Essays on the Micro Foundations of Monetary Policy

by

Daniele Aglio

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To Esra, the woman I love,
every line here brings her caress.

To Primarosa and Santina, they know why.

ABSTRACT

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This dissertation is composed of three essays.

The first essay explores the connection between technological breakthroughs and the subsequent moderation of real and nominal economic activity. By developing a New Keynesian DSGE model that incorporates vintage technology adoption and learning, the impact of learning on the volatility of economic variables is examined. The process of learning and reorganization during the adoption of new technology moderates economic fluctuations, especially in economies closer to the technological frontier. If the central bank does not account for this learning process when measuring potential output and the output gap, it will respond more aggressively to shocks, further attenuating economic fluctuations. This leads to a flattening of the measured Phillips curve. The empirical analysis, which uses cross-country data, supports the main implications of the model. A significant portion of the observed moderation in the sample countries can be explained by an index that proxies a country's proximity to the technological frontier. As the model suggests, countries nearer to the technological frontier, which require more intensive learning processes, exhibit greater moderation in real and nominal economic activity. Other factors, such as openness to trade, central bank independence etc. turn out to be less important.

The second essay studies the role of central bank credibility in affecting agents' inflation expectations and, hence, inflation trends and it contributes to the micro foundation of central bank credibility. A measure of central bank credibility is derived in the context of a New Keynesian framework with agents' imperfect knowledge

about the central bank targets. Agents do not know the central bank's actual inflation target and the effective weight on price stability relative to the output gap. This way, central bank credibility is shown to be the product of agents' beliefs about the central bank's effective focus on price stability and the conduct of monetary policy, and this definition can explain inflation and agents' forecasts in both developed and emerging countries. The model is then estimated through Bayesian techniques, employing surveys about professionals' inflation expectations, as well as official data on CPI, for the case of the US and Turkey. Results indicate that recent long-term inflation forecast trends can be explained by the central bank's credibility level in both countries. In particular, during the recent energy price shock, US inflation expectations remained stable thanks to increased central bank credibility. At the same time, Turkey experienced a deterioration in central bank credibility, with consequent unanchored and highly volatile inflation forecasts. Finally, the model shows that improving central bank credibility leads to anchored expectations and stabilizes the inflation rate.

The third essay estimates the marginal cost curves of heterogeneous firms to provide evidence on the slope of the Phillips curve. The New Keynesian framework is extended to incorporate heterogeneous firms in terms of production technology, thereby delivering an explicit role for resource reallocation. This way, the study estimates firms' pricing equations, utilizing prices and quantities of outputs and factor inputs of French and Dutch manufacturing firms along with exogenous downstream demand instruments from global input-output and trade data to identify the parameters. Firm-level data are from the micro-data infrastructure (MDI) database, newly built under the EU *Technical Support Instrument* project. Model heterogeneity is addressed using a clustering method to classify firms according to their production technology and observed cost shock pass-through. It is, hence, found that more productive firms have flatter marginal cost curves and exhibit a lower price response to changes in output. The aggregate Phillips curve is flatter when the more productive firms absorb a larger portion of demand shocks, which is generally the case. Finally, CompNet micro-based data from several European countries support these findings for the non-farm business sector.

ÖZETÇE

Para Politikasının Mikro Temelleri
Üzerine Denemeler
Daniele Aglio
Ekonomi, Doktora
29 Temmuz 2020

Bu tez üç makaleden oluşur.

İlk makale, teknolojik devrimler ile ardından gelen reel ve nominal ekonomik faaliyet oynaklığının ılımlaşması arasındaki bağlantıyı araştırmaktadır. Yeni teknolojilerin kullanılmasında yaparak öğrenmeyi içeren Yeni Keynesyen bir model geliştirerek, öğrenme sürecinin ekonomik değişkenlerin oynaklığı üzerindeki etkisi inceleniyor. Yeni teknolojilerin kullanılmasında öğrenme ve yeniden yapılanma süreci, özellikle yüksek teknolojik sınıra daha yakın ekonomilerde, ekonomik dalgalanmaları hafifletmektedir. Merkez bankası, potansiyel çıktıyı ve çıktı açığını ölçerken bu öğrenme sürecini hesaba katmazsa, şoklara daha agresif yanıt vermekte ve bu da ekonomik dalgalanmaları daha da yumuşatmaktadır. Bu durum, ölçülen Phillips eğrisinin yataylaşmasına neden olmaktadır. Ülkeler arası verileri kullanan ampirik analiz, modelin ana sonuçlarını desteklemektedir. Örneklem ülkelerde gözlemlenen ılımlılığın önemli bir kısmı, ülkelerin teknolojik sınıra yakınlığını temsil eden bir endeksle açıklanabilmektedir. Modelin de öne sürdüğü gibi, daha yoğun öğrenme süreçleri gerektiren teknolojik sınıra daha yakın ülkeler, gerçek ve nominal ekonomik faaliyetlerde daha büyük bir ılımlılaşma sergilemektedir. Dış ticarete açıklık, merkez bankası bağımsızlığı gibi diğer faktörlerin ise daha az önemli olduğu gözlenmektedir.

İkinci makale, merkez bankası güvenilirliğinin, ajanların enflasyon beklentilerini ve dolayısıyla enflasyon eğilimlerini etkilemedeki rolünü incelemekte ve merkez bankası güvenilirliğinin mikro temeline katkıda bulunmaktadır. Ajanların merkez bankası hedefleri hakkında eksik bilgileri olan Yeni Keynesyen çerçeve bağlamında bir merkez bankası güvenilirliği ölçüsü elde edilmektedir. Ajanlar merkez bankasının gerçek

enflasyon hedefini ve çıktı açığına göre fiyat istikrarı üzerindeki etkin ağırlığını bilmemektedir. Bu şekilde, merkez bankası güvenilirliğinin, ajanların merkez bankasının fiyat istikrarına etkin bir şekilde odaklanması ve para politikası yönetimi hakkındaki inançlarının bir ürünü olduğu gösterilmekte ve bu tanım, hem gelişmiş hem de gelişmekte olan ülkelerde enflasyon ve ajanların tahminlerini açıklayabilmektedir. Daha sonra model, ABD ve Türkiye için profesyonellerin enflasyon beklentilerine ilişkin anketlerin yanı sıra TÜFE'ye ilişkin resmi veriler kullanılarak Bayesyen teknikler aracılığıyla tahmin edilmektedir. Sonuçlar, son dönemdeki uzun vadeli enflasyon tahmin eğilimlerinin her iki ülkede de merkez bankasının güvenilirlik düzeyiyle açıklanabileceğini göstermektedir. Özellikle son dönemde yaşanan enerji fiyatları şokunda merkez bankasının artan güvenilirliği sayesinde ABD enflasyon beklentileri istikrarlı kaldı. Aynı zamanda Türkiye, merkez bankasının güvenilirliğinde bir bozulma yaşadı ve bunun sonucunda sabit olmayan ve oldukça değişken enflasyon tahminleri ortaya çıktı. Son olarak model, merkez bankası güvenilirliğinin arttırılmasının beklentilerin sabitlenmesine yol açtığını ve enflasyon oranını istikrara kavuşturduğunu göstermektedir.

Üçüncü makale, Phillips eğrisinin eğimi hakkında kanıt sağlamak için heterojen firmaların marjinal maliyet eğrilerini tahmin etmektedir. Bu çalışmada, Yeni Keynesyen ekonomik çerçeve, üretim teknolojisi açısından heterojen firmaları kapsayacak şekilde genişletildi ve böylece kaynakların yeniden tahsisi için açık bir rol sunuldu. Bu şekilde, çalışma, gerekli parametreleri belirlemek için Fransız ve Hollandalı imalat firmalarının fiyatları ve çıktı miktarları ile faktör girdilerinin yanı sıra küresel girdi-çıktı ve ticaret verilerinden dışsal alt talep araçlarını kullanarak firmaların fiyatlandırma denklemlerini tahmin etmektedir. Firma düzeyindeki veriler, AB *Teknik Destek Aracı* projesi kapsamında yeni oluşturulan mikro veri altyapısı (MDI) veritabanından alınmıştır. Model heterojenliği, firmaları üretim teknolojilerine ve gözlemlenen maliyet şoklarının geçişkenliğine göre sınıflandırmak için bir kümeleme yöntemi kullanılarak ele alınmaktadır. Bu nedenle, daha üretken firmaların daha düz marjinal maliyet eğrilerine sahip olduğu ve üretimdeki değişikliklere daha düşük fiyat tepkisi sergiledikleri bulunmuştur. Daha üretken firmalar talep şoklarının daha büyük bir kısmını absorbe ettiğinde toplam Phillips eğrisi genellikle gözlendiği gibi daha düz olur. Son olarak, çeşitli Avrupa ülkelerinden alınan CompNet mikro tabanlı verileri, tarım dışı iş sektörü için bu bulguları destelemektedir.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

NOMENCLATURE

CBC	Central Bank Credibility
CN	Combined Nomenclature – European Classification of Goods
DSGE	Dynamic Stochastic General Equilibrium
FRED	Federal Reserve Bank of St. Louis Database
HP	Hodrick-Prescott Filter
HS	Harmonized Commodity Description and Coding System of the World Customs Organization
LIV	Livingston Survey
MDI	Micro Data Infrastructure
NACE	Statistical classification of economic activities in the European Communities
NK	New Keynesian
OECD	Organisation for Economic Co-operation and Development
PRODCOM	European System of production statistics for mining and manufacturing
PWT	Penn World Tables
RBC	Real Business Cycle
SPF	Survey of Professional Forecasters
TCMB	Central Bank of Republic of Turkey
TFI	Technological Frontier Index
UN	United Nations

Chapter 1

THE TECHNOLOGICAL ROOTS OF THE GREAT MODERATION

1.1 Introduction

Is there a connection between a technological breakthrough (such as the advent of a general-purpose technology) and subsequent moderation in real and nominal economic activity? Despite potential skepticism about this link, this paper aims to convince you that such a relationship existed during significant periods of the global economy over the past half-century. The theory proposing this link is straightforward: during periods of rapid technological advancement, particularly following breakthroughs that render existing organizational capital and know-how obsolete, firms must invest in learning and re-optimizing their organizational structures. This imperative is particularly pertinent for firms near the technological frontier. During times of economic expansions, when these firms seek to upgrade their capital, the need for learning slows down their investment. Furthermore, as they climb the learning curve, their productivity remains relatively low for a period. Conversely, during economic contractions, the situation reverses as these firms are likely to benefit from the earlier investments in technology upgrades. This entire process tends to mitigate the transmission mechanism of business cycles, leading to an overall moderation in real economic activity.

But what about nominal variables? Why would nominal variables be moderated under this theory? In a NK DSGE framework, moderation in real economic activity is likely to create some moderation in inflation and other nominal variables as well.

However, the more significant impact on nominal moderation has another reason. Assume that central banks, while measuring the output gap, ignore this learning process. The resulting mismeasurement of potential output will cause central banks to respond more aggressively to shocks, behaving more hawkishly than intended. As a result, nominal variables moderate significantly. In fact, this mismeasurement will also flatten the observed Phillips curve.

In real life, there is another channel contributing to additional moderation that is absent in our setup. The observed extra hawkish stance of the central bank will enhance its credibility, further easing its job of guiding expectations and smoothing fluctuations. This effect is particularly pronounced during temporary supply shocks, where the divine coincidence does not hold.

With this introduction outlining our objective, let's now delve deeper into the details of our hypothesis. Over the past half-century, the world economy has experienced significant changes. For macroeconomists, a key aspect of these changes has been the accelerated pace of technological progress, driven by the innovation of new products and processes. Measuring the pace of technological progress is challenging due to the lack of a clear metric. However, the relative price of equipment is a well-regarded measure, particularly in the literature on investment-specific technological progress. Using this metric, Figure 1.1 plots the logarithm of the relative price of equipment in the U.S. economy over more than a century, taking data from the *Federal Reserve Bank of St. Louis* database (FRED) [1].

The relative price has decreased from 28.4 in 1947, just after World War II, to 0.77 in October 2022, the most recent figure available. Over the past seventy-five years, the relative price of equipment in the U.S. economy has declined nearly 37-fold. This translates to an average annual relative price decline of around 4.9%. The pace of decline has accelerated over time, reaching its peak in the early 2000s, when

[1] Variable *PERIC*, available at https://fred.stlouisfed.org.

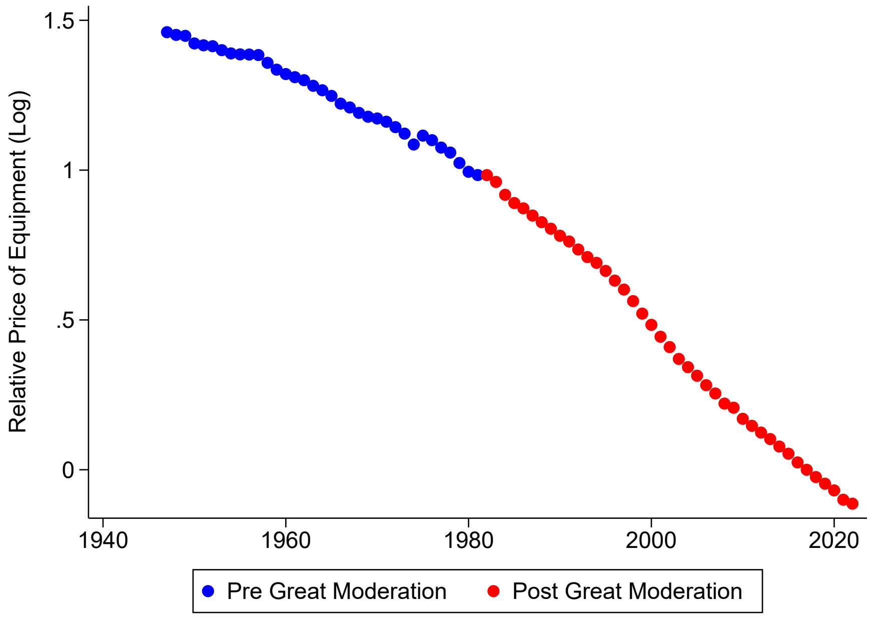


Figure 1.1: Relative price of equipment.

Source: FRED.

Note: Logarithm of relative price of equipment with respect to consumption deflator.

the ten-year moving average of the rate of decline approached 7.8%. This trend is illustrated in Figure 1.2. As it can be seen, the pace of decline increased steadily during the era commonly referred to as the *Information Technology Era*, which is generally considered to have begun around the mid-1970s. This rapid change in technology had important impacts on the global economy.

Another significant change in the global macroeconomic landscape was the so-called Great Moderation. The Great Moderation refers to the period of relative economic stability and low volatility in macroeconomic variables in the United States and other developed countries from the mid-1980s to the early 2000s. Figure 1.3a plots the volatility of output growth before and after the Great Moderation for the sample of countries used in our empirical analysis. With a few exceptions, the sample of OECD economies experienced a decline in output growth volatility in the

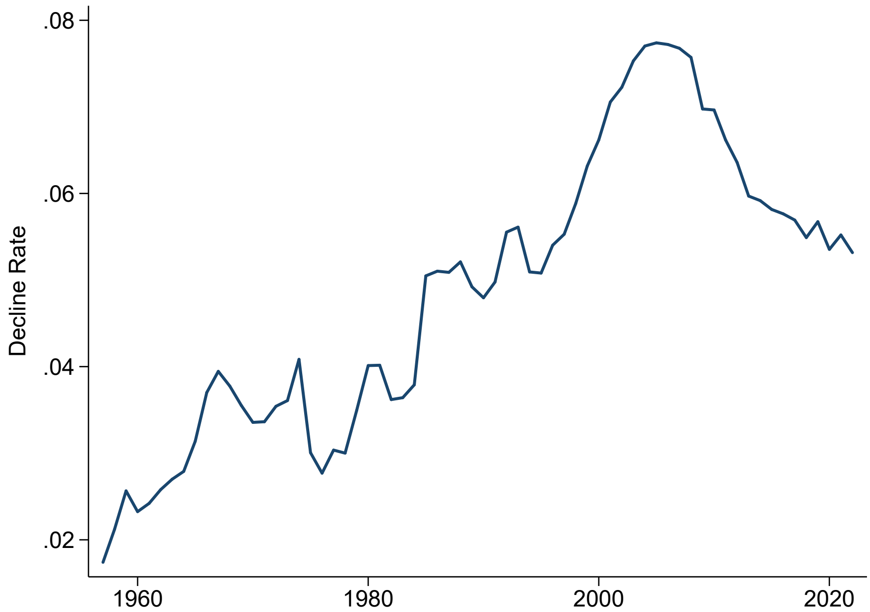


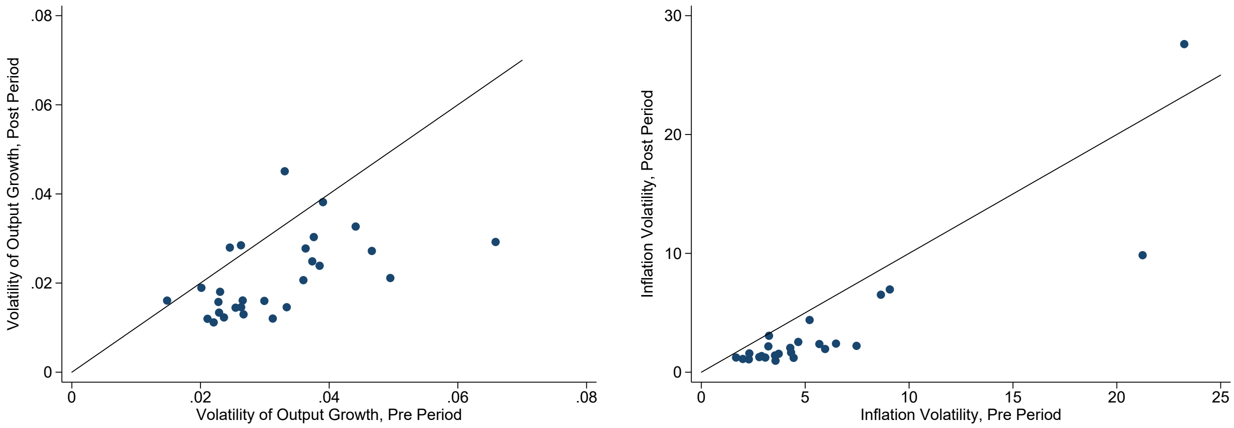
Figure 1.2: Relative price decline rate of equipment.

Source: FRED.

Note: Ten-year moving average of the decline rate in relative price of equipment.

post-Great Moderation era compared to the pre-Great Moderation era. Similarly, Figure 1.3b exhibits the inflation volatility of these countries before and after the Great Moderation. In all countries with the exception of one inflation volatility decreased significantly.

The term was coined by Stock and Watson (2002). This phenomenon has been extensively studied by economists and policymakers, with many theories and explanations put forward for its causes and implications. One prominent explanation for the Great Moderation is the increased use of monetary policy rules, such as inflation targeting, by central banks. According to this view, central banks became more adept at controlling inflation and managing the business cycle, which led to greater stability in the economy. One of the earliest studies on the Great Moderation was conducted by Romer and Romer (2004). They argued that the Great Moderation



(a) (b)

Figure 1.3: Volatility in pre- and post-Great Moderation era.

Note: The panels show volatility of (a) output growth and (b) inflation in the pre- and post-Great Moderation era for the OECD economies in the sample. Also, 45-degree line is reported.

could be explained by improvements in the conduct of monetary policy, particularly the increased focus on inflation targeting and the greater independence of central banks. They found that the decline in macroeconomic volatility was not simply due to good luck or changes in the structure of the economy. Another influential study on the Great Moderation was conducted by Bernanke (2004). Bernanke argued that the Great Moderation was partly the result of improvements in the measurement of economic variables, such as better estimates of inflation and GDP. He also suggested that changes in the structure of the economy, such as the increased importance of the services sector, may have contributed to the decline in volatility.

Another explanation for the Great Moderation is the increased integration of global financial markets, which reduced the impact of domestic economic shocks. This view suggests that the increased openness of the global economy allowed for a more efficient allocation of resources and reduced the likelihood of severe recessions. However, some research has also highlighted the potential downside risks of globalization, such as the greater transmission of financial crises across borders.

In this paper, we establish a theoretical link between rapid technological progress and increased macroeconomic stability. We hypothesize that the increased technological learning and reorganization needs of firms alter the transmission mechanism of business cycles, leading to reduced volatility in both real and nominal variables throughout the business cycle. To study the learning-by-doing effects of new technology, we develop a vintage-capital model of technology adoption within a real business cycle framework. We investigate how a reasonably calibrated learning-by-doing process affects the volatilities of real variables in this context. Our results show that technological learning has the potential to significantly dampen business cycles.

Next, to study the impact of technological learning by doing on nominal variables and central bank decision making, we extend our framework to a New Keynesian DSGE model with vintage technology adoption and learning. Compared to the RBC model with technology learning, the NK DSGE model yields slightly greater moderation of real variables. While inflation volatility also decreases, the reduction is relatively small compared to what is observed in U.S. data. We extend the model to consider a scenario where the central bank is unaware of the learning process while measuring the output gap. In this scenario, the central bank ignores the learning process and measures the output gap accordingly. With this assumption, we demonstrate that the central bank adopts a more hawkish stance, responding more aggressively to technology shocks where the divine coincidence does not hold. This more hawkish behaviour also leads to a flattening of the Phillips curve.

