothesis and the better structure of the economy hypothesis entail a structural change in the characteristics of the economy, implying that an enduring period of high volatility will likely not occur in the future. Differently, the good luck hypothesis identifies the Great Moderation as a fortunate and transitory state, which would be reversed as the magnitude of the shocks increased again.

Despite these considerations, the main characteristic of the reported literature is that, even though several studies found evidence of the Great Moderation being an international phenomenon, the analysis of its sources has predominantly focused on the United States. As a consequence, Cabanillas and Ruscher (2008) have stressed the importance of enhancing our understanding of the Great Moderation by expanding the analysis to other countries, starting from OECD economies that have the advantage of greater data availability. Embracing this challenge, the main goal of this thesis will be to strengthen our comprehension of the Great Moderation by analyzing the Italian case. Specifically, the research question addressed in this work is:

What are the sources of the Great Moderation in Italy?

To answer this question, and for the completeness of this thesis, it is indispensable to firstly identify the extent to which Italy was subject to the Great Moderation and its timing. This will be done in Section 3. However, the results of this first analysis will not be novel, since several studies (see, e.g. Stock and Watson, 2002; van Dijk et al., 2002; Cecchetti et al., 2006; Corić, 2012) already found evidence of reduced volatility in Italy. Our contribution in the first part will be to extend the empirical evidence by considering alternative variables and a longer time period than the one available in previous works.

The main novelty of this thesis will be that of identifying the *sources* of the Great Moderation in Italy, which is the topic of Section 5. To the best of our knowledge, this is the first study carrying out such an analysis. Accordingly, the aim is to provide new evidence on the phenomenon, to be added to the range of studies that examine the United States (and to a lesser extent, the United Kingdom).

Before turning to the core of the analysis, this section will conclude the review of the literature by detailing the reasons that led Italy to be the country in focus.

2.3.1 The Transformation of the Italian Economy During the 1980's

This section shows that relevant developments affected the Italian economy during the 1980's and, since they are very similar to the ones experienced by the United States, it is possible to smoothly extend the hypotheses on the sources of the Great Moderation put forward for the United States to the Italian experience. With respect to the good luck hypothesis, given that it is largely associated with the oil shocks of the 1970's which had a relevant impact on all advanced economies, it is trivial to conclude that it is a possible source of the Great Moderation in Italy as well. Therefore, this section will rather concentrate on the changes in the monetary policy conduct and in the structure of the economy that Italy experienced during the 1980's.

Changes in Monetary Policy Implementation Up until 1971, monetary policy in Italy was constrained by the requirements imposed by the Bretton Woods system and its goal to maintain a fixed exchange rate (Gaiotti and Secchi, 2012). However, the decade starting from the downfall of the international monetary system was characterized by important changes in the conduct of monetary policy, which gradually became subordinate to the needs of the fiscal authority: in 1975, a bill was enforced that obliged the central bank to act as a residual buyer of government securities (Passacantando, 1996). Crucially, during this period and despite the oil crises of 1973 and 1979 that led to relevant increases in inflationary pressures, monetary policy was only used to assure that no government debt would go unsold.

The early 1980's represent a turning point: after inflation peaked to values above 20% as a consequence of the second oil shock, a large consensus was established on the importance of lowering inflation (Toniolo, 2013). Three developments made this possible. Firstly, the "divorce" between the central bank and the fiscal authority in 1981, which abolished the central bank obligation of buying any unsold public debt, created an incentive to implement an anti-inflationary monetary policy (Tabellini, 1987). Secondly, as a consequence of the turn in monetary policy conduct by the United States with the appointment of Volcker in 1979, the Italian central bank, along with other monetary authorities of advanced economies, increased its awareness of the problems associated with high inflation levels, beginning a committed disinflation process (Gaiotti and Secchi, 2012). Finally, joining the European Monetary System in 1979 provided an additional incentive to achieve price stabilization, as a consequence of the need to maintain a stable exchange rate (Visco, 1995).

Overall, the 1980's were characterized by a monetary policy that became significantly more prone to assure low inflation levels and stabilize the economy, and these objectives were largely met: according to Gressani et al. (1988), starting from values above 20%, inflation fell to less than 5% in 1986. Moreover, the process that started in the 1980's continued during the 1990's. In 1992, the central bank was finally provided with the power to directly modify the discount rate, the major tool of monetary policy implementation which, until that year, had been set by the Treasury. Moreover, starting from 1994, the commitment on keeping inflation low was strengthened thanks to the announcements by the monetary authority of its inflation objectives (Visco, 1995).

Changes in the Structure of the Economy Relevant developments affected the Italian economy during the 1980's, making it more flexible and able to react to exogenous shocks. The first change occurred in the labour market. Starting from the end of World War II, Italy had put in place a wage indexation system to protect workers from inflation. This was greatly reinforced during the 1970's: in 1975, the government mandated that workers would see their wages adjusted for inflation with a three-month frequency. This system, according to Lange (1986), represented the "most extensive wage protection in Europe" (p. 30).

This wage indexation system created critical inflationary pressures, but remained in place until the end of the decade. Starting from the early 1980's, however, the system began to be dismantled. In 1983, a reform changed the way in which the indexation was computed and this, according to Gressani et al. (1988), resulted in a 15% reduction in wage protection against inflation. Furthermore, the system continued to be weakened during the 1980's, and was completely abolished in 1991 (Manacorda, 2004). Policymakers, however, did not only relax the wage indexation system in order to modify the characteristics of the labour market: thanks to an extended legislation, modern contractual arrangements were also introduced, which allowed for a higher degree of flexibility in the market (Di Michele, 2008).

Important changes occurred at the firm level as well. According to Rossi and Toniolo (1996), the policies introduced by the government in the labour market substantially helped large and medium size firms to reorganize their internal structure, which made them more prepared to react against possible economic downturns. Moreover, the 1980's were characterized by a substantial increase in the use of new technologies in the production process: for instance, the largest Italian automobile manufacturer, FIAT, had plants where around 85% of the production was carried out by machines (Di Michele, 2008). The increment in capital usage in the production process, together with the developments in the labour market, led Italian firms to reduce their overall labour costs and to boost their investment expenditures (Rossi and Toniolo, 1996). Moreover, these changes allowed firms to abandon the Taylorist management framework and adopt a more flexible structure, so that they could efficiently respond to the sudden changes in sales markets (Di Michele, 2008). Overall, the 1980's saw the establishment of a modern industrial sector in Italy, more similar to those of other advanced economies.

2.4 A Note of Caution

In the previous section we have highlighted that Italy not only began to be affected by smaller exogenous shocks from the 1980's (thanks to lower fluctuations in oil prices), but it also underwent important transformations in both its monetary policy conduct and in the structure of its economy. In the following sections, we will examine the extent to which these changes could account for the Italian Great Moderation.

However, the abundant literature investigating the sources of the Great Moderation in the United States carries one important lesson for this work. This is, there is no single optimal framework that allows to test all of these alternative hypotheses at the same time. Specifically, the better monetary policy hypothesis has been widely tested with the good luck hypothesis through vector autoregression analyses, where policy blocks and non-policy blocks can be easily modelled simultaneously. Differently, testing the better structure of the economy hypothesis has historically implied the analysis of inventories and sales dynamics, together with the examination of the price-setting behavior of firms (see, e.g., McConnell and Perez-Quiros, 2000; Willis, 2003).

In our study, as it will be clear in Section 5, we decided to rely on a framework that is better suited to investigate the monetary policy and the good luck hypotheses. To a lesser extent, we will be able to provide evidence on the better structure of the economy hypothesis, but a thorough examination of this theory, using different methodologies, is required in order to draw any ultimate conclusion on its validity. The reason motivating our choice is that the literature on the United States has posed greater attention on analyzing these two alternative hypotheses, with the better structure of the economy hypothesis mostly taking a residual role. Since our study is the first to investigate the sources of the phenomenon in Italy, we concluded that it would be of higher importance to focus on these two theories. Nonetheless, our results could then serve as a starting point for studies investigating the third hypothesis in a more accurate manner.

3 Existence and Timing

The goal of this section will be twofold. Firstly, in line with our previous discussion (Section 2.3), it will provide evidence on the existence of the Great Moderation in Italy to be added to the bulk of research already conducted in this field. This evidence, as we will discuss further in Section 4, will have relevant implications for the characteristics that a model aiming at describing Italy will need to display. Secondly, it will allow us to identify a period when the beginning of the Great Moderation can be dated, which will be important for the analysis of its sources presented in Section 5. Note that, to avoid possible biases in our results coming from the identification of the beginning of the phenomenon in one specific time point, we will rather determine a *period* when the outset of the Great Moderation can be dated.

To do this, we will begin by presenting the data used in this work and its main characteristics. After having analyzed some descriptive statistics, the results of the test for structural breaks at unknown dates will be displayed. Lastly, we will review the limitations of our methodological approach.

3.1 Data and Pre-Testing

The analysis carried out in this study relies on the use of macroeconomic time series collected with a quarterly frequency. Specifically, the series are those of GDP and its main components (private and public consumption, investment, export and import), the discount rate, the three-month interest rate, the inflation rate and the unemployment rate. The data covers the period going from 1960:Q1 to 2016:Q4, although some series were only available for a shorter time frame. The sources used to obtain the data were both institutional ones, such as the OECD, Eurostat and the Federal Reserve Bank, and academic ones, such as the dataset constructed by Ohanian and Raffo (2012)[1]. A detailed description of the data and its sources can be found in Appendix A.1.

Since we are dealing with time series data, it is required to implement some tests and transformations on our variables to assure they do not contain unit roots. To achieve this goal, we followed the standard procedure highlighted in Enders (2010). This includes the following steps:

1. Relying on economic reasoning and visual inspection of the variables, define whether a series has a trend component or not and, accordingly, apply the first difference operator;
2. Compute the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to select the number of lags to include when modelling each of the series (whenever the two criteria differ, we decided to choose the number of lags selected by

[1] The authors provided an updated version of their original dataset, and their generosity is acknowledged.

Table 3.1: Data Properties and ADF test

	Description	Transformation	Lags	P-value
GDP	Real Gross Domestic Product	$\log(X_t/X_{t-1})$	1	0.00
CONS	Private Consumption	$\log(X_t/X_{t-1})$	2	0.00
GOV	Government Consumption	$\log(X_t/X_{t-1})$	3	0.00
INV	Gross Fixed Capital Formation	$\log(X_t/X_{t-1})$	2	0.00
EXP	Exports of Goods and Services	$\log(X_t/X_{t-1})$	0	0.00
IMP	Imports of Goods and Services	$\log(X_t/X_{t-1})$	0	0.00
CPI	Consumer Price Index	$X_t - X_{t-1}$	5	0.00
3MR	Three-month Interest Rate	$X_t - X_{t-1}$	0	0.00
DR	Discount Rate	$X_t - X_{t-1}$	0	0.00
URS	Unemployment Rate	$X_t - X_{t-1}$	0	0.00

Notes: The p-values of the ADF test were rounded to two decimals.

the BIC, which is more parsimonious);

3. Compute the Ljung-Box Q-statistic to test if there is any remaining serial correlation in the data. In this case, increase the number of lags in the process;

4. Compute the Augmented Dickey-Fuller test (ADF test) to detect the presence of a unit root (Dickey and Fuller, 1979).

Table 3.1 summarizes the transformations applied to the series and the results of the above mentioned procedure to remove possible unit roots. The first two columns provide information on the variables we are using, while the third column details the transformations implemented. GDP and its components display a trend and, accordingly, they are transformed into growth rates by taking the first difference of their logarithm. Differently, following a standard procedure in the literature (see, e.g., Stock and Watson, 2002), the interest rates, the inflation rate and the unemployment rate are transformed using the first difference operator as well, but without taking the logarithm, which would make the series lose their economic meaning. The fourth column displays the number of lags selected for each series, and the fifth column shows the p-values of the ADF tests. Specifically, the last column highlights that we can reject the null hypothesis on the presence of a unit root at the 1% level for all of our series. Thus, all series appear to be stationary and no further transformation of data is needed.

3.1.1 *Prima Facie* Evidence of the Great Moderation

Before beginning the analysis that tests for breaks at unknown dates, the examination of descriptive statistics proves useful to get a feeling of the evolution of our data over time. Specifically, Table 3.2 portrays the changes of the standard deviation of the series during

Table 3.2: The Evolution of Volatility Over Time

	1960's	1970's	1980's	1990's	2000's	2010's	Pre-1982	Post-1982	Ratio
GDP	1.07	1.38	0.63	0.65	0.85	0.48	1.22	0.71	1.71
CONS	0.57	0.82	0.80	0.77	0.45	0.63	0.78	0.70	1.11
GOV	0.25	0.40	0.51	0.67	1.01	0.57	0.33	0.78	0.42
INV	2.81	1.94	1.48	1.94	1.83	1.85	2.36	1.81	1.30
EXP	3.11	4.48	3.86	2.36	3.14	1.23	4.02	2.75	1.47
IMP	3.66	5.35	3.23	3.05	2.47	1.99	4.53	2.74	1.65
CPI	0.87	2.03	0.96	0.37	0.41	0.42	1.56	0.50	3.12
3MR	-	0.85	1.02	1.02	0.48	0.15	1.10	0.72	1.53
DR	0.76	1.12	0.71	0.67	-	-	0.90	0.62	1.45
URS	0.21	0.23	0.19	0.29	0.14	0.17	0.22	0.21	1.05

Notes: The sample size considered is 1960:Q1–2016:Q4 for all variables except 3MR, DR and URS. For 3MR, the sample is 1978:Q4–2016:Q4, for DR it is 1964:Q1–1998:Q4, and for URS it is 1960:Q1–2011:Q4.

the decades starting from the 1960's, and provides the ratio of the volatility of the variables before and after the first quarter of 1982[2].

Interestingly, the table shows that, for all variables but government consumption, the ratio of the volatility before and after 1982:Q1 is greater than one (last column). In general, it seems that the variables follow a trend in which their standard deviations increase during the 1970's, gradually decrease from the 1980's onward, and eventually increase again in the very last years of the sample, probably as a consequence of the recent financial crisis. Overall, these descriptive statistics do point to a reduction in volatility during the 1980's and, keeping this in mind, we can proceed and test the series for possible structural breaks.