In the empirical section, we test the implications of our model using cross-country data, controlling for variables central to other explanations of the Great Moderation. According to our theory, as the pace of technological progress accelerates and a country approaches the global technological frontier, the need for technological learning and reorganization increases. Therefore, countries closer to the global technological frontier and those experiencing greater drops in the relative price of equipment have more to learn (and should invest more in technological learning and reorganization). Consequently, these countries should experience greater moderation in both real and nominal macroeconomic variables. In our empirical strategy, to minimize unnecessary noise, we include only countries that are close to the technological frontier and for which the necessary data are available and are more reliable. Therefore, we narrow our empirical focus to OECD countries. Based on our technological learning theory, we developed an index that proxies the distance of each country to the global technological frontier. Our results align with our theory, showing that countries closer to the technological frontier experienced greater moderation in both real and nominal variables. This measure explains a significant portion of the variation in the data. Furthermore, key elements of other Great Moderation theories, such as a country's openness to trade, central bank independence, and the share of the service sector in GDP, are either not significant or explain only a small portion of the variation.

In Section 1.2, we begin with a brief summary of the significance of learning during the adoption of new technology. Following this, we present our RBC model incorporating learning post-adoption of new technology in Section 1.3. Next, to explore moderation in nominal variables, we extend the model to a NK DSGE framework in Section 1.4. We discuss, then, the simulation results for the calibrated models in Section 1.5. After that, Section 1.6 tests the model implication using cross country data. Finally, Section 1.7 concludes.

1.2 Related Literature

1.2.1 Vintage Capital Models

The literature on vintage capital models in economics explores how different "vintages" of capital, representing different generations of technology, affect economic outcomes. Vintage capital models acknowledge that capital goods are not homogeneous but instead differ by their production date and technological level. This approach allows for a more realistic analysis of economic dynamics, particularly in the context of technological progress and its impact on productivity and growth. The earliest paper on vintage capital models, Malinvaud (1953) developed a model incorporating vintage capital to analyze how different generations of capital goods coexist and impact productivity. Solow (1960) early work on vintage capital models laid the groundwork for understanding how technological change impacts economic growth. He introduced the idea that newer vintages of capital are more productive due to technological advancements.

Aghion and Howitt (1992)'s work on endogenous growth theory incorporates vintage capital models to explain how technological progress drives economic growth. They highlighted the role of research and development (R&D) in producing new vintages of capital. Caballero and Hammour (1994) examine how vintage capital models could explain fluctuations in investment and the business cycle. They focused on the destruction of old vintages and the creation of new ones as a source of economic dynamics.

Cooley et al. (1997) analyze how vintage capital models could explain the observed patterns in economic data, such as the procyclicality of labour productivity and investment. The influential paper by Greenwood et al. (1997) introduces the concept of investment-specific technological change, where technological improvements are embodied in new capital goods, leading to productivity gains when firms invest in new vintages of capital. Jovanovic and Nyarko (1996) explore how firms learn and adapt to new technologies, emphasizing the role of vintage capital in firm-level productivity and competitive dynamics.

Greenwood and Yorukoglu (1997) analyze the significant economic changes and technological advancements that occurred around the year 1974, which they argue was a pivotal year in economic history. The paper delves into the causes and consequences of these changes, with a particular focus on technological progress and its impact on productivity and economic volatility. The authors identify 1974 as a watershed year due to the substantial technological innovations that took place, which significantly altered the economic landscape. These technological advancements required significant investment in learning and integration, leading to an initial productivity slowdown, a phenomenon often referred to as the "productivity paradox". The paper discusses how the adoption of new technologies initially leads to a decline in productivity as businesses and workers adjust to new systems and processes. Over time, as the workforce becomes more proficient with these technologies, productivity begins to increase, leading to overall economic growth.

Moreover, Yorukoglu (1998) explores why productivity growth seems to stagnate or decline despite rapid advancements in information technology (IT). The paper reports that IT investments have a strong learning-by-doing effect, meaning that productivity may initially decline as employees and firms learn to use new technologies efficiently. The model and its empirical tests suggest that the observed productivity paradox may be partly due to the estimation methods that fail to account for the vintage nature of capital and the initial costs of technological adoption.

Hornstein and Krusell (1996) examine how vintage capital models could explain sectoral shifts and changes in the composition of output over time. Also, Hobijn and Jovanovic (2001) analyze the impact of information technology on economic growth, using a vintage capital framework to show how IT investments lead to productivity improvements. Furthermore, Auerbach and Hines (1988) explore the implications of tax policy on investment in new vintages of capital, highlighting how tax incentives can influence the rate of technological adoption and economic growth.

Vintage capital New Keynesian DSGE models incorporate elements of vintage capital theory within the framework of New Keynesian economics. These models combine the microeconomic foundations of DSGE models, which include optimizing behaviour by agents and stochastic shocks, with the concept of vintage capital, which acknowledges the heterogeneity of capital goods based on their age and technological level. Fagnart et al. (1999) explore firm heterogeneity and vintage capital within a DSGE framework, analyzing how different vintages of capital and firm behaviours contribute to aggregate economic fluctuations. The authors demonstrate that incorporating vintage capital can better explain observed economic dynamics and business cycle fluctuations. Aruoba et al. (2013) assess the nonlinearities in DSGE models, focusing on how incorporating vintage capital and other factors can lead to nonlinear economic dynamics. They provide a framework for evaluating the importance of these nonlinearities in explaining macroeconomic phenomena. Fisher (2006) studies the dynamic effects of neutral and investment-specific technology shocks on the economy. The author uses a DSGE model to separate the impacts of these two types of shocks, showing that investment-specific technological change has significant implications for understanding economic growth and business cycles.

1.2.2 Learning Needs and Technology Adoption

There has been a surge in empirical work examining the relationship between learning needs for new technologies and economic fluctuations. Studies have investigated how economic recessions prompt workers to seek additional training and education to remain competitive in the job market. For example, during the 2008 financial crisis, many individuals pursued further education to enhance their skills. Hershbein and Kahn (2018) explore how economic downturns accelerate the adoption of new technologies and the corresponding shift in skill demands.

Research has shown how technological advancements create new employment opportunities, thereby influencing learning needs. Acemoglu and Restrepo (2020) examine the impact of robotics on employment and skill requirements in various industries.

Studies have analyzed how educational systems need to adapt to prepare students for future technological landscapes, highlighting the importance of STEM education and continuous learning. Deming (2017) emphasizes the increasing value of social skills alongside technical skills in a technology-driven economy.

There is substantial research on the need for lifelong learning and how workforce development programs can help workers adapt to technological changes and economic shifts. Goldin and Katz (2008) provide a historical analysis of the interplay between education and technological advancements, emphasizing the need for ongoing skill development.

Research has also focused on the effectiveness of policy measures and corporate training programs in addressing skill gaps created by technological advancements and economic changes. Autor (2015) discusses how policy responses can mitigate the adverse effects of automation on employment.

Some recent empirical work explores the necessity and impact of organizational change when adopting new technologies. Vial (2019) reviews existing literature on digital transformation and emphasizes the need for comprehensive organizational change, including strategy, culture, structure, and processes. Brynjolfsson and Hitt (2000) examine how IT investments are often accompanied by complementary changes in organizational practices, including decentralized decision-making and increased use of team structures.

Bessen (2019) discusses how AI adoption requires significant reskilling and upskilling of the workforce, emphasizing the role of continuous learning and development programs. A seminal work on business process re-engineering by Hammer (1990), underscores the need to rethink and radically redesign business processes to fully leverage new technologies. Davenport (1998) explores the implementation of ERP systems and the extensive organizational change required, including process standardization and integration across departments. Finally, Acemoglu and Restrepo (2020) investigates the impact of robotics on labour markets and highlights the organizational changes necessary to integrate robots into the workforce.

There is empirical evidence suggesting that productivity can initially decline after the adoption of new technologies, the so called "productivity paradox" or "J-curve" effect. Here are some key reasons and empirical findings related to this initial productivity decline. Employees need time to learn and become proficient with new technologies, which can temporarily reduce productivity. Moreover, integrating new technologies with existing systems and processes can be complex and disruptive. The initial costs of implementation, including training, system modifications, and process redesign, can outweigh the immediate benefits. Organizational restructuring and changes in workflows can create temporary inefficiencies. Finally, resistance from employees who are accustomed to old systems can slow down the adoption process and impact productivity. The following influential studies have demonstrated this phenomenon in various contexts.

Brynjolfsson (1993) discusses the paradox where investments in IT did not immediately translate into measurable productivity gains, often due to lags in technology adoption, learning curves, and the need for complementary investments in organizational change. Stratman and Roth (2002) show that the implementation of ERP systems often leads to an initial decline in productivity as organizations undergo significant process re-engineering and employees adapt to the new system. Acemoglu and Restrepo (2020) indicates that while automation and robotics can ultimately lead to productivity gains, the initial phase often involves a period of adjustment and decline in productivity due to changes in workflows and job roles. Vial (2019) argues that digital transformation initiatives often face initial productivity declines due to the complexities of integrating new digital tools, redesigning business processes, and overcoming cultural resistance.

Brynjolfsson and Hitt (1996) find that while firms investing in IT initially experience productivity slowdowns, long-term gains are realized as the technology is fully integrated and complementary organizational changes are made. The initial productivity decline is attributed to learning curves and adjustment costs. The study finds that firms investing heavily in IT experience a short-term productivity decline of around 1-2% in the initial years following the investment. However, after about 5-7 years, these firms see a productivity increase of 5-7%, indicating long-term benefits.

Poston and Grabski (2001) analyze the financial performance of firms post-ERP implementation and find an initial decline in productivity and profitability. These declines are linked to the high costs and disruptions associated with implementing ERP systems. However, over time, firms that effectively manage the change process see improvements in productivity. The study shows an average decline in productivity of approximately 5% in the first year following ERP implementation. This is primarily due to disruptions in business processes and the time needed for employees to adapt. Productivity begin to recover in the second year and shows significant improvement by the third year.

Devaraj and Kohli (2003) show that firms often experience a temporary dip in performance metrics, including productivity, following the adoption of new digital technologies. The initial decline is due to the time required for employees to learn and effectively use the new systems. Firms that provide adequate training and support see quicker recoveries and long-term gains. The study reports a 3-4% decrease in productivity in the first year of digital technology adoption. Over a three-year period, firms that successfully integrate these technologies see a cumulative productivity gain of around 10%.

Graetz and Michaels (2018) use data from several industries to measure the impact of industrial robots on productivity. The authors find that while there are initial productivity declines in some cases due to integration challenges and workforce adjustments, overall productivity increases significantly in the long term as firms adapt to and optimize the use of robots. The analysis finds that the initial introduction of robots in manufacturing leads to a productivity decline of about 1.5% in the first year. However, after four years, productivity increases by approximately 10% due to the efficiencies gained from automation.

Bessen (2019) indicates that AI adoption often leads to an initial decline in productivity as organizations restructure and employees undergo training to work with AI systems. The long-term effects, however, show substantial productivity gains as firms fully integrate AI technologies into their operations. The study indicates that firms adopting AI experience a productivity decline of about 2-3% initially due to the costs of training and integration. Over a five-year period, these firms report productivity improvements ranging from 8-12%, driven by enhanced decision-making and automation capabilities.

1.3 A Real Business Cycle Model with Vintage Technology Learning

In order to analyze the link between technological progress and the Great Moderation, a RBC model with vintage capital and learning by doing is presented in this section. The model is based on Greenwood and Yorukoglu (1997). The economy comprises a representative household and a firm. The production technology exhibits constant returns to scale, making the number and size distribution of firms irrelevant. Therefore, we assume that there is one big firm acting competitively. Also, the firm operates indefinitely and produces output across various plants using capital and labour. Labour is essential for both production and the processes of learning and reorganization.

1.3.1 The Firm

The firm in the economy operates multiple plants, each indexed by the age of its capital stock denoted by j. This capital is purchased the period before the plant is opened. The price of capital declines over time due to investment-specific technological change. Let's envision that one unit of consumption can purchase γ^{t+1} units of capital in period t. Assume that the blueprints for a new plant under construction in period t call for $(\gamma^{t+1})^{\frac{1}{1-\alpha}}$ units of capital. Therefore, the consumption cost of a new plant in period t is $(\gamma^{t+1})^{\frac{\alpha}{1-\alpha}}$. Suppose that capital depreciates at the rate δ per period. Thus, an age-j plant in period t will have $k_{j,t} = (1-\delta)^{j-1}\left(\gamma^{t-j+1}\right)^{\frac{1}{1-\alpha}}$ units of capital. The firm is free to open or close plants as desired. The number of vintage-j plants owned in the current period by the firm is represented by p_j. In the following, we abstract from time index for the ease of notation.

The production technology for a plant of vintage j is given by,

$$F(k_j, n_j, \mu_j; z) = z\mu_j k_j^{\alpha} n_j^{1-\alpha}, \quad 0 < \alpha < 1,$$

where k_j is the capital stock, n_j is the labour input, μ_j is the plant specific productivity, and z is the aggregate productivity whose logarithm follows a AR(1) process. New technologies require learning and reorganization to operate efficiently. A fixed amount of engineering and management input is necessary for this process. Let the optimal learning and reorganization process take T units of time. Labour input necessary for the learning process for a vintage j firm is denoted by m_j,

$$m_j = \begin{cases} a(T-j), \text{ for } 1 \leq j \leq T, \text{ and } a > 0, \\ 0, \text{ otherwise,} \end{cases}$$

where

$$a = (1-\tau)\chi_m \gamma^{\phi_m}, \ 0 < \phi_m, \chi_m.$$

As the pace of technological progress γ increases learning becomes more costly and requires more labour input. The distance of the economy to the technology frontier, τ, also effects the learning need. If the economy is at the technological frontier $\tau = 0$, and it increases monotonically as the economy moves away from the frontier. Its upper bound is one. Plant specific productivity evolves over time due to this learning and reorganization investment. The law of motion for plant level productivity has the form

$$\mu_j = \begin{cases} 1 - b(T-j), \text{ for } 1 \leq j \leq T, \text{ and } b > 0, \\ 1, \text{ otherwise,} \end{cases}$$

where

$$b = (1-\tau)\chi_\mu \gamma^{\phi_\mu},\ 0 < \phi_\mu, \chi_\mu.$$

Following Yorukoglu (1998), the starting value for the learning and reorganization process, or μ_0, is taken to be inversely related to the current level of investment specific technological change. Similarly the time needed for this process, m_0, increases with the pace of technological change. As the rate of technological process increases, the more costly it becomes to adopt the new technology since agents will be less familiar with it.

The plant's optimization problem is, hence, given by

$$V(k_j, \mu_j; z) = \max_{n_j} \left\{ F(k_j, n_j, \mu_j; z) - w(n_j + m_j) + E\left[\frac{V(k'_{j+1}, \mu'_{j+1}; z')}{1+r'}\right] \right\},$$

where w represents the wage rate, and r is the interest rate. The efficiency condition for labour used is

$$(1-\alpha) z \mu_j k_j^\alpha n_j^{-\alpha} = w.$$

A plant will only be created whenever the present value of creating it is nonnegative. In equilibrium there must be zero rents for doing so. Therefore, if

$$qk'_1 - E\left[\frac{V(k'_j, \mu'_j; z')}{1+r'}\right] \begin{array}{l} = 0, \text{ then } p'_1 \geq 0, \\ < 0, \text{ then } p'_1 = 0. \end{array}$$

Suppose in each period that the firm pays out its profits less investment spending in dividends. Current dividends, d, will then be given by

$$d = \sum_{j=1}^{\infty} p_j \left(F(k_j, n_j, \mu_j; z) - w(n_j + m_j)\right) - p'_1 q k'_1$$

The value of the firm after paying dividends is

$$v = E\left[\sum_{j=1}^{\infty} p_j^{'} \frac{V(k_j^{'}, \mu_j^{'}; z^{'})}{1+r'}\right]$$

It is easy, finally, to show that the following arbitrage condition should hold

$$1 + r = E\left[\frac{v^{'} + d^{'}}{d}\right]$$

1.3.2 The Household

The household must decide how much labour l to supply and how to divide his current income between consumption c and asset holdings a next period. Let the agent's momentary utility function be given by

$$U(c, l; \lambda) = \ln(c - \lambda\Theta\frac{l^{1+\theta}}{1+\theta}), \quad \theta, \Theta > 0,$$

where λ represents the deterministic state of technological advance in the household sector. The optimization problem of the agent, then, will take the form

$$W(a; .) = \max_{a'} \{U(c, l; \lambda) + \beta W(a'; .')\},$$

subject to

$$va' = a(d + v) + w(1 - l) - c.$$

The first order conditions associated with the agent's problem are

$$U_1(c, l; \lambda) = \beta E\left[\frac{v^{'} + d^{'}}{d}\right] U_1(c', l'; \lambda'),$$

and

$$U_1(c, l; \lambda)w = U_2(c, l; \lambda).$$

The aggregate state of the world for the economy is described by the vector, $s = (p_1, p_2, ..., p_{T-1}, P, z)$. This gives the number of plants which are at learning and reorganization stage $p_1, p_{2,...,}p_{T-1}$, the total number of mature plants P, and the aggregate productivity z. The equilibrium wage rate, interest rate, dividend payments, and the share price of the firm can all be expressed as a function of the state of the world.

1.3.3 Planner's Problem

The competitive equilibrium of the model economy is Pareto efficient. Hence, we will work with the corresponding planner's problem which is stated below.

$$V(p_1, p_2, ..., p_{T-1}, P, z) = \max_{p_1', n_j, n_P} \left\{ U(c, l; \lambda) + \beta EV \left[(p_1', p_2', ..., p_{T-1}', P', z') \right] \right\}$$

subject to

$$c + p_1^{'} q k_1^{'} = \sum_{j=1}^{\infty} p_j F(k_j, n_j, \mu_j; z) = \sum_{j=1}^{T-1} p_j F(k_j, n_j, \mu_j; z) + z P^{\alpha} n_P^{1-\alpha},$$

$$\sum_{j=1}^{\infty} p_j n_j + \sum_{j=1}^{T-1} p_j m_j = (1 - l)$$

$$p_{i+1}^{'} = p_i,$$

$$P = \sum_{j=T}^{\infty} p_j k_j$$

$$P' = P + p_T k_T,$$

$$\mu_j = \begin{cases} 1 - (1-\tau)\chi_\mu \gamma^{\phi_\mu}(T-j), \text{ for } 1 \leq j \leq T, \\ 1, \text{ otherwise}, \end{cases}$$

$$m_j = \begin{cases} (1-\tau)\chi_m \gamma^{\phi_m}(T-j), \text{ for } 1 \leq j \leq T, \\ 0, \text{ otherwise}, \end{cases}$$

$$z^{'} = z^{\rho_z} e^{\epsilon_z^{'}}.$$

For the simulation analysis in Section 1.5, the model variables are deflated by their balanced growth rate and the model is, then, loglinearized around the steady state. The procedure is explained in Appendix A.1.

Finally, it can be noticed that if there is no learning and reorganization process, i.e. $\mu_j = 1$ for all j, the model collapses to the standard RBC model with investment specific technological change below (Appendix A.2 provides more details).

$$V(P, z) = \max_{P,n} \{ U(c, l; \lambda) + \beta EV [(P', z')] \}$$

subject to

$$c + qP' = zP^{\alpha}n^{1-\alpha} + (1-\delta)qP,$$

and

$$l + n = 1$$

1.4 A New Keynesian Framework with Vintage Technology Learning

To analyze the economic moderation in nominal variables as well, a New Keynesian DSGE model is presented in this section. The model extends the basic NK model with the technological learning discussed above.

1.4.1 The Consumer

There is a representative consumer, who maximizes the following problem over consumption c_t and labour l_t:

$$\max_{c_t, l_t} E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{c_t^{1-\sigma}}{1-\sigma} - \lambda_t \Theta \frac{l_t^{1+\theta}}{1+\theta} \right]$$

subject to:

$$P_t c_t + B_t \leq (1 + R_t) B_{t-1} + W_t l_t + T_t$$

where P_t, B_t, R_t, W_t, and T_t are price index, one-period bonds, nominal interest rate, nominal wage, and transfers, respectively, and λ_t represents the deterministic state of technological advance in the household sector.

The FOCs of the consumer's problem are:

$$\beta E_t \left[\frac{c_t^{\sigma}}{c_{t+1}^{\sigma}} \right] = \frac{P_{t+1}}{P_t(1 + R_{t+1})}$$

$$\lambda_t \Theta l_t^{\theta} = \frac{W_t}{P_t}$$

Moreover, the representative consumer maximizes an index of a continuum of consumption goods in $[0, 1]$, where ϵ is the elasticity of substitution among the different final goods:

$$c_t = \left(\int_0^1 c_t(i)^{1-\frac{1}{\epsilon}}\, di \right)^{\frac{\epsilon}{\epsilon-1}}$$

Minimizing the costs for a fixed amount of c_t, we have the demand for each good:

$$c_t(i) = \left(\frac{P_t(i)}{P_t} \right)^{-\epsilon} c_t$$

1.4.2 The Final Firms

There is a continuum of firms, one for each final good in $[0, 1]$. They are in monopolistic competition and subject to Calvo prices: θ_c share of the firms cannot optimize their price. These firms buy intermediate goods and sell them to the consumers, mainly working as retailers. More precisely, each final firm that can reset its optimal price P_t^*, maximizes the following problem:

$$\max_{P_t^*} \sum_{k=0}^{\infty} \theta_c^k E_t \{ Q_{t,t+k} (P_t^* y_{t+k|t} - P_{Ht+k} y_{t+k|t}) \}$$

subject to:

$$y_{t+k|t} = \left(\frac{P^*}{P_{t+k}} \right)^{-\epsilon} c_{t+k}$$

which leads to the following FOC:

$$\sum_{k=0}^{\infty} \theta_c^k E_t \{ Q_{t,t+k} y_{t+k|t} (\frac{P_t^*}{P_{t-1}} - \mu \frac{P_{Ht+k}}{P_{t+k}} \Pi_{t-1,t+k}) \} = 0$$

where $Q_{t,t+k} = \beta^k E_t \left[\frac{c_{t+k}^{-\sigma}}{c_t^{-\sigma}} \frac{P_t}{P_{t+k}} \right]$ is the stochastic discount factor, and $\mu = \frac{\epsilon}{\epsilon-1}$ is the constant markup, while P_{Ht} is the price of intermediate goods. In balanced growth path, $Q_{t,t+k} = \left(\frac{\beta}{\gamma^{\frac{\sigma\alpha}{1-\alpha}}} \right)^k$.