3.2 Testing for Structural Breaks

Having found promising evidence in the descriptive statistics, we can move to the analysis of structural breaks in the series. One of the features of such an investigation is that we are not only interested in spotting breaks, but also in identifying when these changes occurred. Hence, a test for a break at an unknown date is required. Several methodologies have been developed in the literature to deal with these situations. Among these, we will rely on the procedure highlighted by Stock and Watson (2002) who, in turn, based their analysis on the work of Andrews (1993). This choice is motivated by the fact that the study by Stock and Watson (2002) on the stability of 168 United States macroeconomic variables has been one of the most important contributions on the existence of the Great Moderation, and their methodology has been deemed highly reliable. However, there are relevant drawbacks to this procedure, which we will discuss after having presented our results.

[2]It is important to underline that this date was chosen on the basis of studies pointing to the Great Moderation beginning in the early 1980's. Apart from representing a benchmark in the table, there is no additional meaning attached to such a date.

The methodology we used to test our variables is carefully detailed in Appendix A.3. We only specify here that each series was initially tested for a break in the unconditional variance. As underlined by Stock and Watson (2002), however, a break in the unconditional variance may be driven by a change in the conditional mean of the series, by a change in their conditional variance, or by changes in both the conditional mean and the conditional variance. Thus, each series was additionally tested for a break in their conditional mean and variance to enhance our understanding of the movements in the variables. The following paragraphs present our results.

3.2.1 Results

The results of the analysis are presented in Table 3.3. Overall, there appears to be convincing evidence of the presence of the Great Moderation in Italy: with the exception of private consumption, all variables are subject to statistically significant breaks that tend to occur within a two-decade period centered in the 1980's. Given the presence of studies that test structural breaks for Italian variables, it is possible to confront previous results with the ones provided in Table 3.3. Specifically, I will refer to the studies by Corić (2012), Cecchetti et al. (2006), Mills and Wang (2003) and Stock and Watson (2003a), who only tested the volatility of GDP, and to the study by van Dijk et al. (2002), who considered a larger number of variables in their work.

The analysis by Cecchetti et al. (2006) reports statistically significant breaks in the conditional mean and variance of output volatility. However, the estimates presented in their study are slightly different from the ones reported in the first line of Table 3.3, which seem to be anticipating the breaks: according to the authors, the conditional mean experienced a significant reduction in the fourth quarter of 1979, and the conditional variance in the third quarter of 1983. On the contrary, the break in the conditional mean in our analysis is identified in the fourth quarter of 1970, while the break in the conditional variance is quite close to the one by Cecchetti et al. (2006), in the second quarter of 1982. The relevant difference in the result for the conditional mean may be the consequence, on the one hand, of the different procedure followed by the authors to test their series or, on the other hand, of the smaller sample size that they used, which only began in 1970:Q1 and could have hardly detected a break so early in the sample.

The estimates reported by Corić (2012) date the break in the conditional mean of output volatility in 1979, while the break in the conditional variance is reported in 1978. Again, the estimate of the break in the conditional mean in Table 3.3 anticipates the break found by Corić (2012) but, differently from before, the break in the conditional variance is dated later that the one by the author. Just as before, the differences in the estimates may be due to the different procedure followed by the author in his study, or to the different type of the data used (Corić, 2012, relied on annual observations rather than quarterly ones). In the analysis

Table 3.3: Structural Breaks in the Time Series

	Unconditional Variance	Conditional Mean	Conditional Variance
GDP	1977:Q4***	1970:Q4***	1981:Q2***
CONS	1983:Q2	1980:Q4	1997:Q3
GOV	1992:Q3***	2002:Q1***	1983:Q4***
INV	1970:Q2***	1969:Q1	1975:Q2*
EXP	1980:Q4***	1979:Q2**	1988:Q3***
IMP	1983:Q3***	1970:Q4	1983:Q3***
CPI	1985:Q1***	1976:Q3	1986:Q3***
3MR	1995:Q3***	1984:Q2	1995:Q3***
DR	1973:Q3***	1981:Q3**	1973:Q3**
URS	1994:Q1*	1988:Q1	1973:Q3

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample used was 1960:Q1–2007:Q4 for GDP, CONS, GOV, INV, EXP, IMP, CPI, URS. The sample for 3MR was 1978:Q4–2007:Q4; for DR it was 1964:Q1–1998:Q4.

of Mills and Wang (2003) the results are closer to the ones in Table 3.3: according to the authors, Italy experienced a break in the volatility of output growth "around 1982" (Mills and Wang, 2003, p. 243), which is very close to the estimate of the break in conditional variance of Table 3.3. Finally, the analysis implemented by Stock and Watson (2003a), concluding that Italy experienced the beginning of the Great Moderation before the United States, is in line with our results, since they always date the break before the second quarter of 1984[3].

The study by van Dijk et al. (2002), moreover, allows us to compare estimated break dates for variables other than output growth. Overall, the results are similar: the break dates for exports perfectly match in the two studies, while the imports series breaks in 1988 in van Dijk et al. (2002) and 1983 in Table 3.3; similarly, the inflation series breaks in 1981 in the estimates presented by the authors, while it breaks slightly later, in 1983, in our analysis.

Overall, our results confirm the finding in the literature that points to the presence of the Great Moderation in Italy. For our analysis on the sources of the Great Moderation, the implications of this exercise are twofold. Firstly, it showed that relevant changes affected the Italian economy; as it will be clear in the next section, this has relevant consequences on the characteristics that a model aiming at describing Italy will need to display. Secondly, it allows us to identify a period to differentiate before and after the Great Moderation began, which is is essential to investigate its sources. Following the literature (see, e.g., Galí and Gambetti, 2009), we rely on the break date of the conditional volatility of GDP for this purpose. Accordingly, the beginning of the 1980's will be recognized as the period when the Great Moderation began to be in place.

[3]This is the when the literature agrees on dating the beginning of the Great Moderation in the United States.

3.2.2 Limitations

The most important limitation of the approach we followed in the previous analysis is that it is impossible to detect multiple breaks in the series. In fact, as a consequence of the large length of the time series considered, it is possible that they experienced significant changes in their volatility at several points in time. Nonetheless, the procedure we relied upon tests only those dates in which the likelihood of the break occurring is the highest (the ones associated with the greatest F-statistic, see Appendix A.3 for a more detailed description of our test).

The consequence of this limitation is that the sample used when carrying out the analysis needs to be restricted: despite the available data covering a longer period, the sample ends in the fourth quarter of 2007. Such a choice is motivated by the financial crisis hitting the Italian economy from this quarter onward. By detecting large fluctuations in the volatility of numerous variables, the test may have identified breaks at very recent times. Being interested in changes that involved the Italian economy well before the Great Recession, we therefore decided to consider all observations before that date.

This limitation does not create relevant problems to the analysis that is carried out in this work. In fact, the major contribution of this thesis, as already specified when presenting our research question, is to identify the sources of the Great Moderation in Italy. In this respect, the exercise performed in this section had the goal of providing us with useful information on the nature of our series to implement this analysis in a sound manner. Since it detects relevant changes in the movements of Italian time series and it identifies a period to discriminate before and after the phenomenon began, our chosen framework positively meets this objective. Thus, we can proceed to the analysis of the sources of the Great Moderation.

4 The Model

This section describes the model that was used to analyze the sources of the Great Moderation in Italy. To do so, Section 4.1 will begin by highlighting the features that the model needs to display to be able to discriminate among the possible explanations of the phenomenon proposed in the literature. Afterwards, Section 4.2 will present the characteristics of the model used in the analysis. Finally, Section 4.3 will provide an overview of the methodology followed to estimate the model. However, note that the focus will be on providing the intuition behind the estimation strategy, since the description of the complete estimation procedure would be lengthy (an exhaustive explanation is reported in Appendix A.5).

4.1 Characteristics of the Model

The hypotheses that have been put forward in the literature on the possible sources of the Great Moderation argue that the phenomenon could derive from a change in the monetary policy conduct, from a change in the overall structure of the economy, or from a change in the magnitude of the exogenous shocks hitting the economy, usually identified with fluctuations in oil prices. Moreover, the analysis carried out in Section 3 has highlighted the fact that, starting from the 1980's, the Italian economy has indeed undergone relevant changes in the volatility of some of its major macroeconomic variables. In the following, the aim will be to identify which, among these possible explanations, played the largest role in the Italian experience. To do so, it is necessary to firstly identify a framework that allows to implement such an analysis.

Given the features of the economy that is being modelled, and the hypotheses that we want to discriminate among, some properties need to be displayed by our model:

1. It needs to be multivariate;
2. It needs to allow the parameters that describe the functioning of the economy to vary over time;
3. It needs to allow both heteroskedasticity in the innovations and the simultaneous relations among the variables to evolve over time.

The reason behind the need to have a multivariate model is trivial: to test the extent to which policy actions (related to the conduct of monetary policy) had an impact on the overall volatility in the economy, multiple variables are to be considered. On the other hand, the previously analyzed (Section 2.3.1 and Section 3.2.1) changes in the Italian structure of the economy and in the conduct of monetary policy lead to the second requirement. These developments must be captured by the model: not allowing for time variation in the coefficients, the model would be misspecified and its estimates biased. The third requirement is important to implement a meaningful analysis. In fact, it makes it possible to investigate whether the relations across the variables changed over time and, at the same time, it allows the exogenous innovations to be time varying, which is crucial to test the good luck hypothesis.

A framework consistent with such requirements is the time varying parameter VAR model (hereafter, TVP-VAR) developed by Primiceri (2005). The first requirement is easily satisfied, since VAR models are, by definition, multivariate systems. Furthermore, the second requirement is fulfilled thanks to the fact that, as will be clearer in the next section, the TVP-VAR allows its coefficients to evolve over time. These two characteristics apply to any TVP-VAR in the literature (see, e.g., Stock and Watson, 1996; Cogley and Sargent, 2002). However, Primiceri (2005) introduced a time varying variance-covariance matrix of the error terms in the standard TVP-VAR framework, and this allows it to satisfy the third requirement. In fact, as underlined by Nakajima (2011), this feature serves the role of accounting for the changes in the volatility of the disturbances in the model and in the correlations across the shocks. Thus, satisfying all of the above mentioned requirements, the TVP-VAR à la Primiceri (2005) will be the framework used in the analysis.

The specific features of the TVP-VAR adopted in this work can now be presented.

4.2 Time Varying VAR Used in the Analysis

The model has three variables ($n = 3$). These are the inflation rate and output, that represent the non-policy block in the model, and the interest rate, representing the policy block associated with the conduct of monetary policy[4]. Following the literature (see, e.g., Cogley and Sargent, 2005; Primiceri, 2005; Benati and Mumtaz, 2007; Benati, 2008), the TVP-VAR will have two lags ($p = 2$)[5]. Therefore, the reduced form of the model will be:

$$y_t = c_t + B_{1,t}y_{t-1} + B_{2,t}y_{t-2} + u_t, \qquad t = 1, ..., \mathrm{T}, \tag{4.2.1}$$

where y_t is a $n \times 1$ vector of endogenous variables; c_t is a $n \times 1$ vector of time varying intercepts; $B_{j,t}$, $j \in \{1, 2\}$, are $n \times n$ matrices of time varying coefficients; u_t is a 3×1 vector of heteroskedastic shocks such that:

$$u_t \sim N(0, \Omega_t),$$

where Ω_t is the variance-covariance matrix of the shocks u_t.

The first feature that characterizes time varying VARs can be observed in equation (4.2.1): as

[4] Specifically, following the terminology detailed in Appendix A.1, the variables are CPI, GDP and DR, respectively.

[5] A robustness check was performed allowing $p = 4$ lags. Although minor changes occurred in our estimates, the results presented in the following sections were not altered.

posed by the second requirement outlined above (Section 4.1), the parameters describing the economy are allowed to change over time (note the time subscript, t, in the $B_{j,t}$ matrices). However, it is not immediately clear how this model fulfills the third requirement. Thus, additional specifications will be introduced to uncover these properties of the model.

In order to isolate the structural errors of the TVP-VAR, without loss of generality, the following triangular reduction is performed:

$$A_t \Omega_t A_t{}' = \Sigma_t \Sigma_t{}', \tag{4.2.2}$$

where A_t is a lower triangular matrix such that:

$$A_t = \begin{bmatrix} 1 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 \end{bmatrix}$$

and Σ_t is the following diagonal matrix:

$$\Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & 0 \\ 0 & \sigma_{2,t} & 0 \\ 0 & 0 & \sigma_{3,t} \end{bmatrix}$$

This reduction of the variance-covariance matrix Ω_t allows us to rewrite the model in equation (4.2.1) as:

$$y_t = c_t + B_{1,t} y_{t-1} + B_{2,t} y_{t-2} + A_t^{-1} \Sigma_t \varepsilon_t, \tag{4.2.3}$$

where the structural innovations ε_t can be observed (see Appendix A.4 for a detail description of the computations). Specifically, these follow a normal distribution:

$$\varepsilon_t \sim N(0, I_n),$$

where I_n is an identity matrix with dimension n. All of the coefficients in c_t and in $B_{j,t}$ can be stacked into a vector B_t, so that the TVP-VAR in equation (4.2.3) can be written in more compact notation as:

$$y_t = X_t{}' B_t + A_t^{-1} \Sigma_t \varepsilon_t, \tag{4.2.4}$$

where, given that $\otimes$ denotes the Kronecker product, $X_t{}' = I_n \otimes [1, y'_{t-1}, y'_{t-2}]$.

The structure of the Σ_t and A_t matrices, together with the specification of the model as detailed in equation (4.2.3), helps us identify how this VAR allows both the volatility of the disturbances and the simultaneous relations among the variables to change over time. In fact, the Σ_t matrix, characterized by a diagonal structure, accounts for the heteroskedasticity in the innovations; the A_t matrix, characterized by being lower triangular, captures the changes in the covariances of the shocks over time.

The properties of the A_t matrix are extremely important in the analysis and are worth being discussed further. In fact, as stressed in Section 4.1, the main novelty of the TVP-VAR proposed by Primiceri (2005) is the time varying structure of this matrix. In order to understand why this is the case, note that, slightly rearranging the terms, equation (4.2.2) can be written as:

$$\Omega_t = A_t^{-1}\Sigma_t\Sigma_t'(A_t')^{-1}.$$

This identifies a highly flexible variance-covariance matrix, since all terms are allowed to change over time. On the contrary, this matrix used to be modelled, in previous studies (see, e.g., Cogley and Sargent, 2005), in the following manner:

$$\Omega_t = A^{-1}\Sigma_t\Sigma_t'(A')^{-1},$$

where the A matrix is time invariant. This assumption would imply that the shocks sent to variable i would have a constant effect on variable j over time (Koop and Korobilis, 2010). Consequently, this approach would be too restrictive for the analysis that will be carried out in the next sections, since the developments of the simultaneous interactions across the variables are of crucial importance to understand the ultimate source of the Great Moderation.

The lower triangular structure of the A_t matrix, moreover, has additional implications for our model, as it entails the imposition of a Cholesky decomposition. Specifically, this means that the ordering of the variables will not be irrelevant: each variable will be allowed to have a contemporaneous effect only on those variables ordered after it, while it will affect the preceding ones with at least one period lag. Therefore, economic reasoning on the relations across the variables is required before defining their ordering.

Following Primiceri (2005) and Christiano et al. (1999), the interest rate will be ordered last in the model. This implies that monetary policy can have an impact on inflation and output with at least one period lag, which is a reasonable assumption. With respect to the relation between output and inflation, Primiceri (2005) places inflation in the first equation. Since the literature supports the idea that it is inflation that affects output volatility (Blanchard and Simon, 2001), we will follow the author in this choice as well[6]. Thus, the variables will be ordered in the following manner:

$$Order : \begin{cases} \textit{Inflation Equation} \\ \textit{Output Equation} \\ \textit{Interest Rate Equation} \end{cases}$$

Having specified the relevant properties of the A_t matrix and what they imply for our analysis, we can move to the description of the dynamics of the time varying coefficients in the model.

[6]Note that, to assure the robustness of our results, all of the analysis presented in the following sections was also implemented changing the order of these two variables. Our results did not experience any significant change as a consequence of such a twist.

Following Primiceri (2005), we stack the non-zero and non-one elements of the A_t matrix into the vector α_t, and the diagonal elements of the Σ_t matrix into the vector σ_t. The dynamics of the model are specified in the following manner:

$$B_t = B_{t-1} + \nu_t, \qquad \nu_t \sim N(0, Q), \tag{4.2.6}$$
$$\alpha_t = \alpha_{t-1} + \zeta_t, \qquad \zeta_t \sim N(0, S), \tag{4.2.7}$$
$$\log \sigma_t = \log \sigma_{t-1} + \eta_t, \qquad \eta_t \sim N(0, W). \tag{4.2.8}$$

These assumptions on the dynamics of the model imply that the elements of the A_t, B_t, and Σ_t matrices are modelled as random walk processes. As specified by Primiceri (2005), this choice of modelling the dynamics of the parameters as random walks is harmless and significantly simplifies the estimation procedure[7].

The relations among the innovations in the model are governed by the following matrices:

$$V = Var\left(\begin{bmatrix} \varepsilon_t \\ \nu_t \\ \zeta_t \\ \eta_t \end{bmatrix}\right) = \begin{bmatrix} I_n & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix}, \quad S = \begin{bmatrix} S_1 & 0 \\ 0 & S_2 \end{bmatrix}, \tag{4.2.9}$$

where Q, S, W are positive definite matrices. The structure of V is characterized by a block-exogeneity assumption: the innovations of the model ε_t, ν_t, ζ_t and η_t are assumed to be independent of each other. This structure on the V matrix is necessary, as it makes it possible to understand the results that will be presented in the following sections. In fact, replacing the zero-blocks with non-zero elements would make the innovations in the model correlated with each other. In this way, the possibility of interpreting the impact that each shock generates in the model would be precluded (Primiceri, 2005). On the other hand, as it is standard in the literature (see, e.g., Canova and Gambetti, 2009; Galí and Gambetti, 2009; Gerba and Hauzenberger, 2013), S is modelled as being block-diagonal, which is shown by the fact that the non-diagonal elements of the matrix are zero blocks. This assumption implies that the covariance between inflation and output, $\alpha_{21,t}$, will evolve independently of both the covariance between the interest rate and inflation, $\alpha_{31,t}$, and the covariance between the interest rate and output, $\alpha_{32,t}$.

4.3 Estimation

This section will firstly detail the choice of the sample size used for the estimation. Afterwards, it will show how the parameters of the above specified model were obtained, following the thorough description of the estimation algorithm in Primiceri (2005) and Del Negro and

[7]This is because, in an infinite sample, a unit root process will surely hit an upper or lower bound, which would have unwanted consequences on our analysis. However, since we are using a finite sample, we can keep the random walk assumption. The unit root assumption simplifies the estimation procedure as the number of parameters to estimate is reduced.

Primiceri (2015)[8].

Sample size The data used for the estimation covers 140 quarters over the period 1964:Q1–1998:Q4. The length of this sample was defined on the basis of the need to implement a meaningful analysis and to assure interpretability of the results.

In May 1998 the Council of the European Union announced that Italy had met the convergence criteria to adhere to the third phase of the European Monetary Union (involving the introduction of a common currency), whose activities began in 1999 (Council of the European Union, 1998). As a consequence, when investigating the relations among the conduct of monetary policy, inflation and output, one needs to consider that starting from the establishment of the monetary union, the interest rate prevailing in the Italian economy began to be defined at the European level on the basis of developments occurring in the whole Euro area[9]. This is what justifies the decision of ending the sample in 1998:Q4, since expanding it after this date would prevent us from isolating the relations among the variables to the sole Italian context, with the results losing their meaningfulness. Moreover, since the scope of this work is to investigate the sources of a phenomenon beginning in the early 1980's, this choice does not threaten any of our conclusions.

The beginning of the sample in 1964:Q1, on the other hand, was dictated by data availability issues. Despite studies focusing on the United States tend to have earlier starting observations, our choice allows us to have a sample of more than 15 years before the early 1980's. This adequately fulfills the need of identifying the peculiarities of the dynamics of the variables considered before the emergence of the Great Moderation. Therefore, it does not pose any particular problem to the analysis.

MCMC algorithms and the Gibbs Sampler One of the crucial features of the TVP-VAR in equation (4.2.3) is that, as a consequence of the introduction of time varying coefficients and stochastic volatility, the amount of parameters to estimate proliferates compared to standard, time invariant VARs. The high dimensionality of these models has historically posed the problem of how to avoid over-parameterization, which is the risk of ending up with a model with a larger amount of parameters than the one justifiable given the available data (Everitt and Skrondal, 2010). The solution was eventually found in the use of Bayesian methods that, as stressed by Koop and Korobilis (2010), efficiently deal with highly dimensional models. Accordingly, the estimation procedure will rely on the use of these techniques.

The algorithm used to estimate the parameters of the model is called Gibbs Sampler, which is part of a broader class of posterior simulators identified as Markov Chain Monte Carlo

[8] The estimation of the model and the analysis were implemented in Matlab. Parts of the code used were provided by Benedikt Kolb, PhD student at the European University Institute, whose generosity is acknowledged.

[9] Indeed, the Italian central bank ceased to set the discount rate, crucial tool in the definition of its monetary policy, in the end of 1998.

algorithms (MCMC). Before describing the estimation procedure for the coefficients of the model, detailed in Section 4.2, it is useful to understand how the algorithm works in a simpler environment.[10]

Let us define a matrix containing the data available as $\boldsymbol{X}$. Moreover, let us define $\boldsymbol{\theta}$, a vector containing i parameters aiming at explaining the developments in $\boldsymbol{X}$, as $\boldsymbol{\theta} = (\theta_1, \theta_2, ..., \theta_i)$. Given the data $\boldsymbol{X}$, the interest is usually in estimating the elements of $\boldsymbol{\theta}$. To do so, the general rule followed when applying Bayesian methods is:

$$p(\boldsymbol{\theta}|\boldsymbol{X}) \propto p(\boldsymbol{X}|\boldsymbol{\theta})p(\boldsymbol{\theta}), \tag{4.3.1}$$

where $p(\boldsymbol{\theta}|\boldsymbol{X})$ is the *posterior density*, $p(\boldsymbol{X}|\boldsymbol{\theta})$ is the *likelihood function*, $p(\boldsymbol{\theta})$ is the *prior density* and equation (4.3.1) states that the posterior density will be proportional to the likelihood times the prior. Given the posterior, we will want to identify some of its specific features (for instance, the posterior mean), which are defined as:

$$E(g(\boldsymbol{\theta})|\boldsymbol{X}) = \int g(\boldsymbol{\theta})p(\boldsymbol{\theta}|\boldsymbol{X})d\boldsymbol{\theta}, \tag{4.3.2}$$

where $g(\boldsymbol{\theta})$ is defined as the *function of interest* to the econometrician.

Unfortunately, the integral in equation (4.3.2) can hardly ever be solved analytically. Thus, posterior simulators were introduced: relying on extensions of the Central Limit Theorem, they allow to estimate the features of the posterior distribution we are interested in. Specifically, the idea behind Monte Carlo algorithms is that of recursively taking random draws from the posterior distribution to approximate the *function of interest*, with a degree of uncertainty that decreases as the number of draws increases.

Among MCMC algorithms, the Gibbs Sampler was introduced to deal with situations in which the posterior distribution, $p(\boldsymbol{\theta}|\boldsymbol{X})$, does not take any well-known form (making it impossible to directly draw from it), but conditional posterior distributions, defined as $p(\theta_j|\boldsymbol{X}, \theta_1, \theta_2, ..., \theta_i)$ for $i \neq j$, do instead. When this is the case, it is possible to estimate the *function of interest* by recursively taking random draws from the conditional posterior distributions. Specifically, indicating draws with superscripts and parameters with subscripts (for instance, $\theta_2^{(4)}$ being the fourth draw for the second parameter), the Gibbs Sampler is implemented in the following steps:

1. Choose an initial value $\boldsymbol{\theta}^{(0)}$. For draws $d = 1, ..., D$:
   (a) From the conditional posterior distribution $p(\theta_1|\boldsymbol{X}, \theta_2^{(d-1)}, \theta_3^{(d-1)}, ..., \theta_i^{(d-1)})$, take a random draw, $\theta_1^{(d)}$;
   (b) From the conditional posterior distribution $p(\theta_2|\boldsymbol{X}, \theta_1^{(d)}, \theta_3^{(d-1)}, ..., \theta_i^{(d-1)})$, take a random draw, $\theta_2^{(d)}$;

[10] This section provides a general overview on Gibbs Sampling based on Koop (2003).

(c) From the conditional posterior distribution $p(\theta_3|\boldsymbol{X}, \theta_1^{(d)}, \theta_2^{(d)}, \theta_4^{(d-1)}, ..., \theta_i^{(d-1)})$, take a random draw, $\theta_3^{(d)}$;

(d) Implement this sequential procedure until the conditional posterior of the last parameter, i, is reached. When this happens, take a random draw, $\theta_i^{(d)}$, from the conditional posterior distribution $p(\theta_i|\boldsymbol{X}, \theta_1^{(d)}, \theta_2^{(d)}, ..., \theta_{i-1}^{(d)})$;

2. Make use of the D draws to obtain the *function of interest*.

One problem of the Gibbs Sampler relates to the arbitrariness in the choice of the initial value $\boldsymbol{\theta}^{(0)}$. However, it can be proven that the Gibbs Sampler does in fact converge to a sequence of random draws from the posterior distribution, $p(\boldsymbol{\theta}|\boldsymbol{X})$, regardless of the initial value[11]. Therefore, discarding an initial subset, d_0, of the overall draws taken, D, those draws influenced by the arbitrarily chosen initial value are eliminated from the analysis. This procedure allows to overcome the problem and is widely applied in the literature (see, e.g., Primiceri, 2005; Benati and Mumtaz, 2007; Gerba and Hauzenberger, 2013).

Applying the Gibbs Sampler and prior selection Gibbs Sampling was applied to estimate the parameters of the TVP-VAR specified in Section 4.2. Specifically, the interest is in obtaining the estimates, for each time period, of the following: the coefficients in B_t, the elements of the A_t matrix, the elements of the Σ_t matrix, and the variance-covariance matrices Q, S, and W. Let us stack the B_t matrices for each time period in the matrix B^T, the elements of the A_t matrices for each time period in the matrix A^T, and the elements of the Σ_t matrices for each time period in the matrix Σ^T. Using these matrices and the notation introduced above, we are therefore interested in estimating the joint posterior distribution $p(B^T, A^T, \Sigma^T, Q, S, W|y^T)$, where y^T denotes the data available[12]. This distribution, however, does not take any well-known form but, by accurately selecting priors, the conditional posterior distributions, such as $p(B^T|y^T, A^T, \Sigma^T, Q, S, W)$ or $p(A^T|y^T, B^T, \Sigma^T, Q, S, W)$, will have well-known forms instead.

To make this point clearer, note that the formula in equation (4.3.1) states that the form of any posterior distribution will depend on the form of the prior distribution. The priors chosen in this analysis follow Primiceri (2005), and are characterized by their convenience in this application[13]: the priors for the coefficients B_t, the elements of the A_t matrix and the elements of the Σ_t matrix will be normally distributed, while the priors for Q, S, and W will follow independent inverse-Wishart distributions. Under these assumptions, the conditional posterior distributions will have well-known forms. For instance, the conditional posterior distribution of B^T will be:

$$p(B^T|y^T, A^T, \Sigma^T, Q, S, W) \propto p(y^T|B^T, A^T, \Sigma^T, Q, S, W)p(B_0)$$

[11]The proof can be found in Geweke (1999).

[12]Note that, similarly to the definition of the matrices B^T, A^T and Σ^T, the matrix y^T simply stacks all of the observations y_t.

[13]For a more detailed description of the priors, see Appendix A.5.1.

where $p(B_0)$ is the prior distribution of B^T. The likelihood, $p(y^T|B^T, A^T, \Sigma^T, Q, S, W)$, will have a form that depends on the assumptions posed in Section 4.2: given the normal distributions of the processes in equations (4.2.3) and (4.2.6), it will be normally distributed as well. This, together with the assumption on the distribution of the prior $p(B_0)$, implies that the conditional posterior distribution of B^T will be the product of two normal densities, and will therefore be Gaussian itself.

The complete description of the estimation procedure, together with the specification of the values of the means, variances and degrees of freedom of the prior distributions, can be found in Appendix A.5. To assure the convergence of the Gibbs Sampler, the estimation was carried out relying on 100,000 repetitions, with a burn-in period of 20,000 draws and, to avoid possible autocorrelation, only one every 10 draws was considered. The analysis of the 20^{th}-order autocorrelation, that can be found in Appendix A.5.3, shows that, with some exceptions, the autocorrelations remain below a value of 0.2. Thus, our draws are almost independent among each other, which assures a high efficiency of our algorithm.