The price index is the following:

$$P_t = \left[\int_0^1 P_t(i)^{1-\epsilon}\, di \right]^{\frac{1}{1-\epsilon}}$$

From it, inflation can be derived as follows:

$$\Pi_t^{1-\epsilon} = \theta_c + (1-\theta_c)\left(\frac{P_t^*}{P_{t-1}}\right)^{1-\epsilon}$$

And:

$$P_t = [\theta_c P_{t-1}^{1-\epsilon} + (1-\theta_c)P_t^{*1-\epsilon}]^{\frac{1}{1-\epsilon}}$$

1.4.3 Intermediate Firms

Intermediate goods are a continuum in [0,1] and perfect substitutes. For each good there is a firm h in perfect competition with the others. They sell their good $x(h)_t$ to the final firms that are going to sell each $y(i)_t$ to the consumer. They sell at competitive price P_{Ht}. Each final firm buys the same amount of good from each intermediate firm. Each intermediate firm has vintage capital and learning by doing.

As explained for the RBC model case in Section 1.3, each intermediate firm operates thought plants, featuring vintage capital and learning by doing. A plant is indexed by the technology (age) of its capital denoted by j, and the amount of j plants is s_j. This capital is purchased the period before the plant is opened. The price of a unit of capital declines over time due to investment specific technological change. One unit of consumption can purchase γ^{t+1} units of capital in period t. Consequently, relative price of capital is $q_t = \frac{1}{\gamma^{t+1}}$. We assume that the blueprints of a new plant in period t call for $(\gamma^{t+1})^{\frac{1}{1-\alpha}}$ units of capital. Therefore, the consumption cost of a new plant in period t is $(\gamma^{t+1})^{\frac{\alpha}{1-\alpha}}$. Thus, an age-$j$ plant in period t will have $k_{j,t} = (1-\delta)^{j-1}(\gamma^{t-j+1})^{\frac{1}{1-\alpha}}$.

The production technology for a plant of vintage j is given by (again, we abstract from the time subscript for ease of notation in the following):

$$F(k_j, n_j, \mu_j, z) = z\mu_j k_j^{\alpha} n_j^{1-\alpha}$$

where μ_j is the plant specific productivity. New technology requires learning and reorganization to operate efficiently. A fixed amount of engineering and management input is necessary for this process. Following Yorukoglu (1998), the starting value for the learning and reorganization process, μ_0, is assumed to be inversely related to the current level of investment specific technological change, and the labour needed for this process, m_0, increases with the pace of technological change. The higher the rate of technological process, the more costly it becomes to adopt the new technology. Let the exogenous optimal learning process take T periods of time.

For the NK model as well, we describe the vintage capital learning process as a function of the pace of technological progress γ and the distance of the economy to the technology frontier, τ, as follows:

$$m_j = \begin{cases} (1-\tau)\chi_m \gamma^{\phi_m}(T-j) & \text{if } 1 \leq j \leq T, \\ 0 & \text{otherwise.} \end{cases}$$

And the exogenous plant specific productivity is:

$$\mu_j = \begin{cases} 1-(1-\tau)\chi_\mu \gamma^{\phi_\mu}(T-j) & \text{if } 1 \leq j \leq T, \\ 1 & \text{otherwise.} \end{cases}$$

Each plant's optimization problem is given by:

$$V(k_j, \mu_j, z) = \max_{n_j} \left\{ P_H F(k_j, n_j, \mu_j, z) - W(n_j + m_j) + E\left[\frac{V(k'_{j+1}, \mu'_{j+1}, z')}{1+R} \right] \right\}$$

Hence, the efficiency conditions of the plant's problem are the following:

$$P_H(1-\alpha) z \mu_j k_j^{\alpha} n_j^{-\alpha} = W$$

$$P_H(1-\alpha) z S^{\alpha} n_S^{-\alpha} = W$$

The intermediate firm's problem, given the choice of the plants, is to maximize the total profit through the investment choice (how much of new plants s_1 to create):

$$\begin{aligned} W(s_1, ..., s_{T-1}, S, z) = \max_{s_1} \Bigg\{ & P_H \sum_{j=1}^{T-1} s_j F(k_j, n_j, \mu_j, z) - \sum_{j=1}^{T-1} s_j W(n_j + m_j) \\ & + P_H z S^{\alpha} n_S^{1-\alpha} - W n_S - P_H q s'_1 k'_1 + E\left[\frac{W(s'_1, ..., s'_{T-1}, S', z')}{1+R} \right] \Bigg\} \end{aligned}$$

subject to:

$$s'_{j+1} = s_j$$

$$S' = (1-\delta)S + (1-\delta)s_{T-1}k_{T-1}$$

Therefore, the efficiency condition of the intermediate firm's problem is:

$$P_H q k'_1 = E\left[\frac{W_1(s'_1,...,s'_{T-1},S',z')}{1+R}\right]$$

Finally, to describe the value function of the firm, we derive the following Envelope Theorem equations:

$$W_j(s_1,...,s_{T-1},S,z) = P_H z\mu_j k_j^{\alpha} n_j^{1-\alpha} - W(n_j+m_j) + \frac{W_{j+1}(s'_1,...,s'_{T-1},S',z')}{1+R} \quad \textit{for j=1,...T-2}$$

$$\begin{aligned} W_{T-1}(s_1,...,s_{T-1},S,z) &= P_H z\mu_{T-1}k_{T-1}^{\alpha}n_{T-1}^{1-\alpha} - W(n_{T-1}+m_{T-1}) \\ &+ \frac{W_T(s'_1,...,s'_{T-1},S',z')(1-\delta)k_{T-1}}{1+R} \end{aligned}$$

$$W_T(s_1,...,s_{T-1},S,z) = P_H\alpha z S^{\alpha-1}n_S^{1-\alpha} + \frac{W_T(s'_1,...,s'_{T-1},S',z')(1-\delta)}{1+R}$$

1.4.4 Market Clearing, Productivity Process, and Monetary Policy

To close the model, the following market clearing and accounting equations are necessary.

$$c_t = y_t,$$

$$\int_0^1 y_t(i)\,di = \int_0^1 x_t(h)\,dh,$$

$$x_t = \int_0^1 y_t(i)\,di = \int_0^1 \left(\frac{P_t(i)}{P_t}\right)^{-\epsilon} y_t\,di = P_t^{\epsilon}y_t\int_0^1 P_t(i)^{-\epsilon}\,di = P_t^{\epsilon}y_t[(1-\theta_c)P_t^{*-\epsilon}+\theta_c P_{t-1}^{-\epsilon}],$$

$$x_t = \sum_{j=1}^{T-1} s_j F(k_j,n_j,\mu_j,z) + zS^{\alpha}n_S^{1-\alpha} - qs'_1k'_1,$$

$$\text{and } l_t = \sum_{j=1}^{T-1} s_j(n_j+m_j) + n_S.$$

Furthermore, the logarithm of the productivity process follows a AR(1) process, as reported in the equation below,

$$z^{'} = z^{\rho_z} e^{\epsilon_z^{'}},$$

and the monetary authority implements the subsequent interest rate rule:

$$\frac{R_t}{\bar{R}} = \left(\frac{\Pi_t}{\bar{\Pi}}\right)^{\phi_\Pi} \left(\frac{Y_t + q_{t+1} s_{1t+1} k_{1t+1}}{\bar{Y}_t + \bar{s}_1 \gamma^{\frac{\alpha}{1-\alpha}(t+1)}}\right)^{\phi_Y}.$$

Finally, also in the context of the NK model, the variables are deflated by their balanced growth rate and the model is, then, loglinearized around the steady state in order to undertake the simulation analysis in Section 1.5. Such procedure is explained in detail in Appendix A.3. Moreover, it can be noticed that if there is no learning and reorganization process, i.e. $\mu_j = 1$ for all j, the model boils down to the standard NK model (Appendix A.4 provides more details).

1.5 Simulation Results

To examine the effect of technological learning on economic fluctuations, we simulate both the RBC and the NK DSGE calibrated models (in their loglinearized version). The simulation is implemented to mimic the pre- and post-Great Moderation technological conditions. All the simulations are based on the same productivity shock time series, letting the technological vintage learning need the only difference between pre- and post-Great Moderation.

The calibration is set to deliver quarterly models for the US. The parameters are calibrated as follows (the parameters relating to monetary variables are related only to the NK DSGE model, the rest of the parameters refers to both frameworks): $T = 12$ to reach full learning after 3 years for the post-Great Moderation, as suggested by the relevant literature; $\gamma_{pre} = 1.008$ and $\gamma_{post} = 1.016$ to match the decline in the relative price of equipment from the FRED data for the US, as reported in Figure 1.1; $\tau = 0.$ since the US economy is assumed to be at the technological frontier; $\chi_\mu = 0.0053$ and $\phi_\mu = 119.2$ to deliver 85% initial vintage productivity in pre-Great Moderation, and 62% in post-Great Moderation, following Greenwood and Yorukoglu (1997); $\chi_m = 0.01$ and $\phi_m = 1$ to have 10% of steady state total labour costs on learning in the post-Great Moderation, based on Jovanovic and Nyarko (1996); $\theta = 0.33$ and $\Theta = 2.95$ to deliver steady state labour around 0.36; the rest of parameters are calibrated following the related literature, i.e., $\alpha = 0.35$, $\beta = 0.99$, $\delta = 0.025$, $\epsilon = 6$, $\theta_c = 0.33$, $\phi_\pi = 1.5$, $\phi_y = 0.5/4$, $\rho_z = 0.95$, and $\sigma = 0.95$ (similar to Gandelman and Hernández-Murillo (2015)).

Figures 1.4 and 1.5 show the impulse response functions of economies with and without the learning process in the context of the NK framework. First, the response of employment to a positive productivity shock is much milder in the model with learning. Since production units adopting the new technology are not yet highly productive, employment does not increase as much following a positive productivity shock. Similar moderation effects can be observed in the responses of investment, consumption, and output.

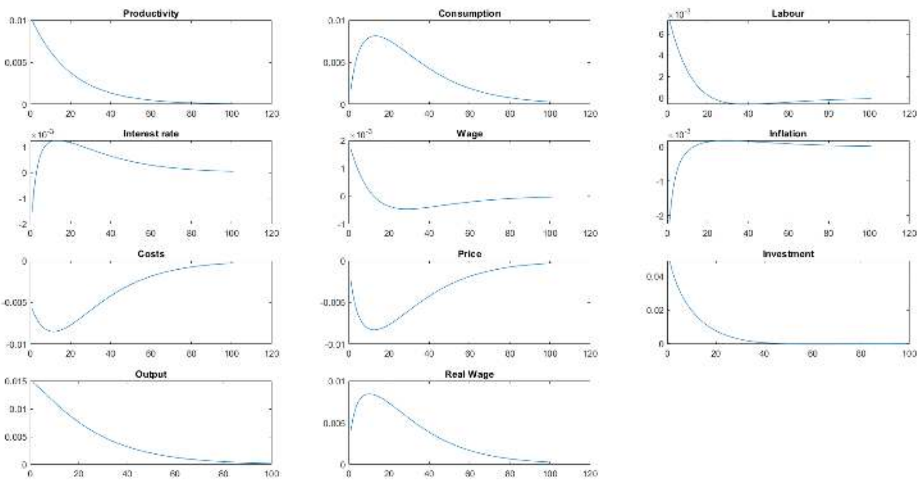


Figure 1.4: Impulse response functions to a positive productivity shock in the economy with learning needs.

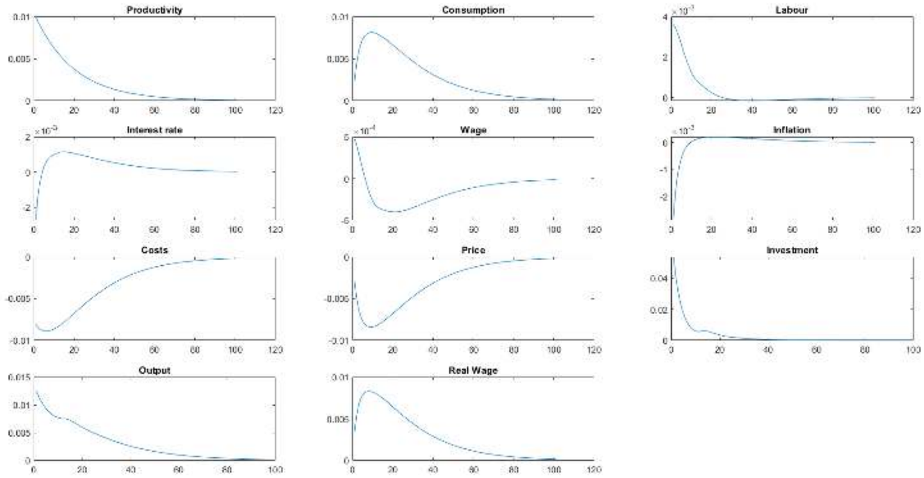


Figure 1.5: Impulse response functions to a positive productivity shock in the economy without learning needs.

Before discussing the results on nominal variables, we should examine the response of the central bank in economies with and without learning. Given the positive productivity shock, the output gap increases, prompting the central bank to stimulate demand by lowering the policy rate. In the economy with learning, the central bank lowers its policy rate more significantly, approximately 40% more at the date of impact. Lower interest rates stimulate both consumption and investment. Although the overall employment response is lower in the economy with learning, a larger portion of labour is allocated to learning and reorganization, as seen in the increased shared of new vintages. Consequently, prices and wages move significantly less in response to the central bank's actions.

Then, Tables 1.1 and 1.2 compare the volatilities of economic variables in the pre- and post-Great Moderation economies, for the RBC and the NK framework, respectively. Overall, volatility moderates significantly in the economy with learning needs due to technological progress. In particular, output and inflation volatility are predicted to decrease by around 25% and 9%, respectively, in the NK model.

Table 1.1: Standard deviation of variables before and after the Great Moderation - RBC model

	Capital Std	Consumption Std	Labour Std	Output Std	Investment Std
Pre	0.208	0.201	0.132	0.211	0.235
Post	0.125	0.165	0.108	0.165	0.217
Moderation	39.9%	17.9%	18.2%	21.8%	7.7%

Note: Simulation results in the RBC model with AR(1) productivity process and iid innovations distributed as $\mathcal{N}(0, 0.02)$. Positive *Moderation* indicates the percentage decrease in volatility between the pre- and post-Great Moderation environment (an increase in the case of a negative sign).

Table 1.2: Standard deviation of variables before and after the Great Moderation - NK model

	Consumption Std	Labour Std	Output Std	Investment Std	Interest Std	Price Std	Real Wage Std
Pre	0.093	0.033	0.118	0.232	0.014	0.095	0.095
Post	0.083	0.017	0.089	0.172	0.013	0.086	0.084
Moderation	10.8%	48.5%	24.6%	25.9%	7.1%	9.5%	11.6%

Note: Simulation results in the NK model with AR(1) productivity process and iid innovations distributed as $\mathcal{N}(0, 0.02)$. Positive *Moderation* indicates the percentage decrease in volatility between the pre- and post-Great Moderation environment (an increase in the case of a negative sign).

1.5.1 What if the Central Bank Fails to Recognize the Learning Process?

In real life, the learning process after adopting a new technology mainly goes unrecognized and unrecorded. What would happen if the central bank in the economy fails to recognize the learning process? In such a case the central bank will mismeasure the output gap and its response to supply shocks will be more hawkishly. To make the argument here more clear consider an economy where the actual potential output is given by

$$Y^*(z) = z \sum s_j \mu_j f(k_j, n_j)$$

where z is the productivity level, s_j is the measure of firms with jth vintage technology, and μ_j is the expertise of the firm in using its technology. Since the central bank fails to recognize the learning process it will measure the output gap as

$$Y^*_{CB}(z) = z\overline{\mu} \sum s_j f(k_j, n_j)$$

where $\overline{\mu}$ is some average of expertise level over all firms. The actual output gap is $(Y - Y^*)$ whereas the output gap the central bank measures will be $(Y - Y^*_{CB})$.

Consider a period with positive technology shock, i.e. $z = z_h$, and the economy is in expansion. Because of increased investment and upgrading of technology, the potential output that the central bank measures, which fails to recognize the increased learning need, will be higher than the actual potential output, $Y^*_{CB}(z_h) > Y^*(z_h)$. Consequently central bank will measure the output gap lower than it actually is, i.e. $(Y - Y^*_{CB}(z_h)) < (Y - Y^*(z_h))$. To stimulate demand central bank will further lower the policy rate. To see this more clearly, let the central bank's decision rule be

$$i(z) = \pi + \rho + \theta_\pi(\pi(z) - \pi^*) + \theta_y(Y - Y^*(z)).$$

With the mismeasurement of the output gap due to ignoring the learning process the central bank's decision rule will read

$$i_{CB}(z) = \pi + \rho + \theta_\pi(\pi(z) - \pi^*) + \theta_y(Y - Y^*_{CB}(z)).$$

Since $Y^*_{CB}(z_h) > Y^*(z_h)$, $i_{CB}(z_h) < i(z_h)$. The opposite will be through during recessions, in other words, $Y^*_{CB}(z_h) < Y^*(z_h)$, $i_{CB}(z_h) > i(z_h)$.

With this mismeasurement of actual output, the central bank will act more hawkishly than intended, further moderating the inflation process. To illustrate this in our model, we incorporate the central bank's ignorance of the learning process and the resulting mismeasurement of the output gap (Appendix A.5 provides more details). Table 1.3 presents the comparative simulation results. As it can be noticed, the mismeasurement of the output gap does not further decrease the volatility of real variables. However, it significantly moderates inflation. The standard deviation of the central bank's policy rate response increases by more than fivefold. This indicates that the central bank adopts a much more hawkish stance, cutting rates more aggressively during expansions and raising rates more aggressively during recessions.

Table 1.3: Standard deviation of variables before and after the Great Moderation in the economy where the central bank ignores the learning process while measuring output gap

	Consumption Std	Labour Std	Output Std	Investment Std	Interest Std	Price Std	Real Wage Std
Pre	0.093	0.033	0.118	0.232	0.014	0.095	0.095
Post	0.084	0.019	0.090	0.157	0.072	0.061	0.084
Moderation	9.7%	42.4%	23.7%	32.3%	-414.3%	36.8%	11.6%

Note: Simulation results in the NK model with AR(1) productivity process and iid innovations distributed as $\mathcal{N}(0, 0.02)$. Positive *Moderation* indicates the percentage decrease in volativity between the pre- and post-Great Moderation environment (an increase in the case of a negative sign).

1.5.2 Can There Be Other Technological Factors behind the Moderation?

In the empirical Section 1.6, we will show that countries close to the world technological frontier experienced more moderation, which is consistent with our hypothesis. Could there be other technological factors behind this moderation, apart from the technological learning theory presented in this paper? One possible factor is the increased price flexibility that firms enjoy due to advancements in information technology. The cost of changing prices has likely decreased significantly with improved information technologies. To test the viability of this alternative explanation for the moderation, we tried to incorporate increasing price flexibility into our framework. One straightforward way to do this is by adjusting the price stickiness parameter θ_c in the Calvo mechanism. In the Calvo mechanism, as θ_c decreases, the fraction of firms that can reoptimize their prices in a given period increases. Table 1.4 reports the simulation results for economies with different price stickiness parameters. The standard deviation of key economic variables for different values of the price stickiness parameter θ_c are reported in the context of our NK model economy.

Table 1.4: Standard deviation of variables for different Calvo settings - NK model

θ_c	Consumption Std	Labour Std	Output Std	Investment Std	Interest Std	Price Std	Real Wage Std
0.1	0.085	0.021	0.091	0.149	0.021	0.087	0.087
0.2	0.085	0.021	0.091	0.152	0.019	0.087	0.087
0.3	0.085	0.021	0.091	0.155	0.017	0.087	0.087
0.4	0.085	0.020	0.091	0.159	0.016	0.087	0.086
0.5	0.084	0.019	0.090	0.163	0.015	0.087	0.086
0.6	0.084	0.018	0.089	0.168	0.014	0.086	0.085
0.7	0.083	0.016	0.089	0.174	0.013	0.085	0.083

Note: Simulation results in the NK model with AR(1) productivity process and iid innovations distributed as $\mathcal{N}(0, 0.02)$, for different values of the Calvo stickiness θ_c.

It is evident from Table 1.4 that real and nominal economic variables, such as output, consumption, and price levels, are not highly sensitive to changes in price stickiness. Furthermore, as θ_c decreases, which would be expected in an economy with more advanced information technology, there is increased volatility in almost all variables, with the only exception of investment. In other words, in our NK model, greater price flexibility leads to less economic moderation. An interesting observation is that the central bank's policy rate response also increases with greater price flexibility.

Does this result have much to do with our framework? Alternatively, in Table 1.5, we report the results from the standard NK model. The observations made above are valid for the standard model as well.

Table 1.5: Standard deviation of variables for different Calvo settings - NK model with no vintage capital learning

θ_c	Consumption Std	Labour Std	Output Std	Investment Std	Interest Std	Price Std	Real Wage Std
0.1	0.094	0.036	0.119	0.221	0.018	0.095	0.097
0.2	0.094	0.036	0.119	0.221	0.017	0.095	0.097
0.3	0.094	0.036	0.119	0.223	0.016	0.095	0.097
0.4	0.094	0.035	0.119	0.224	0.016	0.095	0.096
0.5	0.093	0.034	0.119	0.227	0.015	0.095	0.096
0.6	0.093	0.034	0.118	0.230	0.014	0.094	0.095
0.7	0.092	0.032	0.118	0.234	0.013	0.094	0.094

Note: Simulation results in the standard NK model with AR(1) productivity process and iid innovations distributed as $\mathcal{N}(0, 0.02)$, for different values of the Calvo stickiness θ_c.