5 Analysis: The Sources of the Great Moderation

The following sections aim at providing evidence on the sources of the Great Moderation in Italy making use of the model presented in Section 4. In order to do so, we will firstly implement a forecast error variance decomposition analysis to investigate the dynamics of the relations across our variables (Section 5.1). This exercise will provide useful insights on the possible sources of lower volatility. Afterwards, we will move to the analysis of the impulse responses to investigate the extent to which either monetary policy or the structure of the economy could explain the phenomenon (Section 5.2). Finally, Section 5.3 will portray a counterfactual analysis to shed light on the relevance of good luck within the Italian experience. We will conclude by discussing our results and the limitations of our analysis in Section 5.4.

5.1 Forecast Error Variance Decomposition Analysis

Having estimated the VAR specified in Section 4.2, we will begin our investigation by examining the relations across the variables through a forecast error variance decomposition analysis. This exercise, as indicated in Kilian and Lutkepohl (2017), enables us to identify the fraction of the forecast error variance of each variable that is due to the exogenous shocks in the other variables. Therefore, it represents a measure of the extent to which each variable can explain the movements in the other variables, providing an estimate of their interrelations.

Our analysis, moreover, will be more insightful thanks to the time varying framework that we are using. In fact, it allows us to perform the decomposition at each point in time in our sample, so that we will be able to explore the dynamics of the relations across the variables over time. This way, the changes in the interplay between inflation, output and the interest rate will be easily detected. Thus, this analysis will help us to better understand the developments of the variables and how their interactions evolved, providing us with a first piece of evidence on the sources of the Great Moderation.

Before presenting the results of the forecast error variance decomposition analysis, we will review the method used to implement this exercise.

5.1.1 Method

As underlined in Lutkepohl (2005), the procedure that needs to be followed for the forecast error variance decomposition analysis consists of two steps. Firstly, it is required to estimate the aggregate contribution of the shocks in variable k to the variance of variable j; secondly, the overall forecast error variance (that is, the Mean Squared Error; hereafter, MSE) needs to be computed. Once these two quantities have been obtained, the forecast error decomposition can be easily derived dividing the first estimate by the second, as this will provide the share of the variance of variable j accounted for by the innovations in variable k.

To carry out the first step in the analysis, it is convenient to convert the VAR with two lags in equation (4.2.1) into its companion form:

$$Y_t = C_t + \Lambda_t Y_{t-1} + U_t, \tag{5.1.1}$$

where

$$Y_t = \begin{bmatrix} y_t \\ y_{t-1} \end{bmatrix}, \quad C_t = \begin{bmatrix} c_t \\ \mathbf{0} \end{bmatrix}, \quad \Lambda_t = \begin{bmatrix} B_{1,t} & B_{2,t} \\ I_n & \mathbf{0} \end{bmatrix}, \quad U_t = \begin{bmatrix} u_t \\ \mathbf{0} \end{bmatrix}.$$

The elements of these matrices were introduced before (Section 4.2), and $\mathbf{0}$ is a $n \times n$ zero matrix. Discarding the constant term as in Lutkepohl (2005)[14], the moving average representation of equation (5.1.1), where Y_t is a function of past and present innovations, is:

$$Y_t = \sum_{i=0}^{\infty} \Lambda_t^i U_{t-i}. \tag{5.1.2}$$

Starting from this representation of the original VAR, let us define a $n \times np$ matrix, J, as:

$$J = \begin{bmatrix} I_n & \mathbf{0} \end{bmatrix}.$$

Making use of this matrix and equation (5.1.2), we can see that:

$$y_t = JY_t = \sum_{i=0}^{\infty} J\Lambda_t^i J' J U_{t-i} = \sum_{i=0}^{\infty} \Phi_t^i u_{t-i}, \tag{5.1.3}$$

where $\Phi_t^i = J\Lambda_t^i J'$ and $JU_t = u_t$. These equivalences bind the original definition of the VAR in equation (4.2.1) with its moving average representation in equation (5.1.2). Specifically, the jk-th element of matrix Φ_t^i at time t, $\phi_{jk,i,t}$, will identify the response of the j-th variable to a unit shock in the k-th variable at time t, after i periods.

The problem with this representation, however, is that y_t is expressed as a function of the vector of errors u_t. This is characterized by a variance-covariance matrix, Ω_t, that allows for non-zero correlations across the innovations. As a consequence, when a shock is sent into one variable, it will be impossible to isolate its own contribution to the movements in other variables, since all innovations will be contemporaneously affected. Thus, in order to implement a pure analysis, we need to take into account the triangular reduction of matrix Ω_t implemented in equation (4.2.2). Doing so allows us to write the moving average representation

[14] Note that discarding the constant term simplifies the notation and does not create any problem to the analysis, since we are interested in the interrelations across the variables: the constant terms play no role in this respect.

as:

$$y_t = \sum_{i=0}^{\infty} \Theta_t^i \varepsilon_{t-i}, \tag{5.1.4}$$

where $\Theta_t^i = \Phi_t A_t^{-1}\Sigma_t = J\Lambda_t^i J' A_t^{-1}\Sigma_t$. Thanks to this representation, we can express each variable in the matrix y_t as a function of the structural shocks ε_t, multiplied by the elements in the Θ_t^i matrix. Hence, the jk-th element of matrix Θ_t^i at time t, $\theta_{jk,i,t}$, will identify the response of the j-th variable to a unit shock in the k-th variable at time t, after i periods.

Accordingly, the contribution of the innovations in variable k to the forecast error variance of variable j at time t, after i periods, denoted as $\omega_{jk,i,t}$, will be computed in the following manner:

$$\omega_{jk,i,t} = \sum_{i=0}^{h-1} (\varepsilon_j{}' \Theta_t^i \varepsilon_k)^2 = \theta_{jk,0,t}^2 + \theta_{jk,1,t}^2 + ... + \theta_{jk,h-1,t}^2. \tag{5.1.5}$$

Making use of the elements in the Θ_t^i matrix, it is also possible to detect the overall forecast error variance of variable j after i periods, which is the second step in the procedure in Lutkepohl (2005). Specifically, summing the individual contributions of each variable, n, we will have that:

$$\text{MSE}[y_{j,t}(i)] = \sum_{k=1}^{n} \sum_{i=0}^{h-1} (\varepsilon_j{}' \Theta_t^i \varepsilon_k)^2. \tag{5.1.6}$$

Finally, dividing equation (5.1.5) by equation (5.1.6), the portion of the overall forecast error variance of variable j due to the innovations in variable k will be identified.

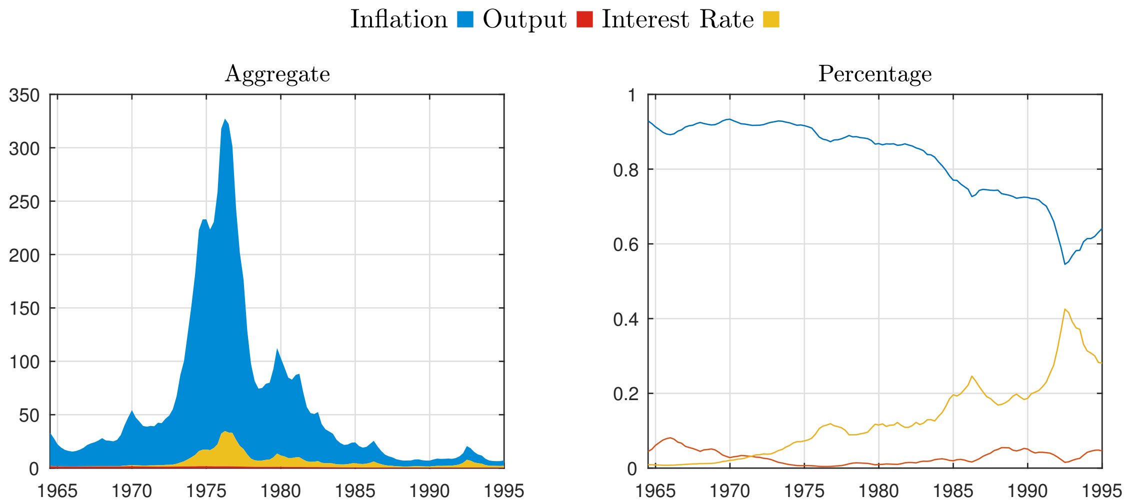
In our analysis, we rely on the decomposition 300 steps ahead ($h = 300$) for each point in time in our sample. The values reported are posterior medians.

5.1.2 Results

The results of the forecast error variance decomposition analysis are presented in Figure 5.1, Figure 5.2 and Figure 5.3, where the decomposition of inflation, output and the interest rate series, respectively, is reported[15]. Specifically, in the graphs on the left side of all figures, called "Aggregate", the height of the coloured area defines the total variance of the variables at each point in time. This area, moreover, is internally divided into different colours, which identify the contribution of each shock to the overall volatility of inflation (Figure 5.1), output (Figure 5.2), and the interest rate (Figure 5.3).

[15] Note that, in these figures, we report the forecast error variance decomposition up to 1995:Q1, even though our sample ends in 1998:Q4. The reason underlying this restriction lies in the fact that, given the high dimensionality of the matrices we are working with, we faced a trade-off between the amount of quarters we could consider and the length of the horizon of the decomposition. Judging the latter more important than the former, we kept our horizon fixed at $h = 300$ and slightly restricted our sample. In fact, most of the action we want to detect occurs much earlier than in those last quarters, which do not carry significant insights to our investigation.

Figure 5.1: Total Variance and Individual Contributions
Inflation



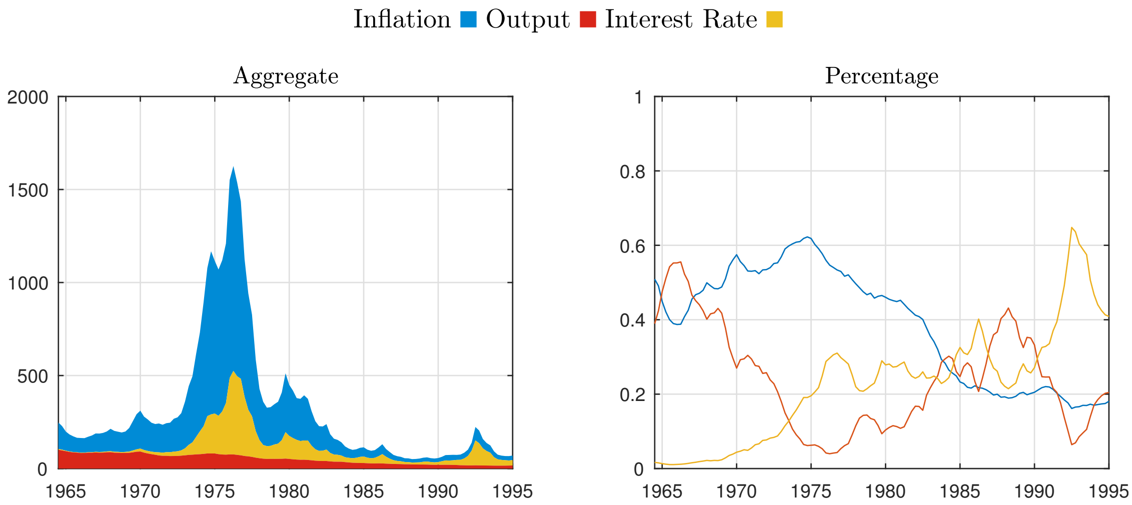
On the other hand, the graphs on the right side of the figures, called "Percentage", provide us with the fraction of the total variance that, at each point in time, can be attributed to shocks sent in one of the three variables used in the analysis. Therefore, these graphs help us understand the dynamics of the relations across the variables, so that a change in the contribution of any variable to the aggregate volatility of either inflation, output, or the interest rate can be easily detected.

Inflation Series Starting with the analysis of the variance of the inflation series on the left side of Figure 5.1, we firstly observe the relevance of the Great Moderation within the Italian context. In fact, we can clearly notice that, starting from the 1970's, the series follows an upward trend up to a spike around 1977. After this, and during all of the 1980's, aggregate volatility diminishes, and eventually reaches very low levels during the 1990's. What emerges from this figure, moreover, is the fact that the volatility of inflation was mainly an exogenous phenomenon, since most of the variance, at each point in time, can be attributed to the innovations in the inflation equation itself[16]. Nonetheless, the relevance of the shocks in the interest rate starts to increase from the first half of the 1970's, as suggested by the increase in the yellow area in the graph.

These findings can be better appreciated by looking at the dynamics of the relative contributions, on the right side graph. The graph clearly shows that the blue line, detecting the portion of total variance due to inflation shocks, remains the highest throughout the whole period considered. Yet, the innovations in the inflation equation tend to account for a smaller percentage of total variance as time passes by and, as shown by the movements of the yellow line, such a reduction is the consequence of an increase in the fraction of volatility due to shocks in the interest rate. In fact, the interest rate series follows an upward sloping trend

[16] When the variance of a process is mainly explained by its own innovations, it is defined an exogenous process (Enders, 2010).

Figure 5.2: Total Variance and Individual Contributions
Output



from the mid-1970's.

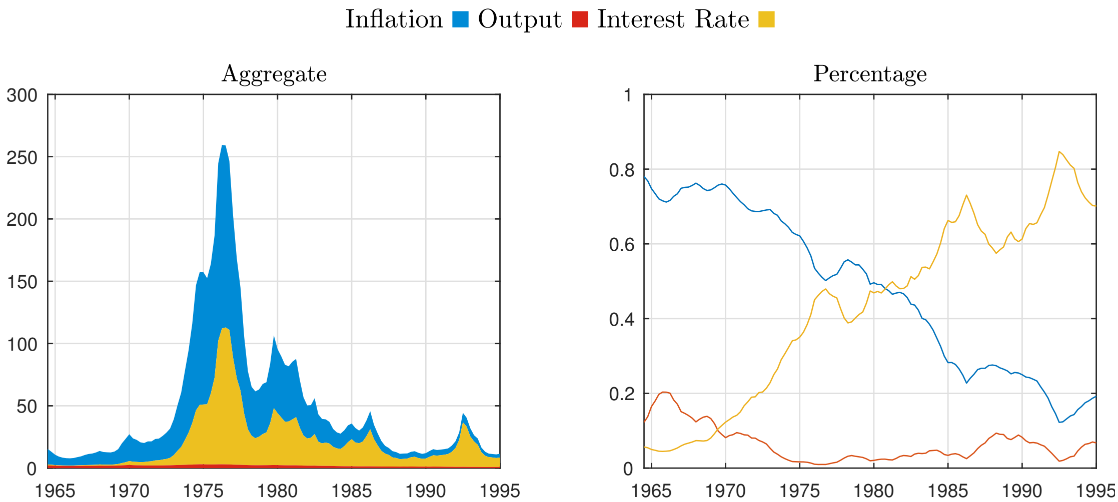
The implications of the empirical evidence provided in the two graphs of Figure 5.1 are highly relevant for our analysis. On the one hand, the greater importance of the innovations in inflation during the whole period highlights the fundamental role that exogenous shocks have had in explaining the change of volatility over time, pointing to a large role of good luck. On the other hand, however, the evidence also supports the better monetary policy hypothesis: the relevance of the interest rate gradually rises, and the timing of the beginning of such an increase, the second half of the 1970's, matches the beginning of the Great Moderation.