1.6 *Empirical Analysis*

The empirical results reported in this section support the main implications of the model. We aim to test two main hypotheses. First, according to our theory, countries that are more significantly affected by the ICT revolution will face a steeper learning curve. To ascend this learning curve rapidly, they will need to invest in software and digitalization of their businesses. Consequently, these economies are likely to experience greater moderation in business cycle fluctuations. Second, countries closer to the global technological frontier will need to invest more in learning, leading to increased moderation in both real and nominal economic activity in those countries.

We will test both hypotheses using a cross-country analysis. Determining which countries to include in our analysis is challenging. To capture the learning effects with relatively low noise, we believe it is best to include countries that are relatively close to the global technology frontier. Another benefit of focusing on relatively advanced economies is that these countries are more similar in dimensions that are difficult to control for. Additionally, the availability of data further limits the number of countries we can include in our analysis.

We extensively use data from the Penn World Tables (PWT) database version 9.1[2], which provides annual information on real GDP, capital investment across various categories, consumption, productivity, and trade. These variables are made comparable across countries using purchasing power parities to convert them to a common currency. The PWT provide information on four types of capital assets: structures (including residential and non-residential), machinery (including computers, communication equipment, and other machinery), transport equipment, and other assets. In particular, the dataset includes the prices and investment levels for each type of asset. In the PWT, the "other" category in capital typically refers to assets that do not fall into the traditional categories of structures, machinery, and transport equipment. This category includes intellectual property products such as software, databases, and research and development (R&D), which account for more than two-thirds of the whole category in the U.S. economy. We focus, hence, on software and other intellectual property capital goods, which is the category that better represents the ICT revolution.

For the first hypothesis, we analyze the relationship between the change in the investment share of this category and the extent of moderation the country experiences. Additionally, we examine the change in the relative price of this category of

[2]For more details on the Penn World Tables, see Feenstra et al. (2015).

investment goods (relative to consumption prices) in the country and investigate its connection with the country's economic moderation.

For this part of the analysis, given our interest in the period before the Great Moderation and the availability of data, we focus on a subset of countries where all the necessary data is available for the pre-Great Moderation period as well[3]. Our sample starts in 1962 and stops in 2007, just before the Great Recession. As commonly argued, we define the pre-Great Moderation period until 1983, the year where the main change in relative price decline rate of equipment is detected, as shown in Figure 1.1, and subsequently the post-Great Moderation era. This way, all the variables we employ in our empirical analysis are statistics based on these two periods.

Before starting the analysis, let's look at the big picture first. Figure 1.6 shows the logarithm of the relative price of other assets between 1962 and 2007, averaged across the countries in our sample. As the reader can observe, the relative price was quite stable before 1975 but started to decrease steadily from the second half of the 1970s. Additionally, Figure 1.7a shows that from 1980 onward, the mean investment in other assets, as a share of GDP, experienced a significant increase in its growth rate. A similar trend is observed for the share of investment in other assets as a proportion of total investment, as shown in 1.7b. As these figures show, after the mid-1970s and 1980s, technological progress in this type of capital accelerated, and firms began to invest more in these assets as a share of their total investment.

We are interested in understanding whether and how these trends correlate with the decline in GDP volatility since the 1980s. To explore this, we use two measures of the Great Moderation for each country. The first measure is the ratio of GDP

[3]The countries included in this first empirical analysis are Australia, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Luxembourg, Mexico, Netherlands, Norway, Portugal, South Korea, Spain, Sweden, United Kingdom, and United States.

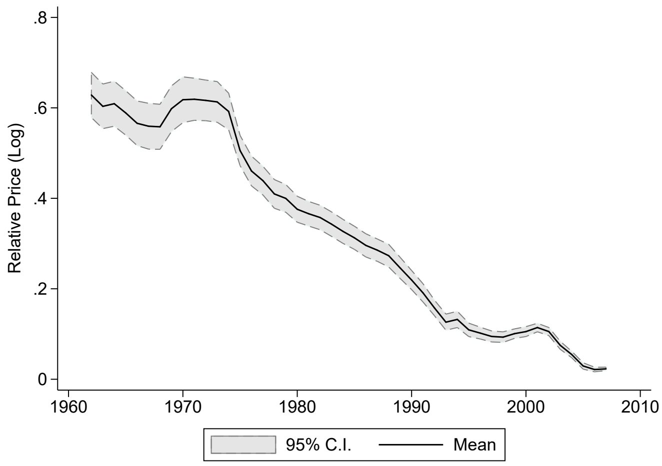
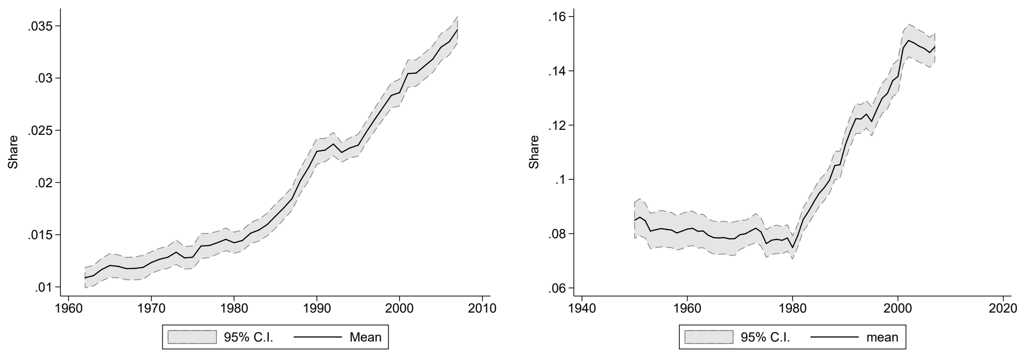


Figure 1.6: Relative price of other assets.

Source: PWT.

Note: Logarithm of relative price of other assets (intellectual property products such as software, databases, and R&D) between 1962 and 2007, averaged across the sample countries.



(a) (b)

Figure 1.7: Investment in other assets as share of (a) GDP and (b) total investments.

Source: PWT.

Note: Investment in other assets (intellectual property products such as software, databases, and R&D), averaged across the sample countries.

volatility between the periods 1984-2007 and 1962-1983. This data is sourced from each country's annual national accounts, obtained from the PWT or the World Bank and filtered through HP filter (with smoothing parameter equal to 100, since we are employing annual data). The second measure of the Great Moderation we use is the ratio of the volatility of year-over-year GDP growth rates between the same periods, with data sourced from the OECD. For this second measure, we report results in Appendix A.6.

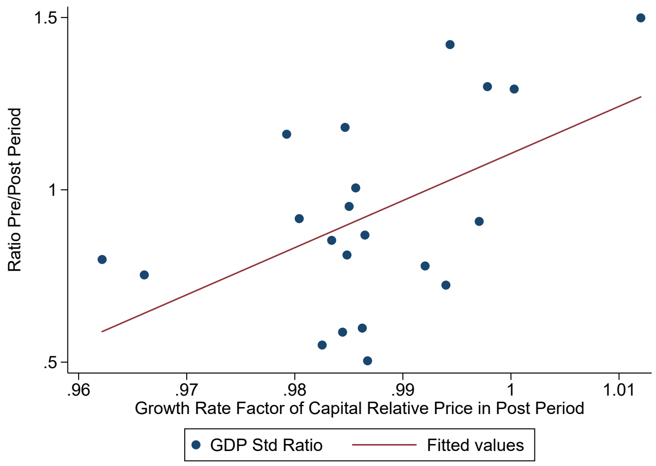


Figure 1.8: Relative price of capital and the Great Moderation.

Source: PWT.
Note: Ratio of real GDP standard deviation between pre- and post-Great Moderation, and relative price growth factor of other assets in the period 1984-2007.

Firstly, we examine the relationship between the Great Moderation variables and the growth of the relative price of capital[4] during the period 1984-2007. As shown in Figure 1.8 (and Figure A.1), there is a positive correlation between the two variables. This implies that countries experiencing a sharper decline in the rel-

[4]From now on, we refer to "other" assets also with the generic term "capital", for the ease of writing.

ative price of capital during the post-1984 period also observed a higher level of the Great Moderation.

Additionally, using data from the PWT, we construct the investment in other assets as a share of GDP and calculate the ratio of this share between 1984 and 2007 to measure the increase in such investment during the post-1980s period. We find that the level of investment is also correlated with the Great Moderation. As shown in Figure 1.9 (and Figure A.2), this investment ratio is negatively correlated with the ratios of GDP volatility and GDP growth volatility, respectively.

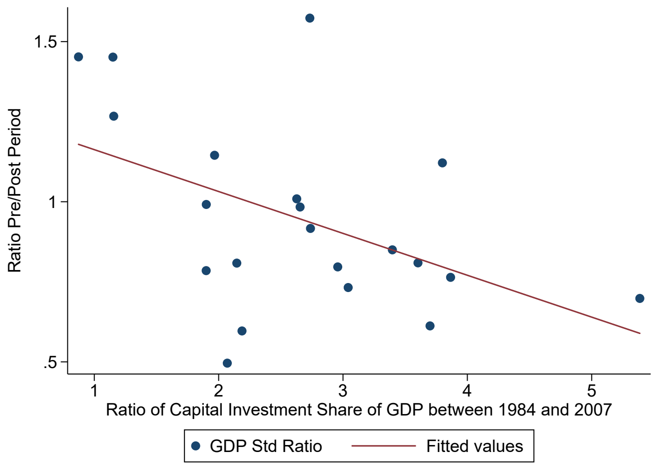


Figure 1.9: GDP share of investment in other assets and the Great Moderation.

Source: PWT.

Note: Ratio of real GDP standard deviation between pre- and post-Great Moderation, and ratio of investment in other assets over GDP between 1984 and 2007.

Furthermore, we report the same graphs using a different measure of the investment ratio. Specifically, we calculate investment in efficiency units by dividing nominal investment by the relative price of capital and then measuring it as a share of GDP. Again, the increase in such investment is shown to be correlated with the decrease in GDP volatility, as seen in Figure 1.10 (and Figure A.3).

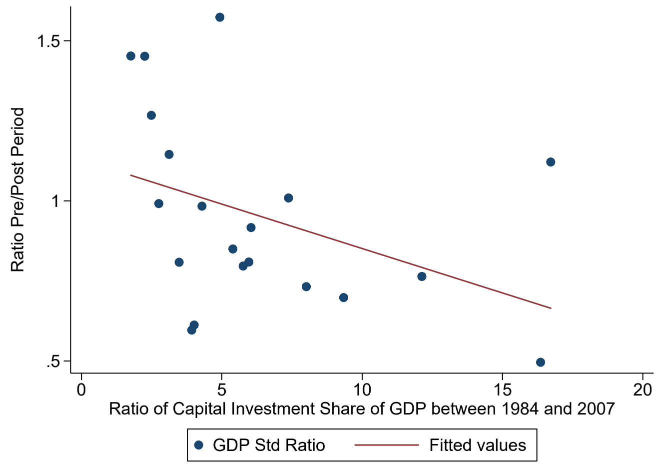


Figure 1.10: GDP share of investment in other assets and the Great Moderation.

Source: PWT.
Note: Ratio of real GDP standard deviation between pre- and post-Great Moderation, and ratio of investment (in efficiency units) in other assets over GDP between 1984 and 2007.

Finally, we calculate the share of investment in other assets as a proportion of total investment and measure the ratio between 1984 and 2007, both in nominal terms and in efficiency units. Figure 1.11 (and Figures A.4 and A.5) shows that this share is correlated with the decrease in GDP volatility. However, there is less evidence of a correlation with the GDP growth rate.

Most of the correlations observed in the graphs are robust to the inclusion of several macroeconomic control variables. In fact, we implement OLS regressions of the Great Moderation variables on the relative price growth factor and the investment share of GDP, respectively. Various models are analyzed, including controls such as the mean of real GDP per capita, the standard deviation of trade openness (measured as the GDP share of imports and exports), the standard deviation of the

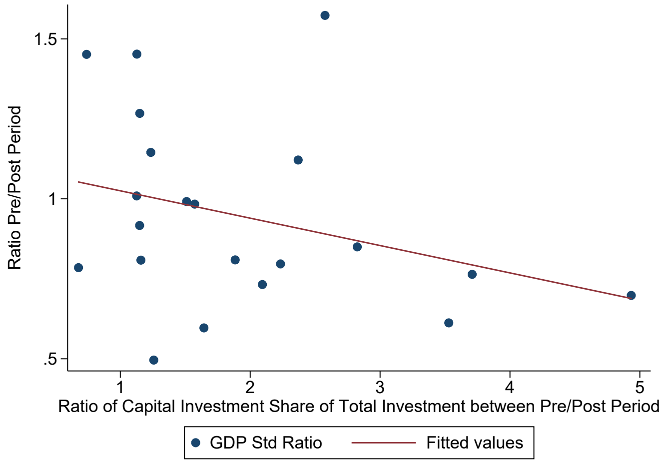


Figure 1.11: Investment in other assets as share of total investment and the Great Moderation.

Source: PWT.

Note: Ratio of real GDP standard deviation between pre- and post-Great Moderation, and ratio of investment in other assets over total investment between 1984 and 2007.

human capital index (based on years of schooling and returns to education), and the standard deviation of CPI inflation and money market interest rates. Means and standard deviations are calculated over the period 1984-2007, with data sourced from PWT, except for inflation and interest rates, which come from the OECD.

As it can be seen in Table 1.6, the relative price factor of other assets is significantly correlated with the decrease in GDP volatility in all models. Actually, most of the controls turn out to be irrelevant. Similarly, the investment share of GDP is significantly correlated with the Great Moderation (see Appendix Table A.1), although this correlation is not robust to the inclusion of all control variables. On the other hand, the investment share of GDP in efficiency units proves to be more robust to the inclusion of control variables (see Appendix Table A.2).

In addition to these results, further support to our theory is provided by ex-

Table 1.6: Relative price of capital and the Great Moderation

	GDP Std Ratio					
Rel. Price	13.66**	12.26*	12.12*	14.40*	18.37**	16.70**
	(5.18)	(6.30)	(6.48)	(6.89)	(7.39)	(6.81)
GDP capita		2.0e-06	2.0e-06	-2.0e-06	-9.0e-07	1.0e-06
		(6.0e-06)	(6.0e-06)	(8.0e-06)	(8.0e-06)	(7.0e-06)
Open Std			0.25	0.21	0.14	0.69
			(0.78)	(0.79)	(0.76)	(0.75)
HC Std				-1.78	-2.17	-2.98*
				(1.80)	(1.79)	(1.68)
CPI Std					0.013	-0.001
					(0.01)	(0.01)
Int Std						0.09*
						(0.04)
Constant	-12.56**	-11.26*	-11.16*	-13.02*	-16.96**	-15.67**
	(5.12)	(6.11)	(6.28)	(6.56)	(7.09)	(6.51)
Obs	21	21	21	21	21	21
R^2	0.27	0.28	0.28	0.32	0.39	0.52

Note: OLS regressions of real GDP standard deviation ratio between pre- and post-Great Moderation on the relative price of capital growth factor in the period 1984-2007, progressively controlling for the mean of real GDP per capita, trade openness, human capital index, CPI standard deviation, and nominal interest standard deviation. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10, + p<0.15.

Table 1.7: Software Capital and the Great Moderation

	Gross Output Std	
Rel. Price	31.30**	
	(13.05)	
Software Investment		-0.013*
		(0.006)
Lab. Productivity	-0.04*	-0.03
	(0.02)	(0.02)
Gross Output	-3.0e-07**	-2.0e-07*
	(1.0e-07)	(1.0e-07)
Constant	-24.34*	4.04+
	(11.99)	(2.58)
Obs	19	19
R^2	0.32	0.26

Note: OLS regressions of real gross output standard deviation ratio between pre- and post-Great Moderation on the software capital relative price growth factor and the software capital investment over gross output ratio between 1984 and 2007, controlling for the mean of labour productivity and gross output. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10, + p<0.15.

amining sectoral data in the US. We utilize data from the EU Klems Growth and Productivity Accounts (2017 release)[5], which include information on the gross fixed capital formation price index (2010=100) and real gross fixed capital formation volume (2010 prices) across industries, according to the ISIC Rev. 4 industry classi-

[5]Available at https://www.rug.nl/ggdc/productivity/eu-klems/.

fication. Specifically, for the software capital, we compute the relative price growth rate factor and the change in investment over gross output ratio during the Great Moderation period, in a similar way as in the cross-country analysis. Then, we regress the real gross output standard deviation ratio between the pre- and post-Great Moderation era on these variables, controlling for for the sectoral mean of real gross output and labour productivity in the post-1984 period. Results are reported in Table 1.7, which shows that the change in relative price of software capital and in its investment share over gross output are significantly correlated with the Great Moderation across US industries.

Our second empirical analysis examines the relationship between a country's proximity to the technological frontier and the moderation in volatility of output growth and inflation. Again, we focus on OECD countries due to the availability of data for both the pre- and post-Great Moderation periods, defined as in the previous empirical analysis. For our analysis of inflation volatility, we further restrict our sample to OECD countries that did not experience chronic high inflation in either period[6].

To measure a country's proximity to the technological frontier, we define a proxy index called the Technological Frontier Index (TFI). This index is the geometric average of four variables closely related to a country's level of technological development: the human capital index (HC), the technological complexity of export products (ExT), GDP per capita ($\overline{GDP}$), and the investment share of software and R&D in the country's total investment ($SoftInv$). Data are taken from PWT, with the exception of ExT, which comes from the World Bank database. Without loss of generality the index is assumed have the following functional form,

$$TFI_i = HC_i^{(1/4)} ExT_i^{(1/4)} \overline{GDP}_i^{(1/4)} SoftInv_i^{(1/4)},$$

[6]For this second part, data availability lets the country list be extended to include also Canada, Chile, Iceland, Israel, New Zealand, Switzerland, and Turkey. For the inflation volatility analysis, Chile, Israel, Mexico, and Turkey will be excluded.

where TFI_i is the Technological Frontier Index of the country i, which is also normalized to be in the range between 0 and 100[7].

As shown in Figure 1.12, this index is highly negatively correlated with the volatility of output growth for the sample countries. This is consistent with the main hypothesis of the model, which suggests that countries closer to the technological frontier experience smoother fluctuations due to a higher need for learning. According to the figure, countries closest to the frontier (with an index close to 100) experienced roughly half the volatility compared to those furthest from the frontier. The correlation between output growth volatility and the technological frontier index is -0.61.

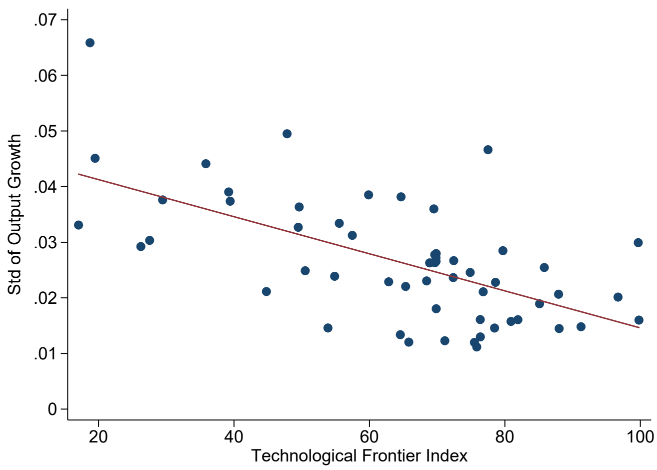


Figure 1.12: Technological Frontier Index and Output Growth Volatility.

Source: PWT and World Bank.

Note: Standard deviation of real GDP growth and Technological Frontier Index in pre- and post-Great Moderation periods.

Similarly, Figure 1.13 shows the relationship between the Technological Frontier

[7]For each country i, TFI_i is normalized as follows: $100 * (1 + \frac{TFI_i - \max(TFI_i)}{\max(TFI_i)})$.

Index and inflation volatility. As hypothesized by our model, there is a strong negative correlation between the two. However, this relationship appears more nonlinear across the entire range of the Technological Frontier Index. The correlation coefficient between these two variables is approximately -0.77.

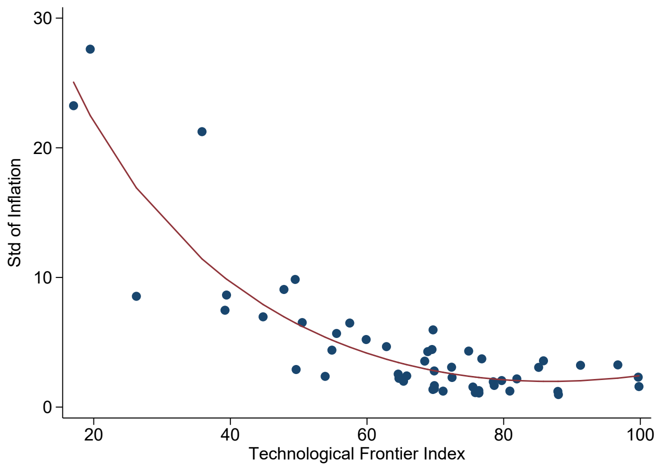


Figure 1.13: Technological Frontier Index and Inflation Volatility.

Source: PWT, OECD, and World Bank.

Note: Standard deviation of Inflation and Technological Frontier Index in pre- and post-Great Moderation periods.

Moreover, Appendix Figure A.6 distinguishes this last relationship between the pre- and post-Great Moderation periods. The red dots represent the post-Great Moderation years, while the blue dots represent the years before this period. It appears that there has been no significant change in the relationship between the two eras. This consistency aligns with our model, which suggests that the distance to the technological frontier affects the learning need similarly in both periods. This justifies our use of a constant parameter for both the pre- and post-Great Moderation periods.

1.6.1 Regression Analysis

We conduct two regression analyses to explore the determinants of output growth volatility and inflation volatility across the sample countries in the two different time periods (pre-Great Moderation and post-Great Moderation era).

For the first analysis (volatility of output growth), we consider the following explanatory variables: CPI inflation, real GDP growth rate, share of services, central bank independence index, trade openness, macroprudential index, an era dummy (1 for the pre-Great Moderation period, 0 for the post-Great Moderation period), and the Technological Frontier Index (TFI) interacted with the era dummy. Data are provided by PWT or OECD as previously stated, with the exception of the share of services from the World Bank, the central bank independence index from Romelli (2022), and the macroprudential index from Cerutti et al. (2017).

We test nine models, presented in Table 1.8. In model 1, we include all explanatory variables. Four variables, i.e., average CPI inflation, average GDP growth rate, and the Technological Frontier Index (TFI) interacted with the era dummy variable, are found to be significant. The R^2 of this regression is close to 0.82. In the next two regression models, we progressively eliminate the insignificant variables, reaching model 3, where five variables, i.e., average CPI inflation, average GDP growth rate, TFI interacted with the era dummy variable, and the macroprudential index (MPI), are significant, with a regression R^2 equal to 0.805.

From the regression results, the explanatory power of these variables is as follows: 25% for both means of CPI inflation and GDP growth rate, while approximately 16% for the MPI, and around 33% for our TFI. For the US, the contribution of the TFI increases to 37%. It must be noticed that the relationship between the standard deviation of the growth rate and the average growth rate is almost inherent to the process, as seen in the Appendix Figure A.7.

Table 1.8: Technological Frontier Index and the Great Moderation

	Output Growth Std								
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TFI*Pre	-0.0002***	-0.0002***	-0.0002***	-0.0004***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***
	(0.0001)	(5.0e-05)	(4.0e-05)	(7.0e-05)	(6.0e-05)	(5.0e-05)	(7.0e-05)	(6.0e-05)	(5.0e-05)
TFI*Post	-0.0002***	-0.0002***	-0.0002***	-0.0003**	-0.0003**	-0.0003***	-0.0003**	-0.0003**	-0.0004***
	(0.0001)	(6.0e-05)	(4.0e-05)	(0.0001)	(0.0001)	(6.0e-05)	(0.0001)	(0.0001)	(5.0e-05)
GDP growth	0.3161***	0.3018***	0.3039***	0.2063**	0.1821**	0.1918**	0.0045	0.0043	0.2043**
	(0.0641)	(0.0602)	(0.0593)	(0.0921)	(0.0845)	(0.0867)	(0.0033)	(0.0032)	(0.0878)
CPI Inflation	0.0003***	0.0003***	0.0003***						
	(1.0e-05)	(4.0e-05)	(4.0e-05)						
Services	0.0001			0.0001			-4.0e-05		
	(0.0001)			(0.0002)			(0.0002)		
Open	0.0027			0.0029	0.0036	0.0039			
	(0.0022)			(0.0033)	(0.0031)	(0.0032)			
CBI	-0.0044			-0.0080	-0.0090	-0.0118*	-0.0095	-0.0093	
	(0.0044)			(0.0067)	(0.0065)	(0.0065)	(0.0069)	(0.0068)	
MPI	-0.0012	-0.0012	-0.0013*	-0.0014	-0.0014		-0.0014	-0.0014	
	(0.0008)	(0.0008)	(0.0007)	(0.0016)	(0.0016)		(0.0016)	(0.0016)	
Pre	0.0014	0.0017		0.0097	0.0081		0.0088	0.0093	
	(0.0058)	(0.0056)		(0.0115)	(0.0112)		(0.0119)	(0.0116)	
Constant	0.0193*	0.0251***	0.0261***	0.0312*	0.0405***	0.0447***	0.0481***	0.0458***	0.0399***
	(0.0105)	(0.0053)	(0.0040)	(0.0178)	(0.0113)	(0.0056)	(0.0169)	(0.0115)	(0.0048)
Obs	56	56	56	56	56	56	56	56	56
R^2	0.821	0.805	0.805	0.621	0.616	0.576	0.575	0.575	0.539

Note: OLS regressions of real GDP y-o-y growth rate standard deviation on TFI interacted with the pre- and post-Great Moderation, controlling for real GDP y-o-y growth rate, CPI inflation, share of services, trade openness, central bank independence index, macroprudential index, and the pre-Great Moderation dummy, depending on the model. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10, + p<0.15.

Including the average level of inflation, which turns out to be quite significant with high explanatory power, might be problematic. According to our theory, if the central bank does not account for the learning process, it will behave more hawkishly, resulting in lower inflation.

To overcome this potential problem in the subsequent regression models we exclude the average inflation from the set of explanatory variables. The resulting final regression with all variables siginificant has the following variables: average GDP growth rate, and TFI interacted with the era dummy variable. The R^2 of the final regression is 54% and TFI interacted with the era dummy variable gets almost 90% explanatory power.

Finally, for the second analysis (volatility of inflation), we consider the following variables: average CPI inflation, standard deviation of real GDP growth, average real GDP growth rate, average share of services, central bank independence index, average trade openness index, macroprudential index, an era dummy (1 for pre-Great Moderation period, 0 for post-Great Moderation period), and the Technological Frontier Index.

We evaluate seven models, which are reported in Table 1.9. In the model 1, we include all variables, resulting in strong explanatory power with an R^2 close to 0.92. As expected, average inflation is highly significant, along with other significant variables such as the standard deviation of real GDP growth, average growth rate, and the Technological Frontier Index, which is strongly significant with a *t-value* slightly above 3.

In the following three models, i.e., models 2, 3, and 4, we gradually eliminate the insignificant variables. This way, in the simplest model 4, we retain only the four significant variables, and the R^2 remains high at around 0.91. According to model 4, approximately 85% of the moderation in inflation volatility can be attributed to the lower inflation level in the post-Great Moderation period, while the distance to the technological frontier (TFI) explains about 9% of the reduction. Additionally, lower volatility in GDP growth accounts for around 35% of the moderation, as it is predicted by our theory as well. However, slower average growth in the post-period economies actually contributes to an increase in inflation volatility by approximately 26%.

Table 1.9: Technological Frontier Index and the Great Moderation

	Inflation Std						
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TFI	-0.065***	-0.059***	-0.067***	-0.069***	-0.206***	-0.197***	-0.19***
	0.021	0.019	0.018	0.018	0.032	0.028	0.027
CPI Inflation	0.435***	0.432***	0.437***	0.455***			
	0.046	0.044	0.044	0.043			
GDP growth Std	91.04*	101.37**	80.31*	81.27*			
	49.92	46.5	42.19	42.57			
GDP growth:	-78***	-81.51***	-76.67***	-64.06***	-85.26*	-87.69**	-86.01***
	27.81	26.81	26.46	25.00	44.63	43.81	42.18
Services	-0.081	-0.083*	-0.055		-0.184*	-0.196**	-0.22**
	0.052	0.048	0.040		0.099	0.083	0.075
CBI	-1.18				-1.29	-1.34	
	1.481				2.93	2.32	
Open	-0.15				-0.5	-0.32	
	0.74				1.45	1.41	
MPI	-0.194				-0.41		
	0.267				0.52		
Pre	-1.282+	-0.707			-0.475		
	0.848	0.661			1.65		
Constant	11.97***	10.43***	9.32***	5.76***	24.95***	32.78***	32.70***
	3.79	3.32	3.16	1.78	5.35	5.02	4.75
Obs	51	51	51	51	51	51	51
R^2 :	0.919	0.917	0.915	0.911	0.662	0.657	0.653

Note: OLS regressions of CPI inflation standard deviation on TFI, controlling for CPI inflation, real GDP y-o-y growth rate standard deviation, real GDP y-o-y growth rate, share of services, central bank independence index, trade openness, macroprudential index, and the pre-Great Moderation dummy, depending on the model. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10, + p<0.15.

What do our results indicate so far? First, the simulation results from our NK DSGE model also suggest a lower impact of increased learning on explaining the moderation in inflation volatility compared to the moderation in economic activity. However, including average inflation and the standard deviation of GDP growth in the regression could lead to an underestimation of the effect of TFI, since our theory predicts a reduction in both due to the increased learning process in the post-Great Moderation era.

Additionally, there tends to be a mechanical relationship between the volatility and the level of any variable. Appendix Figure A.8 illustrates this relationship between the level and the volatility of inflation for the sample economies studied in the pre- and post-Great Moderation periods.

To address the potential problems discussed above, in the last three models (5, 6, and 7), we exclude average inflation and the standard deviation of GDP growth from our regressions. Then, we gradually eliminate the insignificant remaining variables. As a result, in model 7, we end up with three significant variables: average real GDP growth rate, average share of services, and the Technological Frontier Index, with an overall R^2 of 65%.

Interestingly, when we exclude the two variables mentioned above, the share of the service sector becomes quite significant, with a *t-value* of 2.87. Examining the explanatory power of the three variables, we see that TFI's explanatory power increases to 26%, which is closer to our simulation results. The share of the service sector now accounts for the bulk of the explanatory power, at 94%, while the lower average growth in the post-period contributes to an increase in inflation volatility of around 35%.

1.7 Conclusion

We propose a link between rapid technological progress following a technological revolution and the subsequent moderation in the volatilities of economic activity and inflation. During the early phases of technological revolutions and periods of rapid technological adoption, new technologies necessitate significant investment in learning and reorganization. Economies close to the technological frontier are particularly vulnerable to this disruption, resembling creative destruction. As a result, the nature of business cycles in these economies change: expansions become milder and longer, recessions are also milder, and overall cycles become more moderate.

We begin by modeling a vintage capital RBC model with technological learning. Simulation results of the calibrated model show significant moderation in real economic variables due to the accelerated pace of technological progress. Next, to study the impact on nominal variables and monetary policy, we extend the model to a New Keynesian DSGE framework. Thus, we develop a vintage capital NK DSGE model with technological learning. In this model, real variables show further moderation, but the moderation in inflation is modest, accounting for about 20% of the moderation observed in the data. However, if we assume that the central bank in the economy fails to adequately recognize the learning process, it becomes overly hawkish in its policy decisions due to the mismeasurement of potential output. Consequently, the model shows much higher moderation in nominal variables as well.

In our empirical work using cross-country panel data, we test the main assumptions and implications of our model. Consistent with our hypothesis, countries experiencing higher relative price declines and investing more in software capital tend to exhibit greater moderation. Moreover, countries close to the technological frontier tend to experience more significant reductions in the volatility of economic growth and inflation. The variables central to our hypothesis can account for a substantial portion of the moderation in real and nominal economic variables.

Chapter 2

CENTRAL BANK CREDIBILITY: ANCHOR TO STABILITY

2.1 Introduction

Central bank credibility (CBC) is crucial for successfully implementing monetary policy. A reliable central bank can persuade the economic agents that the long-term inflation rate will meet the target and that prices will stabilize, thus integrating this trust into their expectations during decision-making. Although, undoubtedly, CBC is a fundamental tool for effective monetary policy, its definition is not unanimous, particularly if we consider both developed and emerging countries.

During the Jackson Hole meetings, Blinder (2012) defines the main two ingredients for CBC:

> *"Credibility means believability and trust. You build it by matching deeds to words."*

CBC is a complex yet essential component of agents' expectations. Without it, we would hardly witness anchored inflation expectations in developed countries, especially during strong macroeconomic shocks. Even in emerging countries, where inflation forecasts are mostly indexed to current inflation, CBC provides more stable forecasts. However, its ambiguous definition makes it hard to include CBC in forecast models. Hence, this fundamental component is missed in typical monetary models, increasing the risk of bias in predicting future levels of inflation.

We can, however, synthesize CBC as the product of two elements, as suggested in the above citation: beliefs and deeds. In fact, CBC is linked to agents' beliefs about the actual objective of the monetary policy authority. More precisely, agents believe whether the central bank focuses on price stability or, instead, it cares mostly about output growth and stabilization. In addition, agents observe the central bank's actions, which are the second element of CBC. If economic agents believe that the central bank does not prioritize price stability and, subsequently, it is seen to implement expansionary monetary policy, this will further decrease CBC in stabilizing prices. The opposite would happen if, given agents' beliefs, the central bank would undertake a tightening policy. These fundamental characteristics are at the basis of CBC in both developed and emerging economies, as we show in our estimation results.

CBC helps the central bank anchor inflation expectations, which is vital for targeting inflation. Yellen (2006) remarked that with a credible central bank, "the markets do all the work of monetary policy", as market participants act based on accurate predictions of the central bank's actions. Conversely, weak CBC complicates inflation targeting due to the challenge of managing inflation expectations, hence increasing inflation volatility.

In most of the emerging markets, it is harder to establish CBC due to higher initial inflation levels, weaker institutions, greater macroeconomic and political instability, and increased vulnerability to external shocks. Consequently, inflation expectations are generally unanchored and result in more volatile inflation rates and GDP growth, as explained by Fraga et al. (2003).

Our study provides a comprehensive definition of CBC that is valid for both developed and emerging countries, and we analyze its effect on long-term inflation forecasts. In this paper, we develop a measure of CBC in a New Keynesian framework with agents' imperfect knowledge about the central bank targets. In particular, agents do not know the true central bank's inflation target and the effective weight on price stability relative to the output gap.

The macroeconomic literature on nonrational expectations is huge. Mankiw et al. (2003) highlight the concept of "sticky information", where agents update their expectations infrequently due to costs or cognitive limitations, leading to a slower adjustment to new information. Moreover, Marcet and Nicolini (2003) analyze the determinants of recurring hyperinflation episodes and show that their model of boundedly rational learning matches some crucial stylized facts about episodes of hyperinflation in several countries in the 1980s. In addition to these, Milani (2014) implements Bayesian methods to estimate a New Keynesian model with nonrational expectations and learning, arguing that the mechanism that endogenously generates persistence in the economy is based on the learning process of agents. We insert our theoretical measure of CBC in this literature and, to our knowledge, we are the first to micro-found CBC in a macroeconomic model of imperfect expectations and inflation forecasts and to empirically test it.

Our measure of CBC is computed in the context of the imperfect knowledge New Keynesian model proposed by Carvalho et al. (2023) (CEMP). The authors are the first to test the endogenous link between long-term expectations and short-term forecast errors, showing the power of such a link in predicting observed long-term inflation expectations of professionals. We insert our study in this field and test the predictive power of CBC regarding long-term inflation expectations both for the US and for an emerging economy, i.e., Turkey. For both countries, we employ surveys about professionals' short- and long-term inflation expectations, as well as official data on CPI. Moreover, as explained in Section 2.4, we also employ GDP data to calibrate the agents' belief updates about CBC.

Thanks to Bayesian estimation, we show that the predicted long-term inflation expectations are well explained by CBC in both US and Turkey. Moreover, CBC is found to be a predictor of long-term expectations anchoring. In particular, we find that during the recent energy price shock, US inflation expectations remained stable thanks to an increase in CBC, while Turkey experienced a deterioration in CBC, which implied unanchored and highly volatile forecasts.

Therefore, our study contributes to CBC's micro foundation, characterizing it with a measure that helps predict anchoring and long-term inflation forecasts in both advanced and developing economies. Our CBC measure can then become a tool to assess central bank credibility and effectiveness, and it can be used to analyze CBC implications for economic performance.

The related literature shows that a central bank with weak credibility faces heightened inflationary expectations, leading to lower employment and less expansionary policy (Faust and Svensson (2001)). Moreover, gaining credibility improves the trade-off between inflation and the output gap, which is particularly problematic during large energy shocks, as in current years. As credibility strengthens, inflation expectations align with the central bank's target rather than past inflation trends, allowing price stability to be achieved mainly through expectations with fewer adjustments in policy instruments (Tronzano (2005)). This is exactly what we find happening in the US, where credible and prompt action by the Federal Reserve in facing the surge of energy prices increased its CBC and kept inflation expectations anchored; hence, inflation recovered fast to the current reasonable levels. The opposite happened in Turkey, where the monetary policy worsened agents' expectations and CBC, resulting in huge inflation expectations volatility and high inflation rates in recent years.

Our measure provides a comprehensive definition of CBC, which can be applied to all types of economies. Despite the importance of credibility in achieving inflation goals, existing credibility measures in the literature mainly focus on environments where price stability is already present. Therefore, these measures fail to capture the credibility dynamics in emerging countries where CBC is probably most needed. In scenarios where expectations are well anchored, credibility is typically defined as a situation where inflation expectations are insensitive to news releases and monetary policy actions (see, e.g., Gürkaynak et al. (2006); Demertzis et al. (2012)). However, in an inflationary environment, as is typical in emerging economies, inflation expectations are usually indexed to the actual inflation rate. Hence, the previously mentioned definition of credibility may not distinguish between weak and weaker credibility in this context.

A definition of CBC in the context of an inflationary economy was given by Goodfriend (1993), who defined CBC as a decline in long-term interest rates during the inflationary period of 1979-1982 in the US. In fact, long-term interest rates serve as a proxy for inflation expectations at the daily frequency. Hence, a decline in inflation expectations due to monetary policy decisions, net of the temporary inflation rate fluctuations, can be considered as a sign of credibility.

Our methodology of computing CBC as the product of agents' belief about the central bank focus on price stability and the monetary policy conduct can incorporate different economic environments and explain why a certain country features anchored or unanchored expectations. Moreover, our model shows that an improvement in CBC leads to anchored expectations and a stabilization of the inflation rate.

The rest of the paper is structured as follows: Section 2.2 presents the theoretical framework and our measure of CBC; Section 2.3 reports the used data, while Section 2.4 describes the estimation procedure; then, Section 2.5 discusses our results and Section 2.6 concludes.

2.2 The Theoretical Framework

We define central bank credibility (CBC) in the context of a New Keynesian model with imperfect knowledge, structured as in Carvalho et al. (2023) (CEMP) model of long-run inflation expectations. We extend this family of models, including time-varying agents' beliefs about the central bank's target rule: particularly, we add uncertainty about the weight of output gap stabilization in the monetary policy rule. This leads to a measure of CBC that will impact long-term inflation expectations, as it is described in this section.

2.2.1 The Economic Environment

There is a continuum of monopolistic competitive firms facing a price-setting problem subject to quadratic adjustment costs as in Rotemberg (1982).

Firms set optimal price P_{ft} to maximize their expected present discounted value of real revenues:

$$\hat{E}_t \sum_{t=0}^{\infty} \Lambda_t \left[\left(\frac{P_{ft}}{P_t} - S_t \right) \left(\frac{P_{ft}}{P_t} \right)^{-\Psi_t} Y_t - \frac{\Phi}{2} \left(\frac{P_{ft}}{P_{ft-1}} - e^{\gamma \pi_{t-1}} \right) \right]$$

where P_t and Y_t are aggregate price and output, respectively, while S_t are real marginal costs. Moreover, firms consider an exogenous time-varying elasticity of demand across goods from a CES demand function and quadratic adjustment costs indexed to past log inflation. Future revenues are discounted by a stochastic discount factor Λ_t.

From the first-order condition of firm price setting problem, we recover the optimal price equation:

$$\Lambda_t \left[\left(\frac{P_{ft}}{P_t} \right)^{-\Psi_t} Y_t - \left(\frac{P_{ft}}{P_t} - S_t \right) \left(\frac{P_{ft}}{P_t} \right)^{-\Psi_t - 1} \Psi_t Y_t - \Phi \left(\frac{P_{ft}}{P_{ft-1}} - e^{\gamma \pi_{t-1}} \right) \frac{P_t}{P_{ft-1}} \right]$$

$$+\Lambda_{t+1} \left[\Phi \left(\frac{P_{ft+1}}{P_{ft}} - e^{\gamma \pi_t} \right) \frac{P_{ft+1} P_t}{P_{ft}^2} \right] = 0$$

Then, taking a log-linear approximation of the optimal price equation around the zero-inflation steady state and aggregating in a symmetric equilibrium, where firms set identical prices and hold the same beliefs, provides the following aggregate supply curve:

$$\pi_t - \gamma \pi_{t-1} = \mu_t + \hat{E}_t \sum_{t=0}^{\infty} (\alpha \beta)^t [\xi s_t + (1 - \alpha) \beta (\pi_{t+1} - \gamma \pi_t)] \tag{2.1}$$

where π_t is log inflation, s_t is log deviation of marginal costs from the steady state value, and μ_t is a normally distributed and serially independent markup shock, function of the time-varying demand elasticity[1]. Finally, α is the model's stable eigenvalue.

As for the demand side, the representative household maximizes their present discounted value of utility over consumption (C_t) and labour (L_t):

$$\hat{E}_t \sum_{t=0}^{\infty} \beta^t \left[ln(C_t - L_t\right]$$

s.t.

$$P_t C_t + B_t \leq R_{t-1} B_{t-1} + W_t L_t + P_t \Pi_t$$

and

$$C_t = \left[\int_0^1 C_t(j)^{\frac{\Psi_t - 1}{\Psi_t}} dj\right]^{\frac{\Psi_t}{\Psi_t - 1}}$$

where B_t, R_t, W_t, and Π_t are one-period bonds, the interest rate on bonds, wages, and profits from owning firm shares, respectively. The household problem is like in a textbook New Keynesian model[2], where total consumption C_t is a CES function over the continuum of differentiated goods. Hence, the Euler equation is the following (log-linearized):

$$\hat{c}_t = \hat{E}_t \left[\hat{c}_{t+1} - (i_t - \pi_{t+1})\right]$$

and the labour supply equation is derived as follows:

$$\frac{W_T}{P_T} = w_T = C_T$$

[1] From the log-linearization of the firm optimal price equation, $\mu_t = -\xi \frac{\hat{\psi}_t}{\psi - 1}$, where $\hat{\psi}_t$ is the log deviation of the demand elasticity from the steady state value.

[2] See Galí (2015).