Output Series We will now move to the analysis of the volatility of the output series in Figure 5.2. Just as before, the graph on the left side displays a striking increase in volatility during the 1970's, which gradually diminishes during the 1980's and settles to low levels during the 1990's, with the only exception being a small bump around 1992[17]. The relevance of the Great Moderation in the Italian context, therefore, is confirmed with respect to output volatility as well. Moreover, this graph shows that the innovations in inflation and output explained most of the overall variance up to the mid-1970's. From this date onward, the contribution of the interest rate tends to increase, while both those of output and inflation decrease.

The graph on the right side enhances our understanding of the contribution of each innovation. Differently from the analogous graph for inflation, the one in Figure 5.2 displays much more movement, and no single contribution prevailing throughout the whole sample can be identified. Apart from the peculiar dynamics of the red line, that describes the relevance of the shocks in the output equation and follows a sinusoidal path, two features characterize this

[17]This is explained by the interruption in the participation to the European Exchange Rate Mechanism in 1992, as a consequence of speculative attacks to the Italian Lira. This was followed by a sudden increase in the interest rate to solve the crisis (see, e.g., Bassetto, 2006).

Figure 5.3: Total Variance and Individual Contributions
Interest Rate



graph. Firstly, the innovations in inflation, initially determining most of the total volatility of output, begin a downward sloping trend in 1975 and, from year 1984, they are not the largest contributors anymore. Secondly, the innovations in the interest rate, starting from very low levels, move upward during the whole period, eventually becoming able to explain the largest share of total volatility.

Overall, the graphs in Figure 5.2 point to the fact that output volatility, differently from the variance of inflation, can be largely explained by the variables used in our analysis. Thus, they suggest that it was an endogenous, rather than exogenous, phenomenon. Moreover, they indicate that the volatility of inflation accounted for most of the movements in output volatility during the 1970's, and the interest rate had a greater role from the mid-1980's onward. This finding is important, since it points out that understanding the sources of the volatility of inflation is of crucial importance to understand the causes of the Great Moderation. In fact, the shocks in this variable explain the high volatility prevailing before the 1980's both of the output and of the inflation series.

Interest Rate Series In the literature, the Great Moderation is a phenomenon that generally refers to the volatility of inflation and output, and the variance of the interest is not of major interest. Nonetheless, Figure 5.3 provides the forecast error variance decomposition of the interest rate series, which we decided to include because, although it may not be as meaningful as the previous inspections, it conveys relevant information for our analysis.

Looking at the graph on the left side it is possible, once again, to easily spot the 1970's as a period of high volatility of the variable, whose variance gradually diminishes during the 1980's and, apart from the jump around 1992, remains at low levels from then onward. Of greater interest, however, are the relative contributions of the innovations reported in the graph on the right side. In particular, we can see that, similarly to the case of the output series, the period of high volatility (the 1970's) is characterized by a large role of the shocks in the inflation equation. Afterwards, the greatest share of the variance is explained by the innovations in the interest rate itself, which becomes mostly an exogenous process.

Overall, the analysis of the forecast error variance decomposition of inflation, output and the interest rate conveys important implications for our analysis. Firstly, it highlights that the high volatility of the variables during the 1970's was mostly the consequence of the large fluctuations of inflation. The high volatility of inflation, moreover, was mostly accounted for by exogenous shocks (Figure 5.1) and, as a consequence, this analysis points to good luck as a main source of the Great Moderation. Secondly, the empirical evidence reveals that the reduction in volatility was associated with an increase in the relative importance of the interest rate and, in this respect, the analysis suggests that monetary policy might have played a role in explaining Great Moderation as well.

Having obtained such insights from this analysis, the following sections will provide additional tests on the possible sources of the Great Moderation to reach a reliable conclusion.

5.2 Impulse Response Function Analysis

The estimates of the model specified in Section 4.2 will be now used to implement an impulse response function analysis. The goal is to verify the extent to which the empirical evidence provides support for the good monetary policy and better structure of the economy hypotheses, while Section 5.3 will focus on a counterfactual experiment to investigate the relevance of good luck to explain the phenomenon.

The method followed to construct the impulse responses follows Lutkepohl (2005), and partly overlaps with the steps implemented for the forecast error variance decomposition analysis. Specifically, let us recall equation (5.1.4):

$$y_t = \sum_{i=0}^{\infty} \Theta_t^i \varepsilon_{t-i}.$$

As specified before, matrix Θ_t^i will provide the orthogonal impulse responses – i.e., the responses of each variable to shocks sent to the innovations ε_t, which are characterized by the variance-covariance matrix I_n. In fact, the jk-th element of matrix Θ_t^i at time t, $\theta_{jk,i,t}$, will identify the response of the j-th variable to a unit shock in the k-th variable at time t, after i periods. This is exactly what we aim at identifying through this analysis.

The following section will present the results of this exercise. The figures will report the responses over a 20-period horizon, and the estimates used were computed as posterior medians.

5.2.1 Results

The impulse response function analysis is carried out with the goal of testing the validity of the good monetary policy and better structure of the economy hypotheses. To do so, we will firstly send a shock to the inflation and output equations to examine the reaction of the interest rate in two points in time, one before and one after the Great Moderation began[18]. This analysis provides a measure of the degree of activism of monetary policy and, in order for the monetary policy hypothesis to be sustained by the empirical evidence, the reaction of the interest rate to changes in these variables should be markedly stronger after the break. In fact, this would support the idea that monetary actions began to be implemented with the aim of securing lower fluctuations over the business cycle from the 1980's onward.

Afterwards, we will send a unit shock to the interest rate equation, and compare the reactions of inflation and output before and after the beginning of the Great Moderation. As stressed by Primiceri (2005), these shocks represent movements of the interest rate caused by variables different from inflation and output and, therefore, exogenous in our analysis. In line with this reasoning, the better structure of the economy hypothesis predicts that the reactions of inflation and output decreased over time, as this would point to a greater ability of the economy to absorb these exogenous shocks. The empirical analysis will be put in place to test the validity of such a prediction.

Figure 5.4 shows the consequences of sending a unit shock in the inflation and output equations on the interest rate[19]. We can see that, in both graphs on the left side and in line with the developments in the conduct of monetary policy experienced in Italy during the 1980's (reviewed in Section 2.2.2), the magnitude of the responses of the interest rate is higher in 1990:Q1 than it was in 1975:Q1. This means that, after the beginning of the Great Moderation, the interest rate became more responsive to changes in inflation and output. This evidence signals a greater effort of the monetary policy authority to mitigate the fluctuations over the business cycle and to reduce the volatility in the system, supporting the better monetary policy hypothesis.

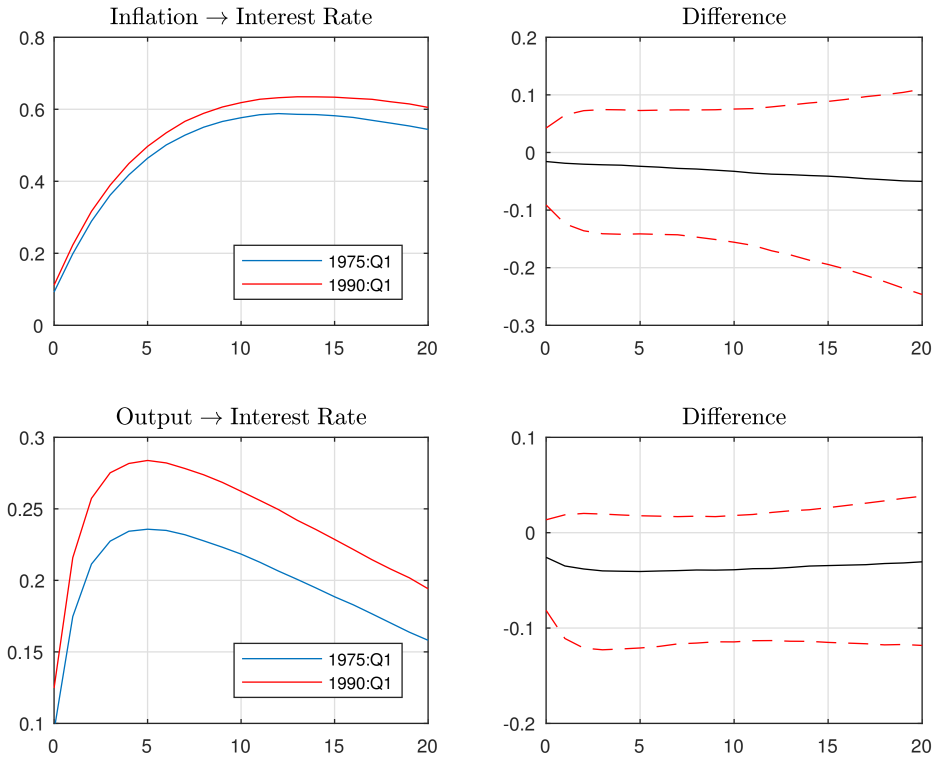
Nonetheless, the implications of the two graphs on the right side scale down the relevance of monetary policy that emerges by looking solely at the dynamics of the responses over time. In fact, these graphs portray the difference between the responses with the 16$^{\text{th}}$ and 84$^{\text{th}}$ percentiles and, in both cases, the discrepancy between the responses is not statistically different from zero[20]. Thus, the empirical evidence, although revealing an evolution of the

[18] Having identified the beginning of the Great Moderation in the early 1980's in Section 3.2.1, the figures show the reactions of the variables in 1975:Q1 and 1990:Q1. Nonetheless, robustness checks were implemented to make sure that changing these dates would not alter the results of the analysis.

[19] Note that both Figure 5.4 and Figure 5.5, as it is standard in the literature on TVP-VARs (Koop and Korobilis, 2010), were constructed by fixing the time varying coefficients to their values in 1975:Q1 and 1990:Q1. See Appendix A.6 for the same analysis implemented allowing the coefficients to change over time. Since there are not significant differences in our results, we do not present these figures here.

[20] These percentiles define a one standard deviation band under normality.

Figure 5.4: Interest Rate Response To Shocks in Inflation (Top) and Output (Bottom)



Notes: The dashed, red lines represent a one standard deviation confidence interval.

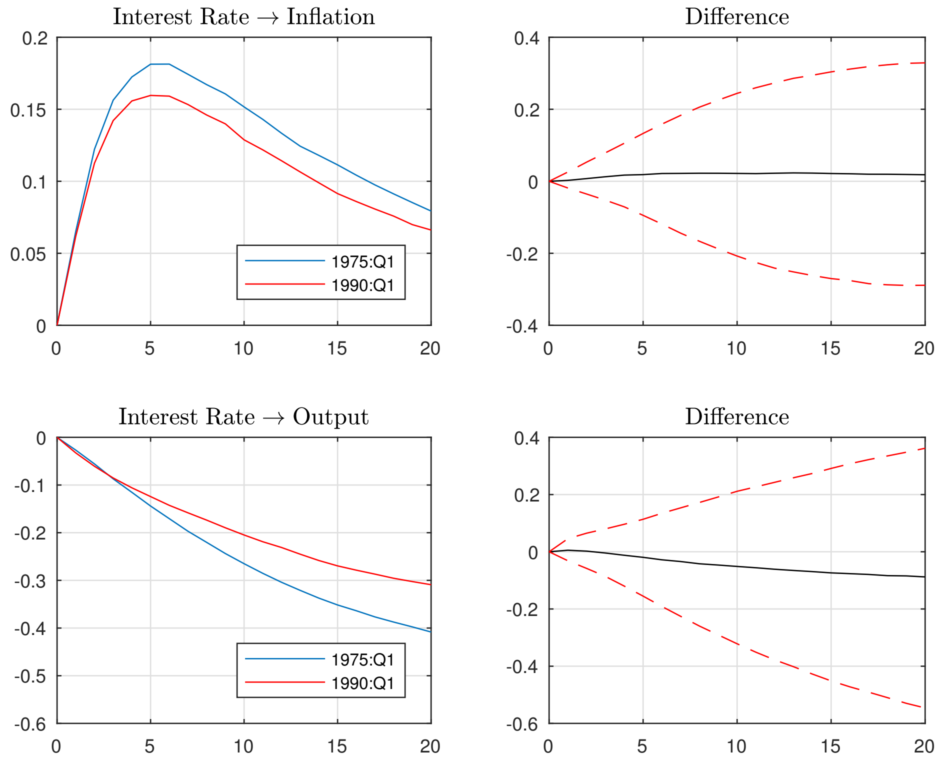
response of the interest rate that indicates a greater emphasis on mitigating volatility, does not allow to conclude in favour of the monetary policy hypothesis unequivocally.

The graphs in Figure 5.5 provide evidence on the responses of inflation and output to unit shocks in the interest rate equation[21]. Similarly to the results above, we do observe changes in the dynamics that are in line with the better structure of the economy hypothesis: in both graphs on the left side, the magnitude of the responses is closer to zero in 1990:Q1, which points to a greater capacity of the system to absorb the shocks. However, the graphs on the right side highlight that the differences of the responses over time are not statistically different from zero: again, the evidence does not fully support the better structure of the economy hypothesis.

Overall, the analysis of the impulse responses shows that relevant developments involved the Italian economy during the 1980's, which are reflected by movements in the responses of the variables that are in line with our expectations. However, the magnitude of the changes was not large enough to conclude in favour of any of the two analyzed hypotheses with certainty, and with this evidence in mind we can move to the analysis of the good luck hypothesis.

[21] In this work, we do not focus on investigating the overall effects of monetary policy on the economy. Nonetheless, it is interesting to note that, as shown in the top left graph of Figure 5.5, our TVP-VAR detects a "price puzzle" for Italy, an empirical regularity firstly noted by Sims (1992) related to the counter-intuitive response of inflation to an interest rate shock.

Figure 5.5: Inflation (Top) and Output (Bottom) Responses To Interest Rate Shocks



Notes: The dashed, red lines represent a one standard deviation confidence interval.