2.2.2 Equilibrium

Output is produced by the following production function where the only input is labour to keep computation light:

$$Y_t = A_t L_t$$

It also corresponds to total consumption, net of aggregate adjustment costs:

$$Y_t + \frac{\Phi}{2}\left(\frac{P_t}{P_{t-1}} - e^{\gamma\pi_{t-1}}\right) = C_t$$

Finally, in this framework, the marginal costs are proportional to consumption:

$$S_t = \frac{w_t}{A_t} = \frac{C_t}{A_t}$$

Therefore, log-linearizing the above equality, we derive the following path for marginal costs, which implies that real marginal costs are constant under flexible prices:

$$\hat{s}_t = \hat{c}_t - \hat{a}_t = \hat{y}_t - \hat{a}_t$$

We can, then, assume that $\hat{s}_t$ in the aggregate supply curve is equal to the output gap x_t.

2.2.3 Monetary Policy

The monetary authority is a central bank implementing optimal monetary policy under discretion, taking into account the structure of the model. The target rule is the following:

$$\pi_t - \gamma\pi_{t-1} + \lambda x_t = \phi_t \tag{2.2}$$

where

$$\phi_t = \rho\phi_{t-1} + \epsilon_t$$

Giannoni and Woodford (2002) show that this criterion is the optimal policy under discretion, given the assumption that the central bank has a zero inflation target.

In this context, monetary policy shock can be viewed as policy mistakes (misunderstanding of the underlying inflation and output gap) or due to the loosening and tightening of monetary policy. Positive ϕ_t refers to an expansionary monetary policy, whereas negative ϕ_t implies a contractionary monetary policy. It could also be seen as communication in one or the other direction.

2.2.4 Agents' Expectations

Here, the core of the model is discussed, and the definition of CBC is introduced.

Agents are characterized by imperfect knowledge about the central bank inflation target (we call the expected inflation target $\bar{\pi}_t$) and the central bank weight on output gap stabilization relative to inflation (λ in equation 2.1, and we call the expected weight $\bar{\lambda}_t$). Imperfect knowledge about the central bank target inflation was introduced by CEMP. Further, we add imperfect knowledge about the importance that the central bank gives to output gap stability with respect to inflation. As we show in the following paragraphs, this gives room to introduce a definition of CBC into the New Keynesian framework. To simplify calculations, we follow CEMP and focus on the anticipated utility solution of the model, which implies that $\hat{E}_t\bar{\pi}_T = \bar{\pi}_t$ for each $T > t$.

Under perfect rationality, expectations would be as follows:

$$\pi_t = \gamma\pi_{t-1} + \frac{\xi}{\xi + \lambda(1-\beta\rho)}\rho\phi_{t-1} + \eta_t$$

where

$$\eta_t = \frac{\lambda}{\lambda + \xi}\mu_t + \frac{\xi}{\xi + \lambda(1-\beta\rho)}\epsilon_t$$

Under imperfect knowledge, instead, expectations are a function of agents' imperfect information (nesting the case of rational expectations):

$$\pi_t = \gamma\pi_{t-1} + (1-\gamma)\bar{\pi}_t + \frac{\xi}{\xi + \bar{\lambda}_t(1-\beta\rho)}\rho\phi_{t-1} + f_t$$

where f_t is the imperfect expectations forecast error. Similar to CEMP, given the above equation, the expectations about the target inflation are equal to long-term inflation expectations:

$$\lim_{T \to \infty} \hat{E}_t \pi_T = \bar{\pi}_t$$

2.2.5 The True Data Generating Process

From the aggregate supply curve 2.1 and leveraging imperfect expectations, the true data generating process becomes:

$$\pi_t = \gamma \pi_{t-1} + (1-\gamma)\Gamma \bar{\pi}_t + f(\bar{\lambda}_t)\phi_t + \tilde{\mu}_t \tag{2.3}$$

where

$$\Gamma = \frac{(1-\alpha)\beta\lambda}{(1-\alpha\beta)(\lambda+\xi)}$$

$$\tilde{\mu}_t = \frac{\lambda}{\lambda+\xi}\mu_t$$

and

$$f(\bar{\lambda}_t) = \frac{\xi}{\xi+\lambda} + \frac{\alpha\beta\rho\xi\lambda}{\bar{\lambda}_t(\lambda+\xi)(1-\alpha\beta\rho)}$$

$$-\left(\frac{\alpha\beta\xi\lambda}{\bar{\lambda}_t(\xi+\lambda)} - \frac{\beta\lambda(1-\alpha)}{\xi+\lambda}\right)\frac{\xi\rho}{[\xi+\bar{\lambda}_t(1-\rho\beta)](1-\alpha\beta\rho)}$$

is a positive (and decreasing) function of $\bar{\lambda}_t$. This relationship gives some initial hint that monetary policy shocks have a different impact on inflation depending on agents' beliefs about the output gap stabilization weight of the central bank. Please see Appendix B.1 for the derivation of equation 2.3.

2.2.6 Learning Process and Central Bank Credibility

In the previous subsections, we introduced the theoretical framework, showing that agents have imperfect knowledge about the central bank inflation target and the policy weight on output stabilization. In the following, we explain how these expectations are formed and show how this leads to the role of central bank credibility.

Learning Process of $\bar{\pi}_t$

Following CEMP, long-term inflation expectations develop through a recursive update, where old beliefs are updated by agents' short-term inflation forecast error, weighted by a learning gain, as follows:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + K_t^{-1} f_{t-1}$$

where the forecast error is derived from imperfect agents' expectations about next period inflation:

$$f_t = (1-\gamma)(\Gamma-1)\bar{\pi}_t + g(\bar{\lambda}_t)\rho\phi_{t-1} + \tilde{\mu}_t + f(\bar{\lambda}_t)\epsilon_t \tag{2.4}$$

and the reciprocal of the learning gain is:

$$K_{t+1} = (K_t + 1)I_{\nu_t<\bar{\nu}} + \bar{g}^{-1}(1 - I_{\nu_t<\bar{\nu}})$$

When expectations are defined as anchored (when they are below the threshold $\bar{\nu}$), the learning gain decreases over time, providing decreasing weight to current inflation forecast errors. Therefore, news about inflation and shock to monetary policy is increasingly irrelevant for agents' expectation formation, which remains stable at $\bar{\pi}_t$. This is exactly the definition of CBC in developed countries, where expectations are mostly anchored and, hence, credibility is typically defined as the case in which inflation expectations are insensitive to news releases and monetary policy actions. Instead, when inflation expectations are unanchored, they update through a constant gain ($\bar{g}^{-1}$), and new forecast errors and monetary policy actions become relevant.

In the following, we provide a micro-foundation of CBC. As stated above, CBC implies anchored inflation expectations in developed economies. However, this definition cannot be generalized to developing countries, where inflation expectations are mostly indexed to current inflation (see Çakmaklı and Demiralp (2020)). In developing countries, where most economies are in inflationary trends, CBC should be defined as the power to affect expectations and stabilize them towards low inflation targets. Moreover, CBC is a combination of agents' beliefs and authority action: the latter aims to effectively influence the formers to meet inflation targets.

Hence, we define CBC as the central bank's power to effectively stabilize expectations to low inflation targets in an unanchored expectations environment until the anchored expectation equilibrium is reached. Once that equilibrium is reached, CBC is needed to keep expectations anchored effectively.

The theoretical model helps us introduce this general definition of CBC. In fact, in a similar fashion as in CEMP, the anchoring threshold is the following:

$$\nu_t = \frac{|\hat{E}_{t-1}\pi_t - E_{t-1}\pi_t|}{\sigma} = \frac{|(1-\gamma)(\Gamma-1)\bar{\pi}_t + g(\bar{\lambda}_t)\rho\phi_{t-1}|}{\sigma} \tag{2.5}$$

where $\hat{E}_{t-1} - E_{t-1}$ is the difference between imperfect and perfect rational expectations, while σ is the standard error of the exogenous shocks $(f(\bar{\lambda}_t)\phi_t + \tilde{\mu}_t)$. As shown by CEMP, the anchoring threshold is a function of the observable forecast errors. Furthermore, from equation 2.5, it can be noticed that it depends on long-term inflation expectations and the product of a function of agents' beliefs about the monetary policy output stabilization weight and the monetary policy trend. This last element is the CBC factor emerging from the model.

Expanding the New Keynesian model with imperfect knowledge, introducing imperfect information about the monetary policy rule, in particular, the central bank's weight on output stability with respect to inflation, lets long-term inflation forecasts be affected by this extra element, which plays the role of CBC that we explained above.

Analyzing CBC more in detail:

$$g(\bar{\lambda}_t) = f(\bar{\lambda}_t) - \frac{\xi\rho}{\xi + (1-\beta\rho)\bar{\lambda}_t}$$

is an increasing function of $\bar{\lambda}_t$, negative (positive) for lower (higher) values of $\bar{\lambda}_t$, with zero point when $\bar{\lambda}_t = \lambda$. Therefore, if agents believe that the central bank focus on output stability relative to inflation is high ($g(\bar{\lambda}_t)$ positive) and the central bank is conducting an expansionary monetary policy (ϕ_{t-1} positive), this combination of beliefs and policy will make the central bank less credible and push expectations above the anchoring threshold, favoring unanchored expectations and higher and more volatile inflation forecasts.

It is important to notice that CBC is not the result of solely agents' beliefs or monetary policy, but it is their product. A certain policy is proper to stabilize inflation expectations depending on the current agents' beliefs. Typically, in an inflationary environment, $\bar{\lambda}_t$ will be high, and a central bank will need to implement a contractionary monetary policy to be credible. On the other hand, if people believe that the central bank is not sufficiently taking into account output stability ($\bar{\lambda}_t$ low), an expansionary monetary policy will increase central bank credibility and avoid volatile unanchored long-term inflation expectations.

The CBC presented in this paper is related to both developed and developing countries. In developed countries, it is the element that helps keep expectations anchored, allowing the monetary authority to implement policies without affecting expectations. In emerging countries, instead, it is the element that helps the central bank to faster reach anchored inflation expectations and, hence, lower inflationary trends.

Learning Process of $\bar{\lambda}_t$

Finally, we present agents' learning process about the monetary policy output gap weight λ. As in the case of the inflation target, agents have imperfect knowledge, and they develop their beliefs about λ as a weighted average of their previous beliefs and an updated estimate of λ. To recursively measure λ, agents behave as econometricians, being aware of the monetary policy rule structure. In fact, agents feature imperfect knowledge only about the target inflation and λ, while they have perfect information about the rest of the economic environment. So, they estimate λ from the previous period realization of inflation and output gap.

Hence, the expectation of the weight on output gap stability ($\bar{\lambda}_t$) is computed as follows, where ω is a constant weight:

$$\bar{\lambda}_t = \omega\bar{\lambda}_{t-1} + (1-\omega)\left|\frac{SD(\pi_{t-1})}{SD(x_{t-1})}Corr(\pi_{t-1}, x_{t-1})\right|$$

where the updating term is derived from a regression of the monetary policy rule on realized inflation and output gap, given agents' beliefs on long-term inflation:

$$\pi_{t-1} - \bar{\pi}_{t-1} = \gamma(\pi_{t-2} - \bar{\pi}_{t-1}) - \lambda x_{t-1} + \phi_{t-1}$$

From the above regression $\lambda = -\frac{SD(\pi_{t-1})}{SD(x_{t-1})}Corr(\pi_{t-1}, x_{t-1})$, where SD and $Corr$ stand for standard deviation and correlation coefficient, respectively. As we explain in Section 2.4, we calibrate $\bar{\lambda}_t$ based on this regression. Theoretically, λ could be estimated as negative from this regression, and it happens sometimes in our estimations. However, given that λ is a weight, we assume that agents employ the absolute term of the coefficient to update lambda.

2.2.7 Discussion about Central Bank Credibility

As explained above, CBC is the product of monetary policy stance and agents' beliefs about central bank weight on output stability relative to inflation. Moreover, it must be noticed that ϕ_{t-1} is included in CBC, not ϵ_t, the current shock to monetary policy. This implies that the trend of monetary policy actions (remember that ϕ_t is an AR(1) process) affects CBC and inflation anchoring, not the current shock. If the central bank is credible and expectations anchored, the current monetary policy shock will not impact long-term inflation expectations and inflation trends.

CBC can feature the following four theoretical situations, as reported in Table 2.1.

When agents believe that $\bar{\lambda}_t$ is high, they expect the central bank to care more about output gap stabilization than inflation stabilization. Therefore, if $\phi_t > 0$, i.e.,

Table 2.1: Theoretical situations for central bank credibility

	$g(\bar{\lambda}_t) > 0$	$g(\bar{\lambda}_t) < 0$
$\phi_t > 0$ - Expansion	Lower CBC	Higher CBC
$\phi_t < 0$ - Contraction	Higher CBC	Lower CBC

there is a monetary policy expansion, this will decrease CBC about its efficacy or willingness to keep the price stable. Hence, ν_t will increase, crossing the threshold and fostering unanchored inflation expectations and increasing the forecast error f_t and long-term inflation expectations $\bar{\pi}_t$.

This is similar to what happened in Turkey in recent years when the central bank started decreasing policy rates in the context of an inflationary trend and agents' doubts about its power to stabilize inflation.

Instead, a tightening monetary policy ($\phi_t < 0$) would have reassured agents about the central bank mission of price stability and, hence, it would have increased CBC. This is what happened in the US at the onset of the energy crisis in 2022: inflationary pressures increased, but expectations remained stable, as we show in section 2.5.

The opposite happens when agents believe that the central bank focuses more on price stability than output stability. Here, a contractionary monetary policy could cast doubts about forthcoming recessions and again make inflation expectations unanchored.

Finally, so far we have described inflationary environments, i.e., economies that did not experience a strong deflationary period in their recent history, such as the US or Turkey. Our definition of CBC fits well for these countries, which include the vast majority of the world. However, a few exceptions are facing endemic deflation, such as Japan. For these countries, anchoring inflation expectations may not be the optimal solution, and hence, CBC should not be defined as the effective power of a monetary authority to keep inflation expectations anchored. However, anchoring implies convergence to the monetary policy targets in the theoretical model. Hence, we could still define CBC as the effectiveness by which the central bank leads inflation expectations towards the target, which should be higher inflation in the case of Japan.

2.3 Data

We estimate the theoretical model through Bayesian techniques, whereas few parameters are calibrated based on the related literature. We will explain the details of this methodology in the next session, while here, we describe the data we employ. The focus is on the US to describe the evolution of CBC and related inflation expectations for the case of a developed country. Moreover, we present the case of Turkey to describe CBC in an emerging country economy.

Since the main object of the model described in the previous section is to explain the evolution of long-term inflation expectations and the CBC underlying such development, we are not using data on long-term forecasts to estimate the model parameters. These data will be used to evaluate the predictive power of the model in Section 2.5. Instead, only data concerning inflation and survey measures of short-term inflation expectations from professional forecasters drive the estimation. We use publicly available data. To ensure comparability with the model, we compute inflation as the log difference in all the measures taken from the data. Furthermore, data are in annualized terms.

For the case of the US, four survey measures of CPI inflation forecasts are available: one- and two-quarter-ahead forecasts from the *Survey of Professional Forecasters* (SPF)[3] and two six-month-ahead forecast measures from the *Livingston Survey* (LIV)[4]. The first LIV measure is calculated as the growth rate between the forecasted CPI level six months ahead and the last monthly price level available to forecasters during the survey. The second measure is the growth rate between the forecasted CPI level six months ahead and the forecasted current CPI level[5]. This way, we can estimate the model using a satisfactory amount of information. Finally, the inflation series is drawn from the *Consumer Price Index for All Urban Consumers: All Items in U.S. City Average* seasonally adjusted measure from US *Bureau of Labor Statistics*[6]. Data are quarterly and cover the period 1955Q1 to 2023Q4, although each survey data spans different sample periods and frequencies. On the one hand, the SPF measures are available quarterly, starting in 1981Q3. On the other hand, the LIV survey is available biannually, with its first six-month-ahead forecast measure covering the full sample, while the second indicator starts only in 1992Q2.

As for long-term inflation expectations, we again leverage the SPF and LIV survey data. In particular, from SPF, we take the five-to-ten years ahead annual average CPI inflation rate forecast[7]. From LIV, instead, we use one-to-ten years

[3] Available at https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/survey-of-professional-forecasters. The measures of one- and two-quarter ahead forecasts are variables *CPI3* and *CPI4*, respectively, in the SPF data, and are mean forecast across individual professional forecasters.

[4] Available at https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/livingston-survey.

[5] The first forecast measure is variable *G-BP-To-6M* from the LIV dataset *Growth of Mean Forecast for the Levels of Survey Variables*, while the second measure is variable *G-ZM-To-6M*.

[6] Available at https://fred.stlouisfed.org/series/CPIAUCSL.

[7] Variable *CPIF5*, estimated as mean across professional forecasters and available at quarterly frequency for the sample 2005Q3 to 2023Q4.

ahead inflation rate forecast[8].

For the case of Turkey, data on inflation and forecasts are taken from the *Central Bank of Republic of Turkey* (TCMB) database[9]. We employ two months- and twelve months-ahead inflation forecasts from market participants as short-term expectations, while twenty-four months- and five years-ahead inflation forecasts as long-term expectations[10]. All inflation measures are in annualized terms, and we consider two-month-ahead inflation forecasts as a proxy for one-quarter-ahead expectations. For the model estimation of the Turkish case, the sample period spans from 2005Q1 until 2023Q4, although we have data on inflation forecasts only from 2014Q1 (or 2018Q4 in the case of five years-ahead expectations).

Finally, we also need data on real GDP to calibrate the updated process of $\bar{\lambda}_t$. Therefore, we obtain quarterly US GDP in billions of chained 2017 Dollars from the *Federal Reserve Bank of St. Louis* database (FRED) [11]. For Turkey, we get GDP in chain-linked volume by expenditure approach (thousand Turkish Liras) from the TCMB database. Both series are available for all the related sample periods.

2.4 Estimation

The model presented in Section 2.2 is estimated through Bayesian methodologies for the case of the US and Turkey to describe the development of CBC (and its effect on inflation expectations) for a developed and emerging country.

[8] Variable *CPI_10Y*, computed as mean across professional forecasters and available at a biannual frequency for the sample 1990Q2 to 2023Q4.

[9] Data from TCMB are available at https://evds2.tcmb.gov.tr/index.php?/evds/serieMarket.

[10] The relative variables in the TCMB database are the followings: *TP.PKAUO.S01.C.U_3*, *TP.PKAUO.S01.E.U_3*, *TP.PKAUO.S01.F.U_3*, and *TP.PKAUO.S01.G.U_3*.

[11] Variable *GDPC1*, available at https://fred.stlouisfed.org.

Since we build CBC inside a New Keynesian model with imperfect knowledge as in Carvalho et al. (2023) (CEMP), we follow the authors' estimation procedure, with the needed adjustments to our extended specifications. These methods have become increasingly popular in macroeconomics in the last decades, at least since Primiceri (2006). However, only the learning process in CEMP assumes firm beliefs are updated using information that is not directly observable to the econometrician. We follow this assumption, including beliefs about the central bank weight on output stabilization as additional unobserved information.

We estimate, hence, a state-space model, whose observation equation is the following:

$$\begin{bmatrix} \pi_t \\ E_t^{st}\pi_{t+k} \end{bmatrix} = \pi^* + H_t' \begin{bmatrix} \bar{\pi}_t \\ \zeta_t \end{bmatrix} + R_t o_t, \tag{2.6}$$

where the left-hand side of the equation represents the observable data, π_t being the annualized CPI growth rate and $E_t^{st}\pi_{t+k}$ the vector of k-ahead short-term inflation expectations (four measures in the case of US, while only two for Turkey, as described in Section 2.3). Our state variables ζ_t are $(\eta_t, \phi_t, \phi_{t-1}, \pi_t)$, where $\eta_t = f(\bar{\lambda}_t)\epsilon_t + \tilde{\mu}_t$ includes the exogenous shocks of the model. Moreover, π^* is the mean inflation rate, and o_t is the measurement error vector attached to the data. Finally, the observation matrix H_t captures the model-implied true data-generating process of inflation and short-term forecasts, and it is consistent with the agents' expectation formation from the theory. Importantly, H_t is time-varying not only due to possible missing observed data (like R_t) but also because it is a function of $\bar{\lambda}_t$.

Due to the typology of agents's learning process, nonlinear estimation procedures are required. In particular, CEMP suggests separating the model states into a subset of nonlinear variables, i.e., $\bar{\pi}_t$ and k_t, and a subset of linear variables, ζ_t, writing the state space representation accordingly. This way, we can implement a marginalized particle filter as in Schon et al. (2005): the linear states are estimated using the linear Kalman filter, while the nonlinear states are estimated using the particle filter. As explained by CEMP, the prediction of the nonlinear state variables can be used to improve the estimates of the linear state variables thanks to their reciprocal dependence. After applying the marginalized particle filter, we complete the estimation using a marginalized smoother. For more detail on the state-space model representation and the estimation algorithm, please see Appendix B.2.

The marginalized particle filter allows us to approximate the posterior distribution of the main parameters of the model, as well as the variances of the measurement errors. We, then, draw from this distribution thanks to the Metropolis-Hastings algorithm[12].

Moreover, a few parameters are calibrated according to the main New Keynesian literature to simplify the estimation procedure. In particular, α, which would correspond to the probability that a firm cannot adjust its reset price in a Calvo setting, is set equal to 0.66, while the discount factor β and the marginal cost coefficient ξ are equal to 0.99 and 0.17, respectively. With this calibration, our mean estimate of Γ results similar to Carvalho et al. (2023) in the US case, although slightly smaller.

Finally, to keep the estimation procedure reasonably fast, we calibrate the new information agents receive to update their beliefs about λ. Hence, consistently with the theoretical framework, we compute the updates about λ through rolling regressions every two years of de-meaned inflation growth on its lag and the real output gap, as the agents would do in our model. This way, the absolute coefficient of the output gap is used to update agents' beliefs. Instead, the marginalized particle filter estimates the agents' learning process weight w (and λ). Thanks to this calibration,

[12] We start the algorithm using a diagonal variance-covariance matrix of the parameters with prior variances and update it recursively through chains of 10 thousand draws until the matrix is stable. Then, we implement the Metropolis-Hastings algorithm with the obtained matrix for the final sample of 50 thousand draws. A step size of 0.2 gives a rejection rate of around 0.62 for the US data and around 0.65 for the Turkish data.

we avoid complex non-linearities in the estimation procedure without losing the explanation power of $\bar{\lambda}_t$.

Table 2.2 reports the estimation results for the case of the US, while the results for Turkey can be seen in Appendix B.3.

Table 2.2: Prior and posterior distribution of structural parameters - US

	Prior distribution			Posterior distribution			
	Distribution	Mean	SD	Mode	Mean	5^{th} Pct	95^{th} Pct
π^*	Normal	2.250	0.400	2.572	2.559	2.263	2.766
$\overline{\nu}$	Gamma	0.050	0.040	0.016	0.017	0.010	0.028
$\bar{g}$	Gamma	0.100	0.090	0.064	0.070	0.051	0.073
γ	Beta	0.500	0.265	0.172	0.178	0.132	0.181
ρ	Beta	0.500	0.200	0.922	0.891	0.780	0.954
ω	Normal	0.900	0.020	0.909	0.906	0.813	0.984
λ	Gamma	0.700	0.200	0.708	0.660	0.562	0.787
σ_{ϵ}	Inv.-Gamma	0.100	2.000	0.105	0.123	0.090	0.130
$\sigma_{\tilde{\mu}}$	Inv.-Gamma	0.100	1.000	0.334	0.335	0.267	0.347
$\sigma_{o,1}$	Inv. Gamma	0.100	1.000	0.335	0.354	0.289	0.364
$\sigma_{o,2}$	Inv. Gamma	0.100	1.000	0.038	0.036	0.025	0.050
$\sigma_{o,3}$	Inv. Gamma	0.100	1.000	0.019	0.020	0.014	0.028
$\sigma_{o,4}$	Inv. Gamma	0.100	1.000	0.070	0.071	0.056	0.074
$\sigma_{o,5}$	Inv. Gamma	0.100	1.000	0.058	0.059	0.045	0.065

Note: The posterior distribution is obtained using a Metropolis-Hastings algorithm. Moreover, the remaining parameters are calibrated according to the main New Keynesian literature: $\alpha = 0.66$, $\beta = 0.99$, and, hence, $\xi = 0.17$.

For US, the estimation is pretty tight, implying a precise detection of the structural parameters. Moreover, the measurement errors are also small, which helps with parameter identification. In general, we obtain similar estimation results as in CEMP, proving that the structural mechanism of inflation and expectations development provided by the authors is still in place. In particular, a small degree of price indexation is revealed, as is expected in more developed economies. However, the constant learning gain and the anchoring parameter exhibit the main difference with a model without CBC. In our results, in fact, the constant gain of unanchored expectations is between 0.05 and 0.073 at the 90 percent posterior boundary, implying a negligible weight on observations after around 2.5 years. When long-term inflation expectations are unanchored, they are still sensitive to short inflation forecast errors. However, more explanatory power has gone to the dynamics of the forecast error itself, which is also a function of CBC. The extension of an imperfect knowledge New Keynesian model to include CBC, hence, keeps the explanatory power of the simpler model but adds a possible explanation of what is at the basis of long-term forecast trends.

Moreover, the anchoring threshold $\bar{v}$ is smaller than in a model without CBC. In a model without CBC, this estimation would imply a higher sensitivity of firms to turn to constant learning gain for a small deviation of long-term inflation expectations from the trend inflation π^*. In our model, instead, this implies that CBC plays a more important role in shaping the characteristics of agents' expectations.

Furthermore, it is worth noticing that λ is estimated to be between 0.56 and 0.78 in the 90 percent posterior credible interval, implying a higher relative weight on inflation stability than output. This can be viewed as evidence of the implementation of the Taylor principle in the US. Finally, the updating weight ω is found to be, on average, around 0.9 consistently with persistent beliefs. This supports the idea of sticky agents' beliefs about the conduct of monetary policy, together with the lag between the change in policy and the update of expectations.

Appendix B.3 provides more details on the Turkish case. Here, it is sufficient to notice that the estimated structural parameters are found to feature higher variance due to the shorter sample period and the more volatile data. Moreover, in Turkey, expectations are found to be more indexed to past inflation, as is typical in emerging economies, and the weight on output stability with respect to inflation is larger than 1, implying less focus on price stability than in the case of the US and a violation of the Taylor principle. A mean value of 0.79 for $\bar{g}$ also implies a high weight on current forecast errors in updating long-term inflation expectations. Finally, ω results close to 1, providing evidence for persistent beliefs in the case of Turkey as well.

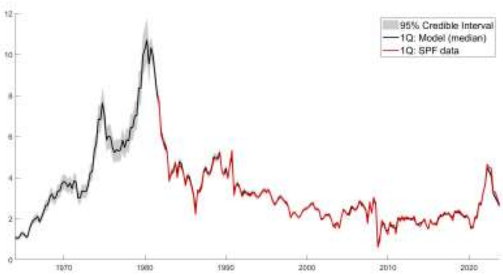
2.5 Results and Discussion

The estimated model results are now presented. We first report the model predictions relative to the time series used to estimate the parameters, mainly the short-term inflation expectations. Then, we present the model prediction power regarding long-term inflation expectations, which are not included in the estimation information set, compared with the model without CBC. This way, we show the dynamics of CBC and its role in affecting agents' expectations. We first present the results for the US and, subsequently, for Turkey.

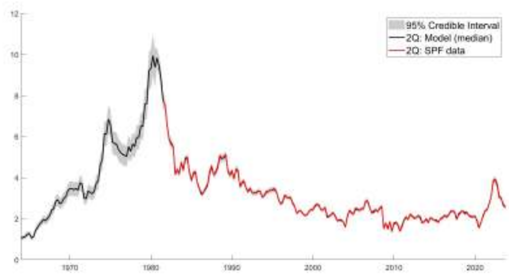
2.5.1 The US Case

Figure 2.1 reports the US observable data used for the Bayesian estimation described in Section 2.4, compared to model predictions. 95% credible intervals are included as well. The model fit is very close to all the time series. This would be expected, given that these data are employed to estimate the model parameters. However, the goodness of the fit supports the robustness of the model's predictive power and the efficacy of the estimation procedure. In particular, the model predicts faithfully the rise in inflation and short-term expectations in 2022 and 2023 and the following decrease at the end of 2023.

However, analyzing the model's prediction power regarding long-term inflation expectations is more important. These time series are, in fact, the signal of CBC's effectiveness in anchoring forecasts toward stable inflation paths. Figure 2.2 compares the model prediction about long-term inflation expectations and the observed data from SPF and LIV surveys. Model and survey data are referred to five-to-ten years and one-to-ten years inflation expectations.



(a)



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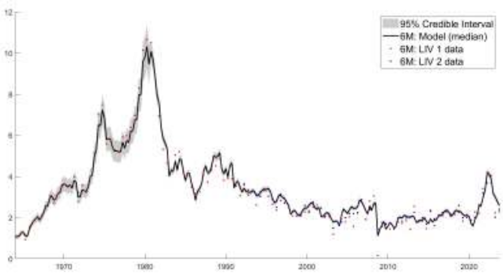

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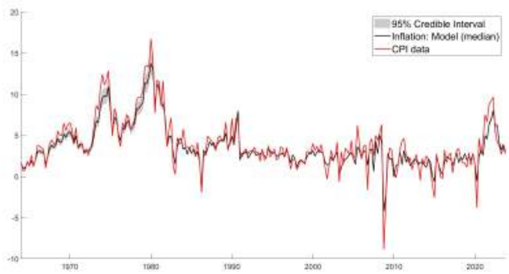


(d)

Figure 2.1: Short-run expectations and inflation: model vs data. (a) 1Q-ahead, (b) 2Q-ahead, (c) 6M-ahead, (d) current inflation.

Note: The panels show the evolution of (a) one-quarter- and (b) two-quarters-ahead inflation expectations from SPF, (c) six-month-ahead forecasts from LIV, and (d) the evolution of inflation from FED, compared with model predictions.

The graph in Figure 2.2 proves that the theoretical framework is a valid tool to predict agents' long-term inflation expectations. The model, in fact, reproduces very similar trends to those observed in the data for all the available years. It fits well with the downward trend in forecasts in the 1990s and the long, flat subsequent trend until the recent period, while the survey observations are included in the 95% credible interval for nearly all the sample. Moreover, the model reports high levels of long-term inflation expectations during the 1970s and 1980s, as described in several data.

As can be noticed, even though recent years have experienced a surge in inflation due to energy costs and political instability in several areas of the world (particularly the war in Ukraine), long-term inflation expectations remained stable for all this period. They were, in fact, anchored, as shown in Figure 2.3.

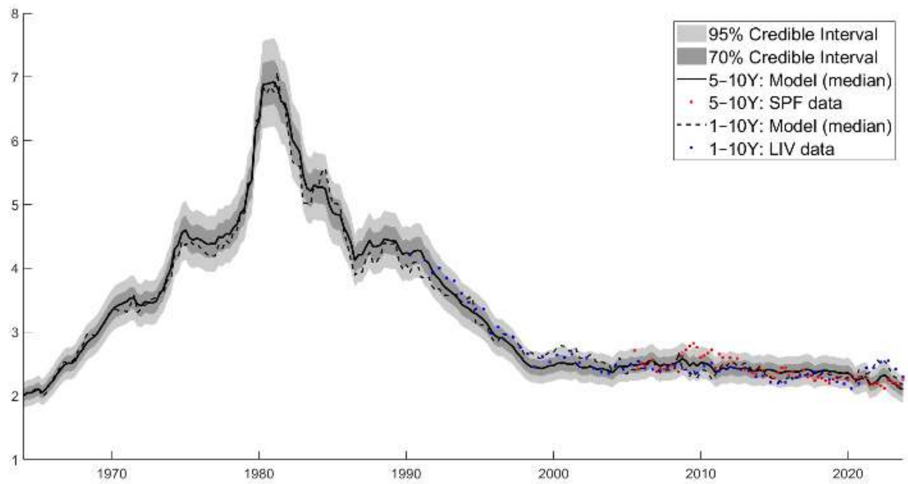


Figure 2.2: Long-run inflation expectations: model vs data.

Note: The panel shows the evolution of five to ten years inflation expectations from SPF and one to ten years forecasts from LIV, compared with model predictions.

The relationship between long-term inflation expectations and anchoring is already well documented by Carvalho et al. (2023), who describe how anchored expectations kept long-term forecasts stable in recent years, particularly during the 2008 Great Recession. The authors show that long-term inflation forecasts are strongly connected to agents' beliefs about the central bank inflation target, which are recursively updated through the learning gain. When expectations are anchored, current inflation news impacts long-term forecasts weakly. This mechanism clearly still works in our theoretical framework. However, our extended model can provide a micro foundation of the reason why these expectations remained anchored during this period and explain the missing surge in long-term inflation forecast after the recent energy crisis. It can explain the mechanism that stands at the basis of the long-term inflation expectations, which we show is a measure of CBC.

To fully appreciate how our measure of CBC works in the model, we compare the evolution of the agents' learning gain in Figure 2.3 with CBC, as defined in our model and reported in Figure 2.4. It is useful to remind here that CBC is the product of monetary policy and agents' beliefs about the actual weight of output gap stability with respect to inflation that the central bank pursues. When are measure of CBC is positive, the central bank loses credibility about its willingness or effectiveness in keeping inflation stable, increasing the probability of unanchored forecasts and an increase in inflation volatility.

As can be seen by the comparison of the two graphs, from the 1960s, expectations were on a path toward anchoring. However, CBC's credibility deteriorated in the 1970s, and the Federal Reserve turned to implement policies that decreased agents' beliefs about its power in keeping inflation at stable and low levels. This loss in CBC resulted from the combination of loose monetary policy and agents' beliefs that the central bank was more focused on stabilizing output than inflation. This is exactly the CBC measure we estimate in our model and shown in Figure 2.4. We see that the pick of this deterioration corresponds to the oil crisis in 1979. As a consequence of that, inflation expectations became unanchored and remained so until the end of the 1980s. Then, following a period of improved CBC during the 1980s, forecasts

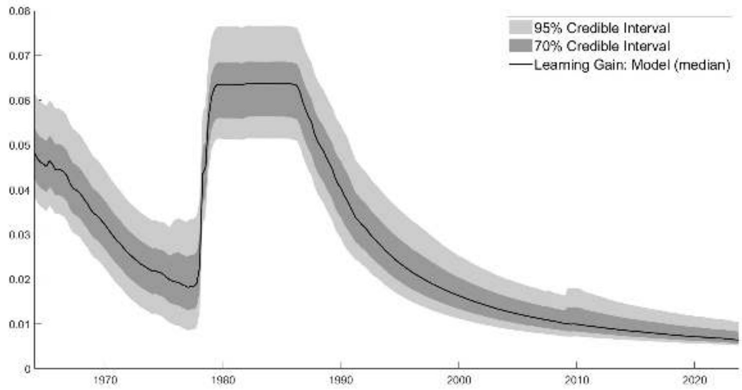


Figure 2.3: Learning gain.

Note: The panel shows the learning gain as defined in the model.

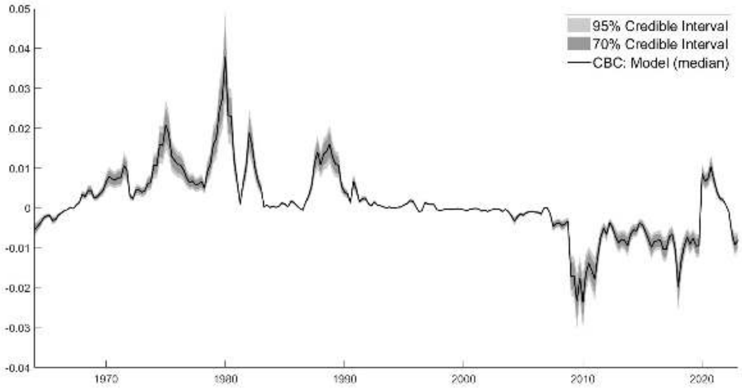


Figure 2.4: Central bank credibility.

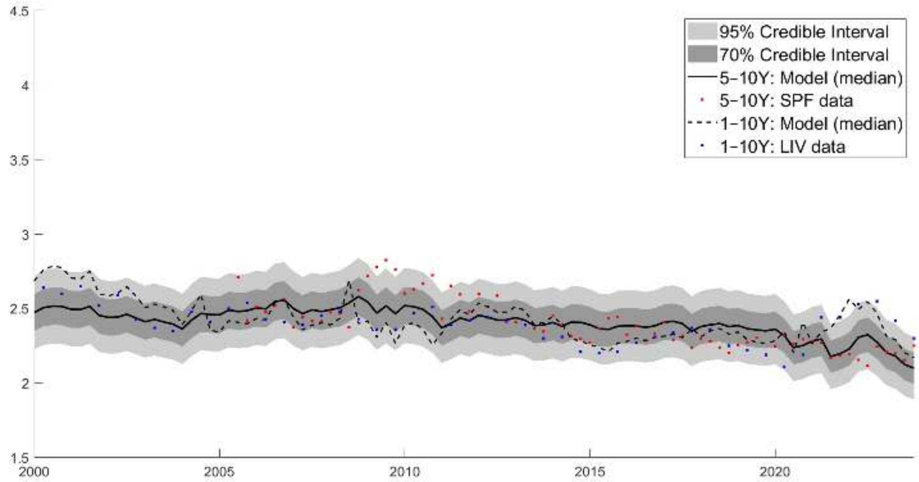
Note: The panel shows central bank credibility as defined by the model.

started being anchored again. Our measure of CBC aligns with the well-established explanation of a turning point in US monetary policy after the appointment of Paul Volcker as Chairman of the Federal Reserve in 1979.

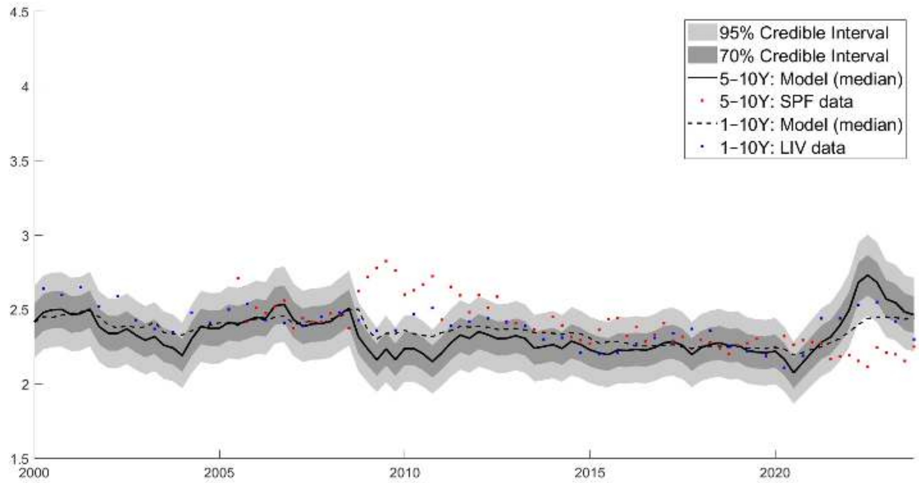
After the 1970s, the US monetary policy turned out to have been credible in pursuing the objective of inflation stabilization: our CBC measure is always close to zero or even negative after the 1970s, supporting this way stable and low inflation expectations. Only at the end of the 1980s can we still detect a small deterioration in CBC, but for a short period, which did not affect the trend toward anchoring. The comparison of Figures 2.3 and 2.4 also reports that CBC has a lagged effect on anchoring. The development of inflation expectations follows periods of high or low CBC. Therefore, if the central bank can maintain CBC for years, short episodes of deterioration of CBC due to, for example, large economic shocks will not affect long-term inflation expectations.

In particular, our model can describe the mechanism that kept the long-term inflation forecast well anchored during the recent large shock to energy costs. In fact, at the surge of the COVID-19 pandemic, CBC risked deteriorating, as can be seen at the end of the sample period in Figure 2.4. However, here, our CBC measure plays a crucial role: agents' beliefs became more pessimistic about inflation stability, given the shock to the economy, and agents increased their expected λ, pushing up the CBC factor. However, the prompt actions of the Federal Reserve, mainly tighter monetary policy after the energy costs shock in 2022, immediately brought our measure of CBC to lower levels again, ensuring the anchoring of expectations, which remained stable during the current energy price inflation, as evident in the data.

To acknowledge the robustness of this underlying mechanism, comparing the model performance in predicting long-term inflation expectations with and without CBC is also fruitful. To do that, Figure 2.5 compares the fit of the model with CBC to the model where we assume perfect information about the parameter λ in the central bank target rule, hence eliminating CBC from agents' expectation formation. The comparison is made for the period after 2000. The model without CBC fits the data well, although its time series looks slightly more varying than when we include CBC. However, if we turn off CBC, the model misses the stable path of agents' inflation expectations after 2020.



(a)



(b)

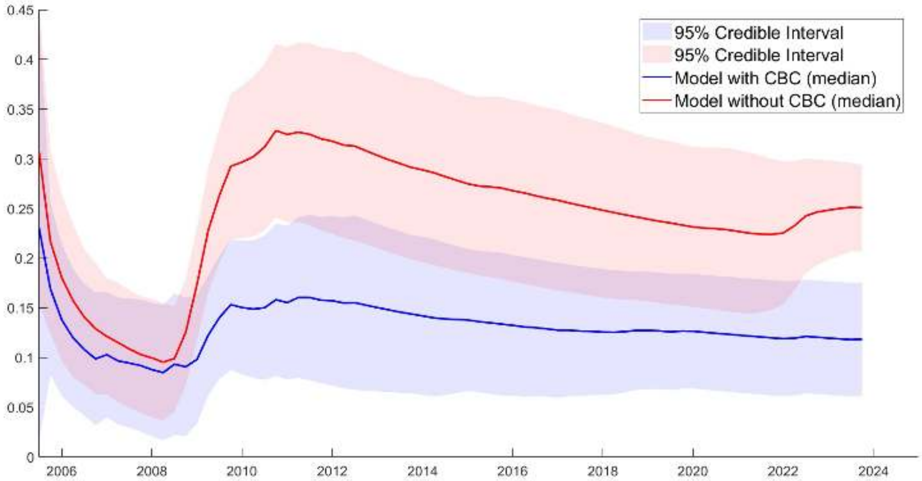
Figure 2.5: Long-run inflation expectations (a) with and (b) without CBC.

Note: The panels show the evolution of five to ten years inflation expectations from SPF and one to ten years forecasts from LIV, compared with model predictions.