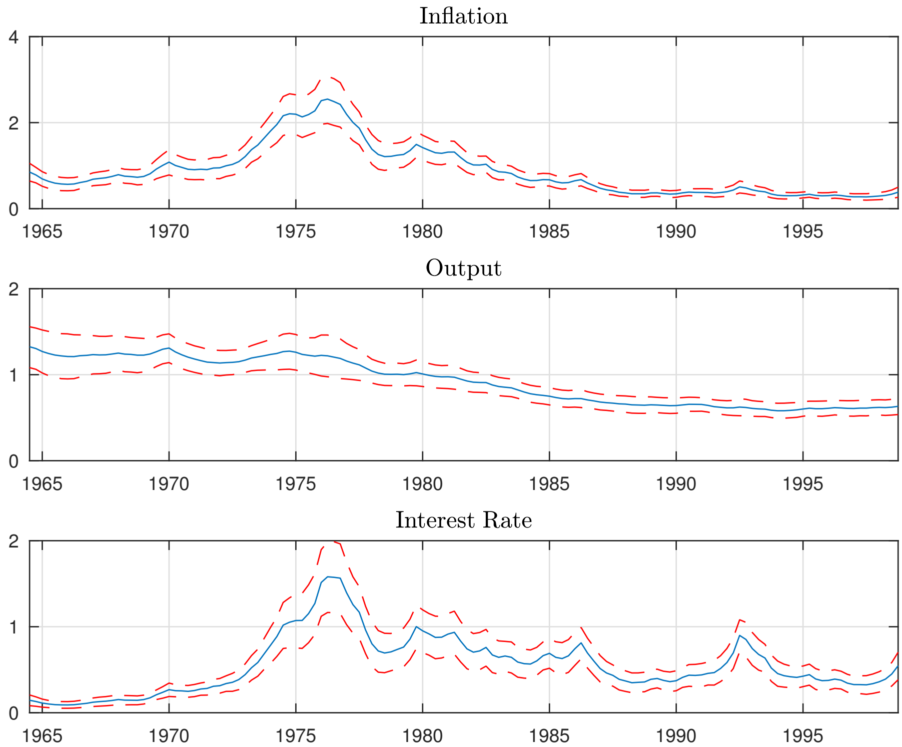
5.3 Good Luck: A Counterfactual Analysis

This section aims at shedding light on the hypothesis that the Italian Great Moderation was the consequence of good luck, implying that lower aggregate volatility was determined by a reduction in the magnitude of the shocks hitting the economy.

As a primary step in this analysis, we will investigate the evolution of the size of the shocks that can be obtained from our model, reported in Figure 5.6. As it appears evident, these were indeed much larger during the 1970's compared to the subsequent decades. Specifically, the series of inflation and of the interest rate are characterized by an increase in the magnitude of the shocks from the beginning of the 1970's up to a spike around 1977, when the series began a downward movement. The output series, on the other hand, displays a steadily high magnitude of the shocks during the late 1960's until slightly before the beginning of the 1980's, starting from when a gradual reduction of the size in the shocks occurs down to the beginning of the 1990's, when the series stabilizes.

Thus, this evidence provides *prima facie* support to the good luck hypothesis. However, we deem this not enough to conclude in its favour, and decide to implement a counterfactual analysis for this purpose. Specifically, this analysis will simulate how the series would have looked like if, in the 1970's, monetary policy had been implemented the way it was conducted

Figure 5.6: Posterior Mean of the Residuals of Inflation, Output and the Interest Rate



Notes: The dashed, red lines represent a one standard deviation confidence interval.

during the 1990's. Keeping the magnitude of the innovations fixed will allow us to isolate the role of the exogenous shocks in explaining the Great Moderation. In fact, it will be left to the data to show whether, given the size of the shocks during the 1970's, a more efficient monetary policy could have mitigated its effects. If this does not appear to be the case, then the evidence will be pointing toward a crucial role played by the size of the innovations, and good luck will need to be recognized as the ultimate source of the Great Moderation in Italy.

Before presenting and discussing the results of this exercise, we will review the method applied to carry out the investigation.

5.3.1 Method

To implement the counterfactual analysis we rely on the procedure detailed in Kilian and Lutkepohl (2017), which can be divided in two steps. Firstly, we need to isolate the $n \times 1$ vector of structural shocks from our model for each time period. In order to do so, let us adjust the VAR in equation (4.2.3) so that the vector of exogenous shocks is expressed as a function of the other parameters:

$$\varepsilon_t = A_t \Sigma_t^{-1} \times [y_t - c_t - B_{1,t} y_{t-1} - B_{2,t} y_{t-2}]. \tag{5.3.1}$$

Since we have already estimated the coefficients on the right hand side of equation (5.3.1), the sequence of unit-variance structural errors can be trivially obtained and stored.

The second step of the analysis requires us to make use of these residuals to reconstruct the series of inflation and output to see how they would have looked like, in the 1970's, had the monetary policy in that period been like the one implemented during the 1990's. Considering the order of our variables detailed in Section 4.2 and the VAR in equation (4.2.3), we employed the estimated innovations ε_t to simulate the series y_{it}, $i \in \{1, 2\}$[22], fixing the coefficients describing the monetary policy behavior to their values in the 1990's. Specifically, when constructing the series, we anchored the third rows of the c_t, B_t and A_t matrices, that account for the parameters related to the interest rate movements, in the following manner:

$$c_t = \begin{bmatrix} c_{1,t} \\ c_{2,t} \\ c_{3,\text{1990's}} \end{bmatrix}, \quad B_t = \begin{bmatrix} B_{1,t} \\ B_{2,t} \\ B_{3,\text{1990's}} \end{bmatrix}, \quad A_t = \begin{bmatrix} 1 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 \\ \alpha_{31,\text{1990's}} & \alpha_{32,\text{1990's}} & 1 \end{bmatrix}$$

As it may create some confusion, let us specify that, in the analysis, the estimates used in the third rows (identified with the subscript "1990's") are the mean values of the coefficients of interest during the 5-year long time period 1988:Q1–1992:Q4. In line with the analysis in Primiceri (2005), we decided to make use of mean values, instead of the estimates in one specific quarter, to keep the analysis as general as possible and reduce the probability of having results biased by potential peculiarities of the coefficients in one specific time point[23].

5.3.2 Results

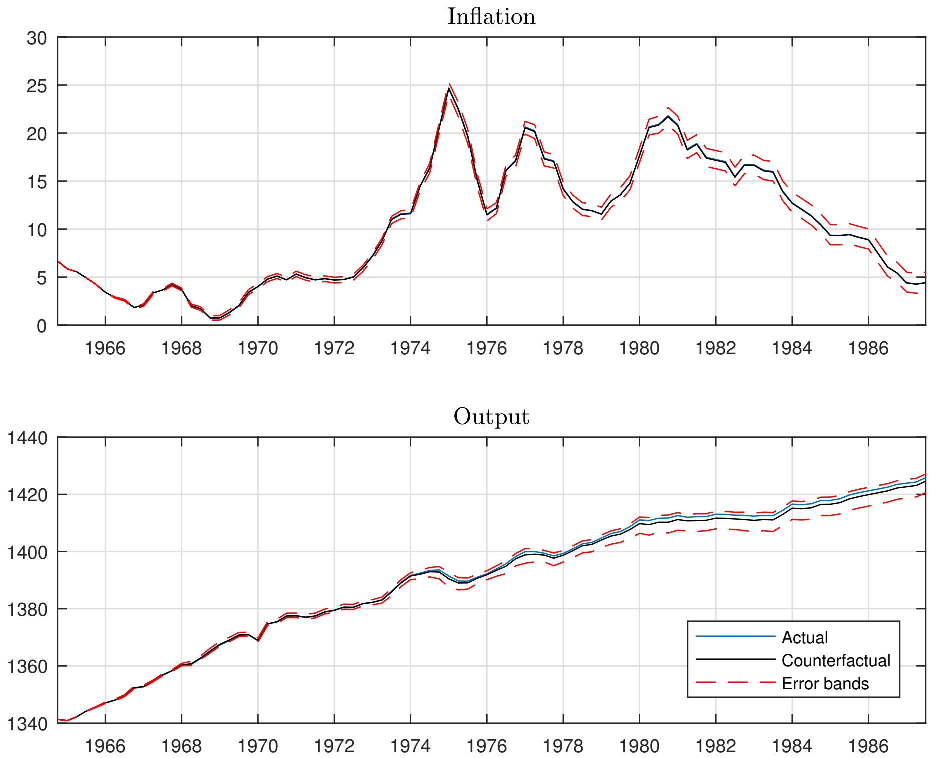
The results of the counterfactual analysis are presented in Figure 5.7. For both the inflation and output series, the blue line detects the actual developments of the variables over time, while the black line highlights the movements that the series would have followed, had the monetary policy of the 1990's been implemented throughout the whole period considered. As shown in the inflation graph (top panel), the actual series and the counterfactual one are very close during the whole time frame, making it almost impossible to distinguish them. Similarly, in the output series (bottom panel), the counterfactual line overlaps the one accounting for its actual values until the late 1980's, when the two slightly diverge, yet remaining within the confidence interval bands.

Overall, the estimates presented in Figure 5.7 firmly point to a large role of good luck to explain the Great Moderation in the Italian context. In fact, the results in the Figure support the hypothesis that, given the size of the shocks hitting the economy during the 1970's, implementing a more efficient monetary policy would have not made any difference to the aggregate volatility of the system. This empirical evidence suggests that the reduction

[22] 1 and 2 stand for the inflation and output series, respectively.

[23] Robustness checks were implemented to make sure that changing these dates would not alter the results of the analysis.

Figure 5.7: Actual and Counterfactual Series of Inflation and Output



Notes: The dashed, red lines represent a one standard deviation confidence interval.

of the size of the shocks needs to be attributed the largest role in explaining the Great Moderation. This holds true even though, as highlighted by the impulse response analysis, the developments experienced by the Italian economy during the 1980's surely helped it to better react to exogenous shocks.

5.4 Discussion and Limitations

Having presented the results of our empirical analysis, we can now move to the conclusions that we can draw from this evidence and to an evaluation of the limitations of our study.

This work investigated the sources of the Great Moderation in Italy making use of a TVP-VAR à la Primiceri (2005), since the characteristics of this model allowed us to implement this analysis in a sound and reliable manner (this was discussed in Section 4.1).

Having estimated the model specified in Section 4.2, we carried out three exercises to discriminate among the possible sources of the phenomenon. The first analysis was implemented via a forecast error variance decomposition (Section 5.1). The results of this exercise suggested that the high volatility of our variables was mostly due to the fluctuations of inflation, accounted for by exogenous shocks – thus, pointing to good luck as the major source of the Great Moderation. Yet, this analysis also attributed a minor role to monetary policy, since the importance of the innovations in the interest rate tended to increase over time.

The second analysis, based on impulse responses, had the goal of testing the extent to which monetary policy, or a better structure of the economy, could have led to the reduction in volatility (Section 5.2). Our results, even though suggesting relevant changes in the characteristics of the Italian economy in line with the predictions of those two hypotheses, highlighted that the magnitude of these developments was not large enough to lead to the Great Moderation.

Finally, the counterfactual analysis assessed if indeed the Great Moderation was only the consequence of good luck (Section 5.3). This exercise allowed us to isolate the impact of the exogenous shocks by simulating how the variables would have behaved if monetary policy had been optimally implemented throughout our whole sample. The results showed that the magnitude of the shocks would have produced the same outcome regardless of the monetary policy conduct, which led us to conclude that good luck needs to be attributed the role of ultimate source of the Great Moderation in Italy.

This study can thus be classified in the literature supporting the thesis that the Great Moderation was the consequence of good luck. Therefore, our results suggest that the positive outcomes associated with this phenomenon could be rapidly reversed if the magnitude of the exogenous shocks rose again. Crucially, this implies that although volatility has been low for several decades, this will not necessarily be the norm in the future. In this respect, the increase in the fluctuations of major macroeconomic variables since 2007 could be interpreted as the end of the Great Moderation, led by an upsurge in the size of exogenous shocks (see, e.g., Canarella et al., 2010)[24].

Moving to the limitations, the analysis in this section relied on the application of techniques that are used in the context of vector autoregression analysis, with relevant modifications to take into account the time varying nature of our model. Implementing the impulse response function and forecast error variance decomposition analyses does not create any specific problem, and the exercise boils down to the correct interpretation of the output provided by the data. With respect to the counterfactual analysis, however, there are important potential drawbacks that need to be discussed.

As it is clear from the description of the method followed to implement that experiment, the procedure to obtain the counterfactual series relies on the introduction of an alternative policy behavior in the system, and later observe the consequences that this would have had to the variables of interest. Therefore, this approach disregards the critique posed by Lucas (1987), who stressed the fact that rational agents would react to changes in policies, modifying their actions and adapting their expectations to effectively respond to such developments. The counterfactual experiment, on the contrary, was implemented without allowing any change

[24]Yet, the study by Clark (2009) showed that the Great Moderation is not over: more evidence is needed to establish a larger consensus on this issue.

but the one involving the monetary policy conduct, which implies that the possibility that agents would adapt their behavior to the new contingencies was not contemplated.

This is an important limitation of our investigation that, potentially, could alter the results presented in Figure 5.7. A possible way to overcome this issue would be that of developing a Bayesian DSGE model similar to the one developed by Justiniano and Primiceri (2008), where it is possible to introduce the behavior of forward-looking agents in the analysis. However, this would require us to change the framework used to carry out the analysis, switching from a TVP-VAR to a DSGE model, which is why we cannot provide this robustness check in this study. Overall, we believe that given our chosen framework (that of a TVP-VAR model), which has been widely applied in the literature for the analysis of the sources of the Great Moderation, the counterfactual experiment still provides relevant insights, although one needs to be aware of its limitations.

6 Conclusion

The Great Moderation, denoting a long-lasting period of reduced volatility in major macroeconomic variables, has been among the most important features of the economic landscape since the early 1980's. Several studies have been implemented to investigate its sources, since positive outcomes are associated with low volatility and the sustainability of the Great Moderation depends on its determinants. Despite being an international phenomenon, the literature has focused on exploring its sources only considering the experience of the United States. As a consequence, several authors (see, e.g., Cabanillas and Ruscher, 2008) have stressed the importance of extending the analysis to other countries.

This work has embraced this challenge by examining the sources of the Great Moderation in Italy. We firstly documented the reduction in the volatility of Italian series, providing empirical evidence on the presence of the phenomenon in this country as well. Afterwards, we implemented several tests to analyze the extent to which the hypotheses put forward in the literature on the sources of the Great Moderation could explain the Italian experience. Specifically, employing a TVP-VAR model, we implemented: (i) a forecast error variance decomposition analysis; (ii) an impulse response function analysis; (iii) a counterfactual experiment. Although our results pointed to a role played by the better monetary policy conduct, the empirical evidence provided by our investigation identified good luck as the ultimate source of this phenomenon. Thus, our study supports the idea that the Great Moderation will not necessarily be the norm in the future, since the occurrence of an increase in the magnitude of exogenous shocks hitting the economy could overturn this state.

The implications of our study for future research are threefold. The first one relates to the limitations of our work. As specified in previous sections, the framework we relied on is better suited to investigate the monetary policy and the good luck hypotheses, while the better structure of the economy hypothesis could only be examined to a lesser extent. Therefore, building on our analysis, a more accurate investigation of the latter would help to obtain a comprehensive picture on the Italian experience. The second implication relates to the contribution of our study to the literature aiming at understanding the sources of the Great Moderation. Highlighting the relevance of exogenous shocks to explain the phenomenon, our findings entail that the determinants of the Great Moderation were not tied to country-specific developments in Italy. Therefore, it is of interest to explore if this was the case in other countries as well, since it would imply that the low volatility experienced by a multitude of regions had a common ultimate source. Thus, we add to the literature emphasizing the relevance of expanding the analysis of the Great Moderation to other countries. The last implication relates to the research on the future of the Great Moderation. Our results indicated that volatility could rapidly increase as a consequence of higher exogenous shocks. The 2007 crisis may represent such an increase and, given that the length of time from its beginning now allows to carry out robust analyses, evidence on whether the phenomenon is still ongoing could be constructed.

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A Appendix

A.1 Data Characteristics and Sources

Table A.1 provides the description of all of the data that was used to implement the analysis presented in this thesis. The first column ("Name") identifies the name of the variables as they appear in the charts displayed in previous sections of this work, while the adjacent column provides a short description. As specified by the third column, all of the variables were collected with a quarterly frequency, with the exception of the discount rate. Consequently, we transformed this series into quarterly frequency by simply taking the average of monthly observations over a three-month period. The fourth column identifies the sample for which the data was available, while the fifth column provides the sources of the data. Specifically, data on GDP and its components together with the series on the three-month interest rate was obtained from the OECD Stats database, data on the discount rate was obtained from the Federal Reserve Economic Data database (FRED), while data on unemployment was provided both by FRED and Eurostat. Quarterly data on the active population was provided by Ohanian and Raffo (2012). Finally, the last column ("Code") identifies whether the variable was used in the analysis carried out in previous sections (Code = 1), or whether it was only used to construct variables used in the analysis (Code = 2). The next section will present how this latter data was used.

Table A.1: Data

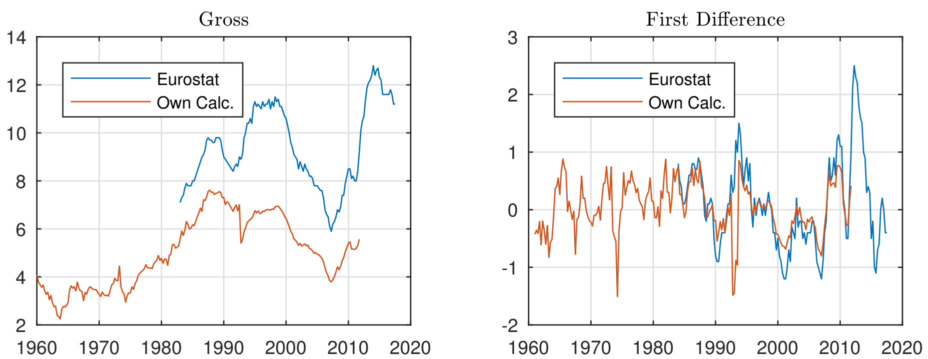
Name	Description	Freq.	Sample	Source	Code
GDP	Real Gross Domestic Product	Q	1960:Q1–2016:Q4	OECD	1
CONS	Private Consumption	Q	1960:Q1–2016:Q4	OECD	1
GOV	Government Consumption	Q	1960:Q1–2016:Q4	OECD	1
INV	Gross Fixed Capital Formation	Q	1960:Q1–2016:Q4	OECD	1
EXP	Exports of Goods and Services	Q	1960:Q1–2016:Q4	OECD	1
IMP	Imports of Goods and Services	Q	1960:Q1–2016:Q4	OECD	1
CPI	Consumer Price Index	Q	1960:Q1–2016:Q4	OECD	1
3MR	Three-month Interest Rate	Q	1978:Q4–2016:Q4	OECD	1
DR	Discount Rate	M	1964:M1–1998:M12	FRED	1
URS	Unemployment Rate - Survey	Q	1960:Q1–2011:Q4	Own Calc.	1
UR	Unemployment Rate	Q	1983:Q1–2016:Q4	Eurostat	2
UG	Gross Unemployment - Survey	Q	1960:Q1–2011:Q4	FRED	2
POP	Active Population (age 15–64)	Q	1960:Q1–2016:Q4	OR2012	2

Notes: In the Frequency column, Q stands for "Quarterly", while M stands for "Monthly".

A.2 Unemployment Rate Used in the Analysis

The unemployment rate that was used in the analysis is the one defined as "URS" in table A.1, which was computed using data on gross unemployment provided by FRED and on the active population provided by Ohanian and Raffo (2012). The problem with the unemployment rate provided by Eurostat lies on its availability: in order to implement the analysis on the presence of a structural break, it is required to have a sample period that starts before the 1980's, when the beginning of the Great Moderation is usually dated. The series provided by Eurostat, however, only starts in 1983. Consequently, we used the data on gross unemployment provided by FRED (survey based) and, dividing it by the active population, we obtained an estimate of the unemployment rate in Italy for a longer period. Clearly, this is a second-best option. However, as the graphs in Figure A.1 show, the two series are highly correlated (correlation coefficient of 74% when considering gross numbers; correlation coefficient of 72% when considering the first difference) and, taking into account that what matters the most for a meaningful analysis is the evolution of the variable over time, we believe the analysis we implemented using this variable to be reliable. Nonetheless, it must be noted that the FRED series presents a peculiar drop in the fourth quarter of 1992. Given the fact that the series is survey based, we believe that there might have been problems in the detection of gross unemployment during that quarter. As a consequence, caution is required when interpreting the results.

Figure A.1: Unemployment Rate



A.3 Break Test Method

As a primary step, the unconditional variance of the series is tested for a break at an unknown date. In order to achieve this, the following procedure is applied.

Unconditional Variance

1. To test the unconditional variance, take the absolute value of the demeaned series. Specifically, for series y_t, the demeaned series y_t^d is computed as:

$$y_t^d = |y_t - \bar{y}|, \qquad t = 1, ..., \mathrm{T}$$

where $\bar{y}$ represents the mean value of the series;

2. Assume that the break occurred at time κ, which is the date identified by the earliest observation in the center 70% of the sample[25];

3. Regress the absolute value of each demeaned series against a constant (c) and a dummy variable (D_t) that equals one whenever $t \geq \kappa$:

$$y_t^d = c + \beta D_t + e_t, \qquad D_t = \begin{cases} 0, & \text{if } t < \kappa \\ 1, & \text{if } t \geq \kappa \end{cases}$$

4. Compute the F-statistic (F_κ) and store it;

5. Repeat the procedure detailed in steps 2 and 3 recursively, moving the assumed break date forward until time $\kappa + n$ is reached, which identifies the latest observation in the center 70% of the sample;

6. Select the largest F-statistic, called the QLR-statistic:

$$QLR = max(F_\kappa, F_{\kappa+1}, F_{\kappa+2}, ..., F_{\kappa+n})$$

7. Compare the QLR-statistic with the critical values defined in Stock and Watson (2003b) to conclude whether the break was statistically significant.

Having identified a significant change in the unconditional variance of a series provides very little insight on the sources of the break. In fact, a break in the unconditional variance may be driven by a change in the conditional mean of the series, from a change in their conditional variance, or from changes in both the conditional mean and the conditional variance (Stock and Watson, 2002). As a consequence, it is necessary to consider a framework where changes

[25] As stressed by Stock (2003), in order to obtain reliable critical values to identify whether a break in the series was statistically significant, only those dates within the center 70% of the sample need to be considered.

in these dimensions can be detected. Accordingly, each series is additionally tested for a break in their conditional mean and variance. Modelling them as the following AR process serves such a purpose. Specifically, for each series y_t, let us define:

$$y_t = \alpha_t + \phi_t(L)y_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim WN(0, \sigma^2) \tag{A.3.1}$$

where $\phi_t(L)$ represents the lag polynomial and, crucially,

$$\alpha_t + \phi_t(L) = \begin{cases} \alpha_1 + \phi_1(L), & \text{if } t \leq \kappa \\ \alpha_2 + \phi_2(L), & \text{if } t > \kappa \end{cases} \qquad Var(\varepsilon_t) = \begin{cases} \sigma_1^2, & \text{if } t \leq \tau \\ \sigma_2^2, & \text{if } t > \tau \end{cases}$$

Therefore, this specification allows the conditional mean of the series to break at time κ and the conditional variance to break at time τ, which are potentially different dates. Making use of this framework, we will now present the procedures followed to test the variables.

Conditional Mean

1. Each series is modelled as the AR process defined in equation (A.3.1), with the number of lags defined in line with the analysis specified in Table 3.1;
2. Assume that the break occurred at time κ, which is the date identified by the earliest observation in the center 70% of the sample;
3. Regress the series against a constant, their lags and a dummy variable that equals one whenever $t \geq \kappa$;
4. Repeat steps 4 to 7 as specified when testing the unconditional variance.

Conditional Variance

1. Using the estimates of the parameters describing the AR processes obtained to detect the structural breaks in the conditional mean, it is possible to construct the series of the residual terms:
$$\widehat{\varepsilon}_t = y_t - \widehat{\alpha}_t + \widehat{\phi}_t(L)y_{t-1}$$
However, depending on whether a statistically significant break in the conditional mean was identified, there are two options:
   (a) If a statistically significant structural break in the conditional mean was identified at time κ, then the residuals are constructed allowing the parameters of the AR processes to change after time κ. Specifically:
$$\widehat{\varepsilon}_t(\kappa) = \begin{cases} y_t - \widehat{\alpha}_1 - \widehat{\phi}_1(L)y_{t-1}, & \text{if } t \leq \kappa \\ y_t - \widehat{\alpha}_2 - \widehat{\phi}_2(L)y_{t-1}, & \text{if } t > \kappa \end{cases}$$

(b) If, on the other hand, there was no statistically significant break in the conditional mean of the series, then the residuals will simply be:

$$\widehat{\varepsilon}_t = y_t - \widehat{\alpha}_1 - \phi_1(L)y_{t-1}, \quad \forall\, t$$

2. Take the absolute value of the residuals;

3. Repeat steps 2 to 7 as specified for the test in the unconditional variance.

A.4 Computations Related to the Triangular Reduction

We here portray the computations implemented to obtain the VAR representation in (4.2.3), making use of equations (4.2.1) and (4.2.2).

We start by recalling the representations for the TVP-VAR in (4.2.1):

$$y_t = c_t + B_{1,t}y_{t-1} + B_{2,t}y_{t-2} + u_t \qquad t = 1, ..., \mathrm{T}, \tag{A.4.1}$$

and of the triangular reduction in (4.2.2):

$$A_t\Omega_t A_t' = \Sigma_t\Sigma_t'. \tag{A.4.2}$$

Multiplying both sides of equation (A.4.1) by $\Sigma_t^{-1}A_t$, we obtain:

$$\Sigma_t^{-1}A_t y_t = \Sigma_t^{-1}A_t c_t + \Sigma_t^{-1}A_t B_{1,t}y_{t-1} + \Sigma_t^{-1}A_t B_{2,t}y_{t-2} + \Sigma_t^{-1}A_t u_t.$$

Adding $(I_n - A_t^{-1}\Sigma_t)y_t$ to both sides of the previous equation, we get:

$$y_t = (I_n - \Sigma_t^{-1}A_t)y_t + \Sigma_t^{-1}A_t c_t + \Sigma_t^{-1}A_t B_{1,t}y_{t-1} + \Sigma_t^{-1}A_t B_{2,t}y_{t-2} + \Sigma_t^{-1}A_t u_t.$$

Solving for y_t and defining $u_t = A_t^{-1}\Sigma_t\varepsilon_t$, we lastly obtain:

$$\begin{aligned} y_t =& (\Sigma_t^{-1}A_t)^{-1}\Sigma_t^{-1}A_t c_t + (\Sigma_t^{-1}A_t)^{-1}\Sigma_t^{-1}A_t B_{1,t}y_{t-1} + \\ &+ (\Sigma_t^{-1}A_t)^{-1}\Sigma_t^{-1}A_t B_{2,t}y_{t-2} + (\Sigma_t^{-1}A_t)^{-1}\Sigma_t^{-1}A_t u_t \Rightarrow \\ \Rightarrow y_t =& c_t + B_{1,t}y_{t-1} + B_{2,t}y_{t-2} + A_t^{-1}\Sigma_t\varepsilon_t, \end{aligned}$$

which corresponds to the TVP-VAR representation with structural innovations ε_t in equation (4.2.3).

We also show that the variance-covariance matrix of the innovations ε_t is the identity matrix I_n. Firstly, note that, using the triangular reduction in (A.4.3):

$$A_t\Omega_t A_t' = \Sigma_t\Sigma_t' \Rightarrow \Sigma_t^{-1}A_t\Omega_t A_t'(\Sigma_t^{-1})' = I_n. \tag{A.4.3}$$

Let us now recall that $u_t = A_t^{-1}\Sigma_t\varepsilon_t \Leftrightarrow \varepsilon_t = \Sigma_t^{-1}A_t u_t$. Consequently, the variance-covariance matrix of ε_t, $\Sigma_{\varepsilon,t}$, will be:

$$\Sigma_{\varepsilon,t} = \mathbf{E}(\varepsilon_t\varepsilon_t') = \Sigma_t^{-1}A_t\mathbf{E}(u_t u_t')A_t'(\Sigma_t^{-1})' = \Sigma_t^{-1}A_t\Omega_t A_t'(\Sigma_t^{-1})' = I_n, \quad QED.$$

A.5 TVP-VAR Estimation Procedure

A.5.1 Priors

Prior selection is one of the most controversial aspects in Bayesian econometrics. As it is clear from Bayes formula in (4.3.1), the prior density $p(\theta)$ is characterized by the fact that it does not depend upon the data. In fact, the prior identifies any information available to the econometrician about the parameter of interest before looking at the data, and the way in which this is constructed is clearly relevant for the outcome of the estimation procedure. Following the literature using TVP-VAR models, this work relies on the use of data based priors: a sample of 10 years (40 observations) starting in 1964:Q1 was used to estimate the parameters of a time invariant VAR with two lags, whose coefficients were later used to define the mean and variance values of the prior densities.

It is important to note that this sample was also used to estimate the TVP-VAR coefficients, since omitting the first ten years of observations would determine an excessively small sample to implement an analysis of developments taking place before and after the Great Moderation started. This is not problematic *per se*: although some authors prefer to discard the sample used for the definition of the priors, the literature presents studies in which this is not the case (see, e.g., Gerba and Hauzenberger, 2013).

Prior selection is made to obtain well-known forms of the conditional posterior distributions and ease the estimation procedure. To do so, the conjugate prior distributions specified in section 4.3 were chosen[26]. The upcoming selection of the parameters defining the prior distributions follows Primiceri (2005), and is justified by the importance of author's study in the literature on TVP-VARs.

For the normal prior distributions of the elements of B^T and A^T, identified with B_0 and A_0 below, the mean values were obtained from the OLS point estimates $\hat{B}_{OLS}$ and $\hat{A}_{OLS}$ of the time invariant VAR, while the variances ware obtained as four times the variance of the respective time invariant VAR. Differently, the identity matrix I_n was chosen as the variance covariance matrix of the prior distribution of the elements of Σ_t, $\log \sigma_0$, while its mean is the logarithm of the OLS point estimate, $\log \hat{\sigma}_{OLS}$. For the prior distributions of the hyperparameters W, S_1, and S_2, the degrees of freedom were chosen as one plus the dimension of each matrix, while for Q the degrees of freedom are set to 40 (the size of the sample used when estimating the time invariant VAR). Finally, constant fractions of the OLS variances multiplied by the degrees of freedom were used as the scale matrices of these distribution.

[26] A conjugate prior distribution, when multiplied by the likelihood, will yield a posterior falling in the same class of distributions of the prior density Koop (2003).

Overall, the prior selection can be summarized as:

$$\begin{aligned}
B_0 &\sim N(\hat{B}_{OLS}, 4 \cdot V(\hat{B}_{OLS})),\\
A_0 &\sim N(\hat{A}_{OLS}, 4 \cdot V(\hat{A}_{OLS})),\\
\log \sigma_0 &\sim N(\log \hat{\sigma}_{OLS}, I_n),\\
Q &\sim IW(0.0001 \cdot 40 \cdot V(\hat{B}_{OLS}), 40),\\
W &\sim IW(0.0001 \cdot 4 \cdot I_n, 4),\\
S_1 &\sim IW(0.01 \cdot 2 \cdot V(\hat{A}_{1,OLS}), 2),\\
S_2 &\sim IW(0.01 \cdot 3 \cdot V(\hat{A}_{2,OLS}), 3).
\end{aligned}$$

where $\hat{A}_{1,OLS}$ and $\hat{A}_{2,OLS}$ are the blocks of $\hat{A}_{OLS}$ corresponding to the elements of S_1 and S_2[27].

A.5.2 The Gibbs Sampler Algorithm

Before detailing each step of the estimation procedure, some adjustments are needed to take into account the corrections of Del Negro and Primiceri (2015) to the original algorithm proposed by Primiceri (2005), which is the one we followed in this study. Specifically, let us define a matrix H_t such that $H_t = \log(\Sigma_t \Sigma_t')$. Consequently, the elements of H_t will be:

$$H_t = \begin{bmatrix} \log \sigma^2_{1,t} & 0 & 0 \\ 0 & \log \sigma^2_{2,t} & 0 \\ 0 & 0 & \log \sigma^2_{3,t} \end{bmatrix}$$

Such a transformation is implemented because Σ_t enters the model multiplicatively, which raises problems when trying to estimate its elements: by considering the matrix H_t, this problem is overcome. The trade-off of implementing this transformation, however, is that it is also required to convert ε_t into $\log(\varepsilon_t^2)$. While ε_t is a vector of normally distributed random variables, $\log(\varepsilon_t^2)$ will be a vector of random variables with a $\log \chi^2(1)$ distribution instead. Fortunately, Kim et al. (1998) developed a methodology to approximate the elements of $\log(\varepsilon_t^2)$ by a mixture of normal distributions. The cost of implementing such a procedure is that of having to include a vector $s^T = \{s_t\}_{t=1}^T$, such that each indicator variable s_t will select the normal approximations to use for each element $\log(\varepsilon_t^2)$, in the Gibbs Sampler.

The Gibbs Sampler will be performed in the following steps:

1. Initialize A^T, Σ^T, s^T, Q, S_1, S_2 and W (all of the parameters but B^T);
2. Sample B^T from $p(B^T | y^T, A^T, \Sigma^T, s^T, Q, S_1, S_2, W)$;

[27] As specified in section 4.2, S_1 refers to the element identifying the covariance between inflation and output ($\alpha_{21,t}$), while S_2 refers to the elements identifying the covariances between the interest rate and both inflation and output ($\alpha_{31,t}$ and $\alpha_{32,t}$).

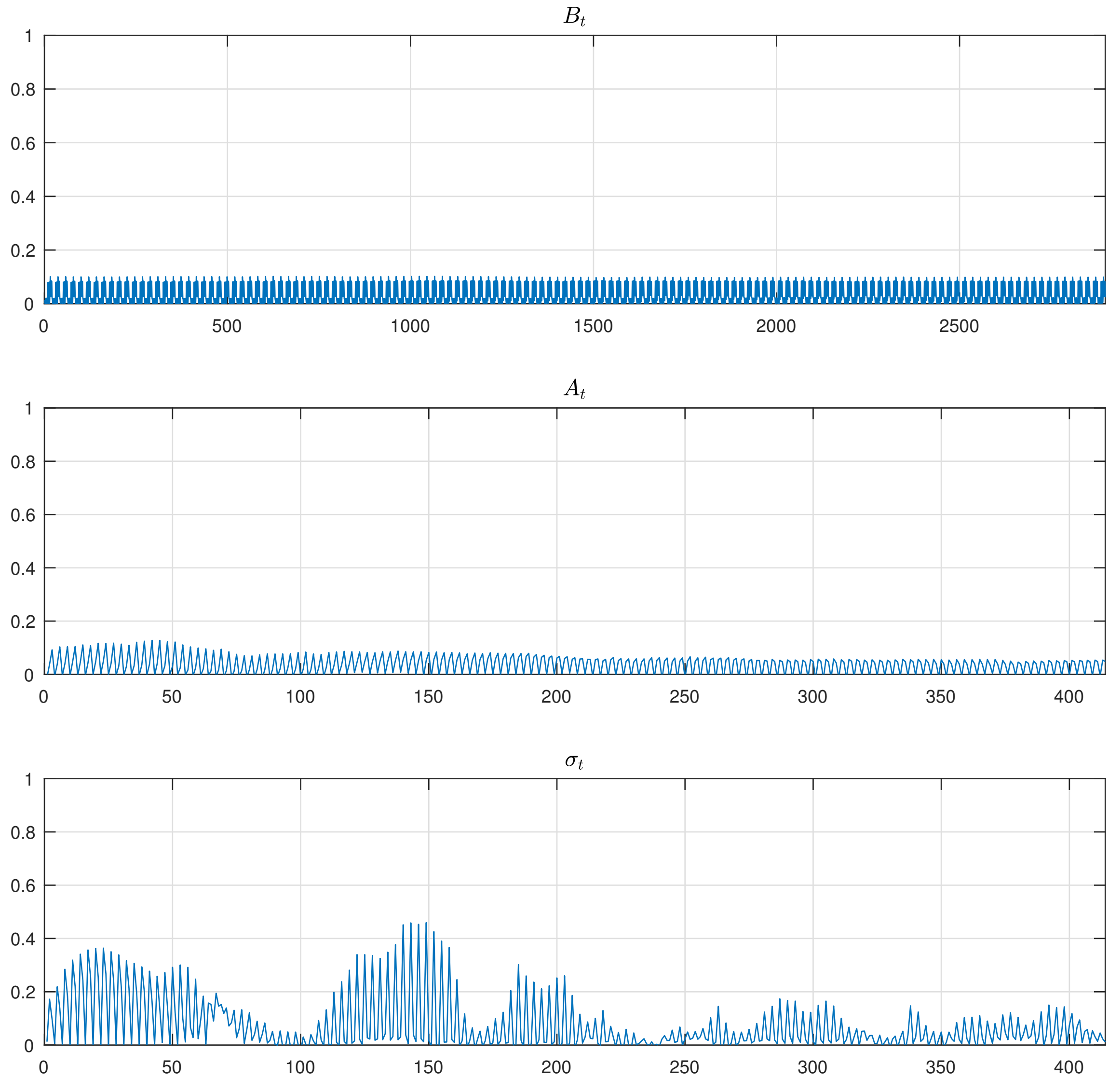
3. Sample Q from $p(Q|y^T, B^T, A^T, \Sigma^T)$;
4. Sample A^T from $p(A^T|y^T, B^T, \Sigma^T, s^T, Q, S_1, S_2, W)$;
5. Sample S_1 from $p(S_1|y^T, B^T, A^T, \Sigma^T)$;
6. Sample S_2 from $p(S_2|y^T, B^T, A^T, \Sigma^T)$;
7. Sample s^T from $p(s^T|y^T, B^T, A^T, \Sigma^T, Q, S_1, S_2, W)$;
8. Sample Σ^T from $p(\Sigma^T|y^T, B^T, A^T, Q, S_1, S_2, W)$;
9. Sample W from $p(W|y^T, B^T, A^T, \Sigma^T)$;
10. Return to 2 for as many repetitions as it is necessary to assure the convergence of the Gibbs Sampler (in our case, 100,000 times).

Sampling B^T, A^T and Σ^T requires the use of the algorithm developed by Carter and Kohn (1994); sampling Q, S_1, S_2 and W implies drawing from inverse-Wishart distributions; sampling s^T, as specified above, requires the algorithm developed by Kim et al. (1998).

A.5.3 Convergence of the Gibbs Sampler Algorithm

Figure A.2 displays the 20$^{\text{th}}$-order autocorrelation of the draws in the Gibbs Sampler. To interpret these graphs, note that the lower the autocorrelation across the draws, the higher the independence of each draw from the others – thus, the higher the efficiency of our algorithm.

Figure A.2: 20$^{\text{th}}$-order Sample Autocorrelation

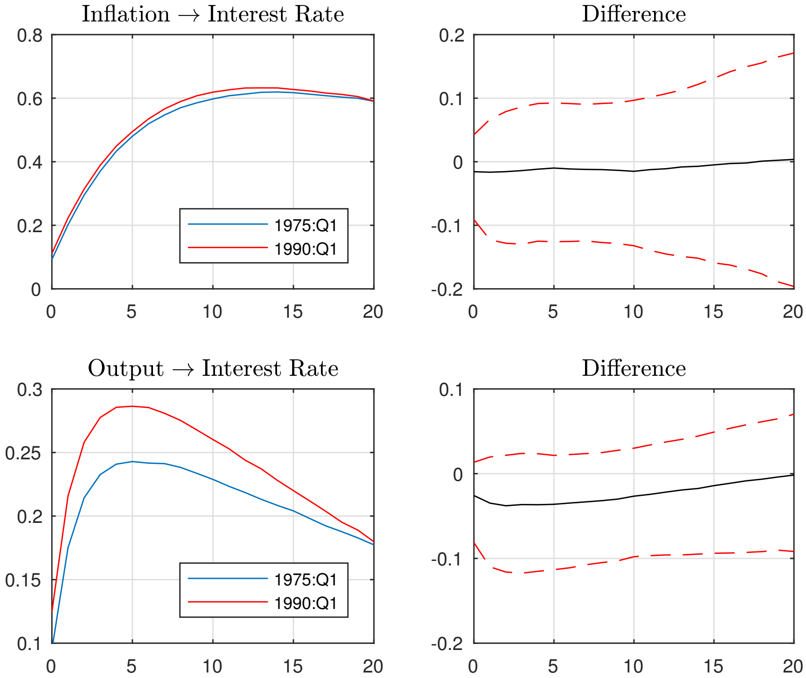


Notes: The individual parameters are ordered on the horizontal axis one after the other.

A.6 Time Varying IRF Figures

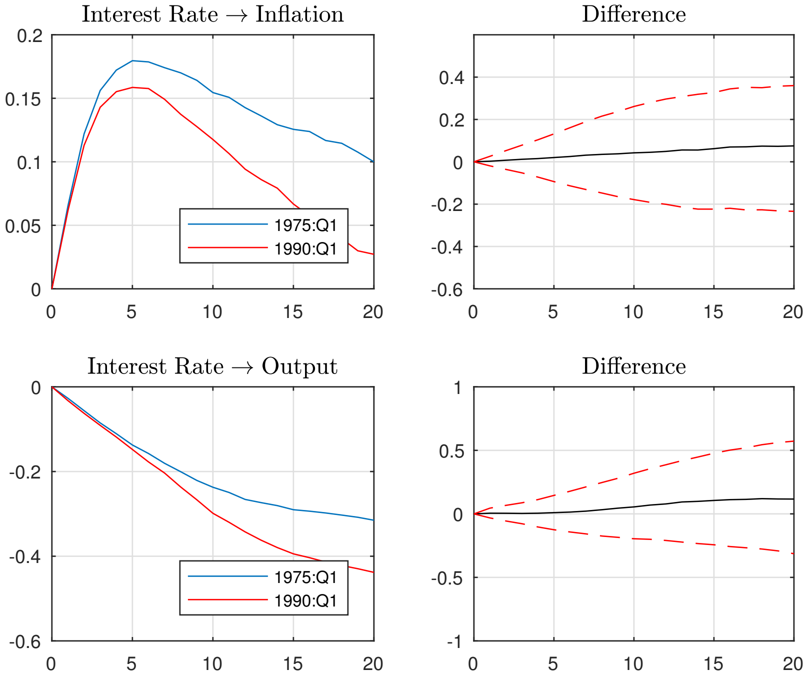
The following figures present the impulse responses with time varying coefficients.

Figure A.3: Interest Rate Time Varying Response To Shocks in Inflation and Output



Notes: The dashed, red lines represent a one standard deviation confidence interval.

Figure A.4: Inflation and Output Time Varying Responses To Interest Rate Shocks



Notes: The dashed, red lines represent a one standard deviation confidence interval.