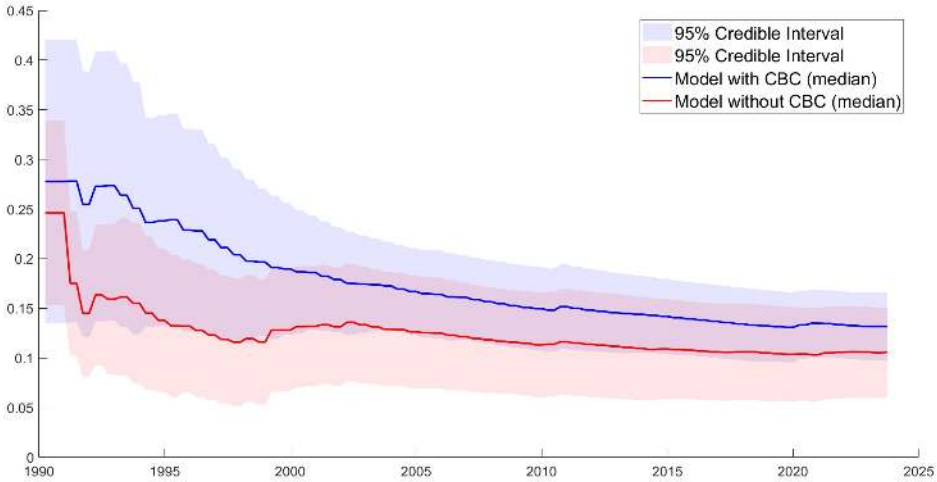
This proves what we explained above: the Federal Reserve implemented a tight monetary policy, strengthening its credibility in dealing with the current inflationary pressures, hence keeping inflation expectations anchored and stable even while facing the huge energy crisis. Hence, in the model, CBC works as an extra element that further decreases the weight of current forecast errors affecting long-term forecasts and keeps expectations stable. This can also be seen in equation 2.4 of the model, where the weights on shocks depend on agents' beliefs. Hence, even if also in a model without CBC, expectations remain anchored, including CBC delivers a better fit in the presence of huge inflationary shock to the economy and a precise explanation of the mechanism underlying expectation formation.

Therefore, our estimates support a CBC explanation for the recent energy crisis. Notwithstanding the big jump in current inflation, with the consequential increase in current forecast errors, the US central bank implemented its monetary policy tools promptly, keeping high credibility in dealing with the inflationary pressures in the eyes of economic agents, who didn't change their long-term inflation forecast. As a consequence of that, inflation could also return to reasonable levels in a short period, and inflation expectations remained anchored as is typical in developed countries with CBC.

The evaluation of the model with CBC can also be assessed quantitatively in Figure 2.6. In the graph, root mean square errors (RMSE) are reported from the fit of the models with and without CBC compared to long-term forecasts from the SPF and LIV survey data. RMSE are calculated from the starting year of the available data (1990 for LIV, while 2005 in the case of SPF) and recursively updated with additional quarterly data at each point in time. CBC improves the model predictions, especially for inflation forecasts that are five-to-ten years ahead and particularly at the end of the sample period, during the recent inflationary crisis. As for inflation forecasts that are one-to-ten years ahead, there is no significant difference between the model with CBC and a model without it, showing that even the base model is



(a)



(b)

Figure 2.6: Comparison of RMSE between models with and without CBC.

Note: Panel (a) shows the comparison of RMSE between the model with and without CBC in explaining five to ten years inflation expectations from SPF, while panel (b) shows the same comparison in explaining one to ten years inflation expectations from LIV.

still a very good predictor of data.

From the US case, therefore, we conclude that our measure of CBC, defined as a function of agents' beliefs about central bank objective rule and monetary policy stance, is a valid tool to assess central bank performances in keeping inflation forecast stable and, hence, delivering anchored inflation expectation typical of a developed economy.

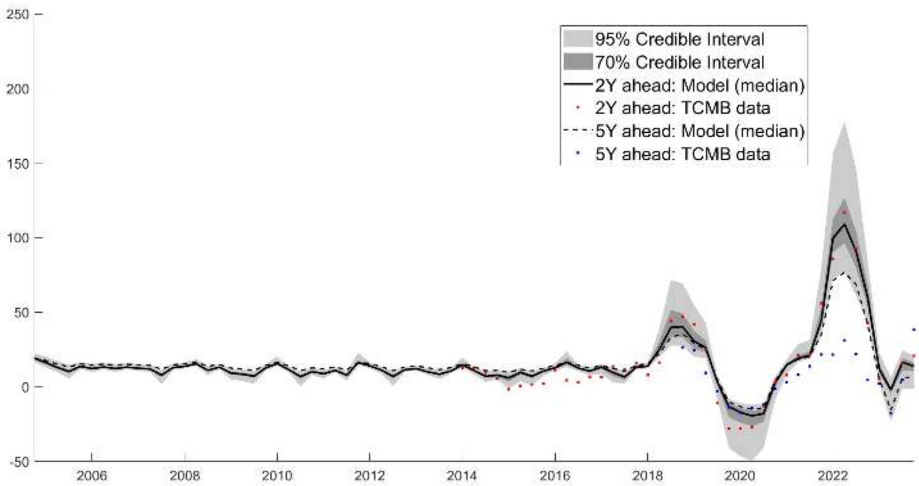
This same mechanism is also shown to be at the basis of inflation expectation formation in an emerging country such as Turkey, as we explain in the following subsection.

2.5.2 The Case of Turkey

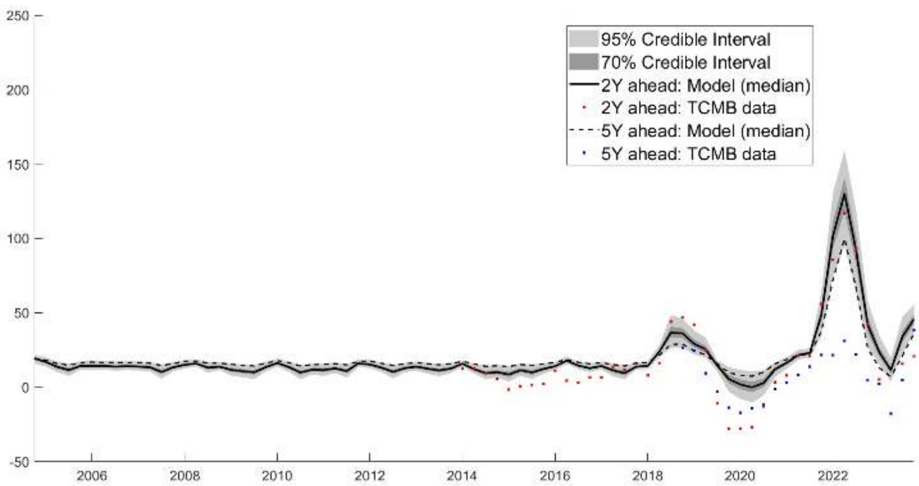
Regarding the Turkish case, we present the model predictions regarding long-term inflation expectations, focusing on the CBC developments and their impact on forecasts. We refer the reader to Appendix B.3 for what concerns short-term inflation expectations predictions of the model. Figures B.1, B.2, and B.3 report the model fit with respect to the data used in the Bayesian estimation. In the case of Turkey, the model produces a pretty good fit of data, even if these are more volatile than in the US case.

Figure 2.7 provides the model long-term forecast predictions with CBC and without it, compared to observed data from the TCMB. Moreover, Figures 2.8 and 2.9 report the agents' learning gain and the CBC from the estimated model, respectively. Now, we can analyze how CBC works in the context of an emerging country where inflation expectations are mostly unanchored. Again, the model describes the same underlying mechanism: CBC is the product of agents' expectations about the central bank's focus on price stability and monetary policy stance.

As can be noticed by Figure 2.7, long-term inflation expectations have become much more volatile since 2018. Again, the model with CBC can better fit the observed data from the TCMB surveys. This shows the importance of CBC, especially



(a)



(b)

Figure 2.7: Long-run inflation expectations (a) with and (b) without CBC.

Note: The panels show the evolution of two and five years ahead inflation expectations from TCMB, compared with model predictions.

for emerging countries where inflation forecasts are more indexed to current inflation.

As a matter of fact, Figure 2.8 reports the development of the learning gain since

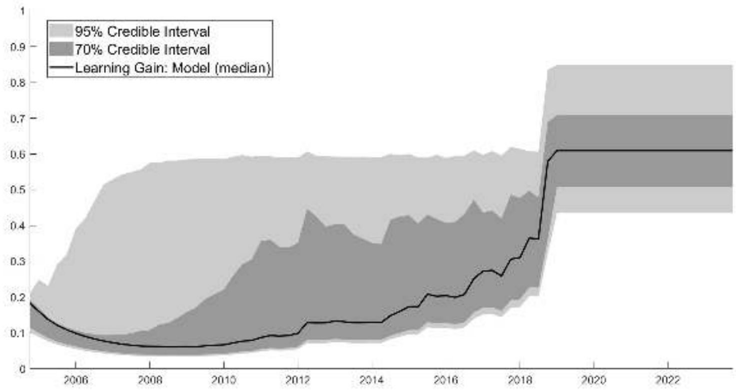


Figure 2.8: Learning gain.

Note: The panel shows the learning gain as defined in the model.

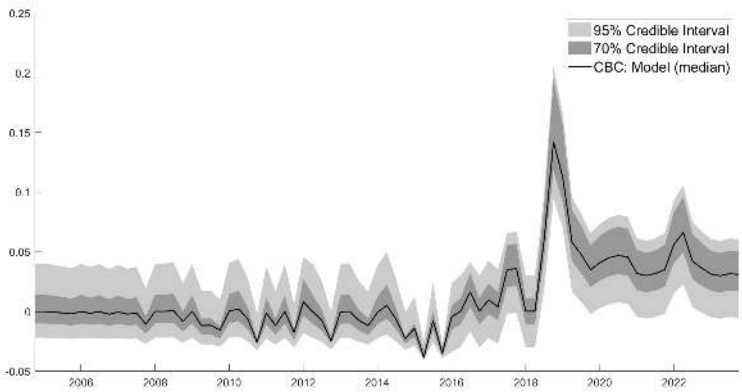


Figure 2.9: Central bank credibility.

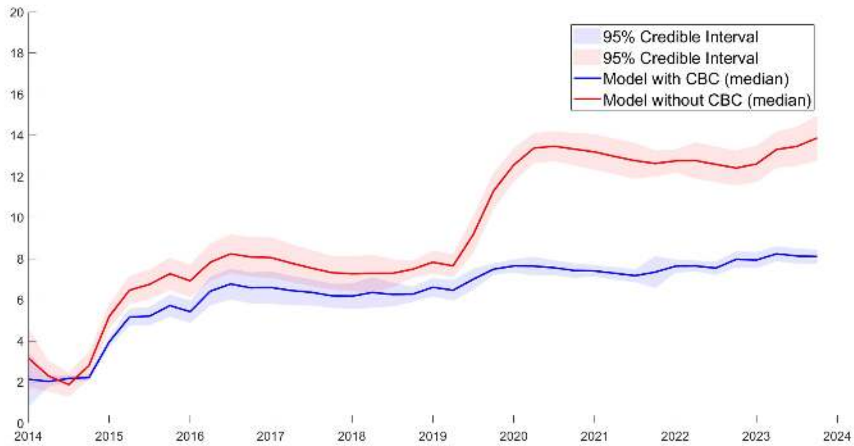
Note: The panel shows central bank credibility as defined by the model.

2005. Even if the estimation is quite volatile due to the nature of the observable data and the short sample period, a slight path to anchoring expectation can be detected in the early 2000s. After that, forecasts become increasingly unanchored, implying a much higher weight on current forecast errors and, hence, more volatile long-term inflation expectations. The turning point seems to be 2018, when there is a huge and steady jump to unanchored inflation expectations, translating into high variance in forecast data.

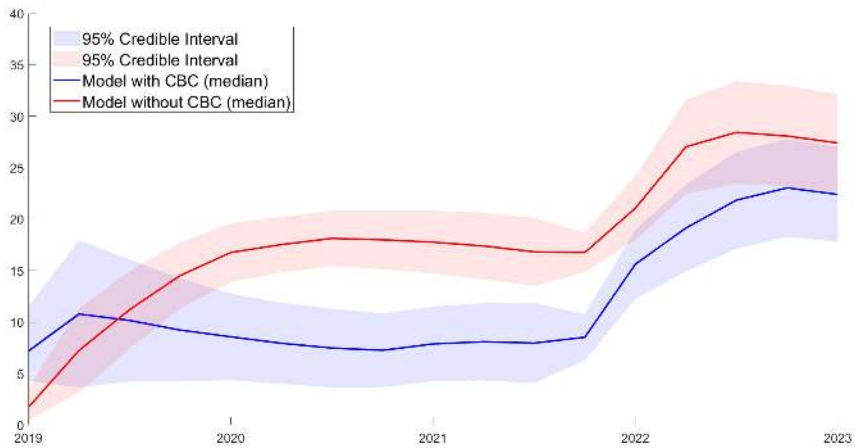
CBC can explain these trends. In fact, we can see from Figure 2.9 that CBC is quite stable until 2016, then it started deteriorating. Notably, it experienced a large worsening in 2018 and remained worse than in the pre-2016 period until the end of the sample. This is mainly because agents in Turkey believed that the central bank's focus on price stability had decreased during the last years of high inflation. They started believing that the parameter λ was higher. In response to that, the Turkish central bank pursued an expansionary monetary policy during those years, and, hence, CBC deteriorated as predicted by the theoretical framework. More recently, the Turkish central bank increased the target interest rates, improving CBC and lowering long-term inflation expectations. However, only a prolonged and stable tight monetary policy will let the inflation forecasts start a path toward anchoring.

Finally, as for the US case, Figure 2.10 presents a quantitative assessment of the model with and without CBC in predicting the long-term inflation expectations for Turkey. The model that includes CBC is shown to fit better both two- and five-year-ahead inflation expectations from the TCMB surveys. The main difference in predicting performance with respect to a model without CBC is particularly evident after 2018, further supporting the idea that that year was a turning point for CBC in Turkey.

To sum up, our micro-founded CBC is shown to explain the development of long-term inflation expectations both in a developed economy and an emerging country. The different definitions usually given to the two types of economies can be consistently unified through a unique mechanism underlying the relationship between agents' beliefs and the conduct of monetary policy. This explanation is well supported by the model fit to the observed data for both the US and Turkey. CBC is a fundamental tool for central banks to keep forecasts anchored and effectively deal with macroeconomic shocks, especially large cost increases. Our analysis also suggests that emerging economies would reach anchored inflation expectations sooner if their central banks implemented the correct monetary policy, meaning the policy that fosters stable and low inflation expectations.



(a)



(b)

Figure 2.10: Comparison of RMSE between models with and without CBC.

Note: Panel (a) shows the comparison of RMSE between the model with and without CBC in explaining two years ahead inflation expectations from TCMB, while panel (b) shows the same comparison in explaining five years ahead inflation expectations from TCMB.

2.6 Conclusion

We extended a New Keynesian model with imperfect knowledge to include a measure of CBC. This allowed us to evaluate the prediction power of CBC and its effect on anchoring and the development of inflation forecasts.

Our model can explain why the US turned to anchor inflation expectations after the inflationary period in the 1970s and why Turkey could not do the same in recent years. CBC is found to be the basis of the anchoring mechanism, fostering forecasts and inflation stability over time. In particular, the model shows that recent inflation trends are shaped by CBC, with the US keeping a stable path thanks to the intervention of the Federal Reserve, while Turkey experienced highly volatile inflation and forecasts after expansionary monetary policy by the Turkish central bank.

Hence, empirical results strongly support the hypothesis that CBC significantly affects inflation and expectations stability. Especially in the presence of large macroeconomic shocks, monetary policy actions shape agents' beliefs and give signals that maintain a high level of CBC or deteriorate it.

This paper contributes to the literature by providing a comprehensive and micro founded measure of CBC, which is based on individuals' beliefs and the conduct in monetary policy, and is applicable both in developed countries and emerging economies. This measure has high predictive and explanatory power for inflation and expectations and can also be estimated to assess the central bank's effectiveness in pursuing price stability and to analyze CBC effects on several economic performances.

Future research should follow two directions: first, the micro foundation can be analyzed deeply by directly linking central bank decisions to the characteristics of agents' beliefs; second, applied research or policy institutions should construct a CBC index based on our theoretical explanation to study its implications for monetary policy effectiveness and price stability.

Chapter 3

HETEROGENEOUS TECHNOLOGY AND THE PHILLIPS CURVE

3.1 Introduction

While inflation is cooling in Europe, the debate on the tight monetary policy remains hot. The argument hinges on the slope Phillips curve, i.e., the relationship between economic slack and changes in prices or wages, conditional on expected inflation. Has the flattening of the slope that was perceived in the previous decade continued or suddenly reversed, allowing for a less costly disinflation?

In the context of the New Keynesian model, the Phillips curve slope is determined by multiple factors. In the first place, an increase in price stickiness, modeled by a lower frequency with which firms can adjust prices (Calvo pricing), flattens the Phillips curve. A next macroeconomic determinant is the degree to which wages increase as labour markets tighten: a higher wage response leads to a steeper Phillips curve for a given amount of cost pass-through. The reduced form relationship between activity and prices can also become steep when inflation expectations react positively to small shocks. With credible monetary policy, the Phillips curve may be flatter by keeping expectations well anchored. Further, the Phillips curve may be nonlinear, resulting in a flatter slope when slack is high. Finally, the slope of the Phillips curve is affected by supply shocks, such as steepening with an exogenous increase in prices of (imported) inputs or flattening owing to new technology. Our paper takes almost all of the above factors as given and explores the effect of heterogeneous technology at the firm level. In particular, we show that firms with higher production technology levels feature lower marginal costs and flatter supply curves. The paper also discusses cost pass-through and non-linear responses to demand shocks at the firm level.

A recent review by Baba et al. (2023) synthesizes the literature on estimating the Phillips curve slope, highlighting various factors other than economic slack that can explain recent episodes of inflation and disinflation. The textbook by Galí (2015) explains the basic New Keynesian mechanism for flattening the Phillips curve through price stickiness. Roberts (1997), instead, assumes staggered contracts to derive the slope of the Phillips curve from nominal wage rigidities. More recently, Siena and Zago (2024) show that labour market fluidity, i.e., more hiring and separation, decreases the slope of the Phillips curve in the New Keynesian framework, and, using microdata report that routine jobs are less fluid and disappearing, hence a reason for the flattening of the Phillips curve. Although we do not deal directly with the labour market, our technology explanation of the slope of the Phillips curve can shed light on the degree of wage inflation pressures following an increase in firm production.

In addition, the New Keynesian literature highlights agents' expectations. Lucas and Rapping (1969) report the relevance of expectations for the slope of the Phillips curve and point out the instability of the inflation-slack relationship over time. Since then, a line of research in monetary economics became increasingly focused on studying the implications of rational expectations (see Woodford and Walsh (2005)) and imperfect knowledge learning (see, e.g., Bullard and Mitra (2002) and Carvalho et al. (2023)). Related to that is central bank credibility, defined as the situation when inflation expectations are insensitive to news releases and monetary policy actions (see, e.g., Demertzis et al. (2012). This paper estimates firm pricing equations leveraging rational expectations.

With expectations given, literature hones the relationship between activity and prices, either in factor or output markets. On price change and output, Boehm and

Pandalai-Nayar (2022) show that US manufacturing industries' supply curves are convex and inflationary pressures are higher when the production capacity limit is reached. Their finding is close to our technology perspective since the flattening of the supply curves that we detect for the more productive firms can be explained by the fact that advanced technology can expand the capacity limit of a firm. If this is the case, or whether the technology progress implies a generic flattening along the firm production scale, it is a question for future research.

Also, Gagliardone et al. (2023) find that the elasticity of marginal costs to the output gap is decreasing, hinting that supply shocks can still be relevant for the steepening of the slope of the Phillips curve, while demand shocks are less inflationary. The reason why the elasticity of marginal costs decreased is linked to improvements in productivity, as our theoretical explanation implies.

This study's contribution to the literature is to empirically evaluate the effect of firms' production technology heterogeneity on the slope of the Phillips curve. We show that the aggregate Phillips curve can be derived from firms' pricing behaviour and that firms are characterized by different marginal cost curves along the production technology distribution. Therefore, the more the most productive firms are the ones to respond to demand shocks, the flatter the Phillips curve. Our theoretical framework is close to Andrés and Burriel (2018), who model the flattening of the Phillips curve through the interaction between firm productivity heterogeneity and strategic competition. However, our work focuses on technology and supply conditions, rather than strategic market interactions between firms, and controls for different residual demands faced by firms.

Until the recent period of increasing inflation, much empirical macro literature was concerned with finding evidence and explanations for a flattening Phillips curve. Recent developments saw a rapid increase in inflation due to various shocks to sectoral demand, aggregate demand, and supply conditions. In this context, the literature about the time-varying Phillips curve is rich (Hooper et al. (2020)). As we reported above, frictions vary over time, marginal costs are affected by technological trends, and the Phillips curve is also affected by the evolution of markups, just to name some factors. Moreover, a better stabilization policy can have contributed to observed flattening at the macro level. Finally, recent literature focuses on market concentration effects on the Phillips curve: Fujiwara and Matsuyama (2022) show how market power flattens the Phillips curve.

However, there is still little identified evidence about the slope of the Phillips curve (Nakamura and Steinsson (2018)). In particular, we need disaggregated data to understand the appropriate margin at which to measure marginal costs. We need both within and between firm margins to find the macro price effect of shocks faced by suppliers. Pricing decisions occur at the firm level and depend on production conditions, as well as market structure and expectations. This determines the reaction to aggregate and firm-specific demand and supply shocks. Firms take into account the current and lagged state, possibly (re)actions of other firms, and expectations of future states and, hence, are hypothesized to act such as to maximize the present discount value of expected profit. In this context, macro time series are generated by aggregating data from maximizing firms and thus reflecting micro-level actions and resource allocation associated with interactions. Consequently, micro-foundations are misapplied in the segment of the macroeconomic literature that assumes a representative firm. The appropriate "marginal cost" to apply in the Phillips curve estimation is the marginal cost of the supplier at the margin; disaggregated data can help reveal the margin of interest.

In order to answer this need, we build a New Keynesian framework with heterogeneous firms. Firms are heterogeneous in their production technology and, hence, are characterized by different productivity levels and output elasticity. In equilibrium and with details depending on market structure, more productive firms have lower marginal costs and a higher share of the market, as well as dynamically higher markups. Most importantly, if a demand shock occurs, the most productive firms are capable of reacting more in terms of an increase in output, while they will raise their prices less, thereby gaining higher shares of the market. Hence, demand shocks are met more by the most productive firms, and this micro behaviour has macro consequences: the Phillips curve becomes flatter when the more productive firms increase their share of the market following demand shocks.

We test our theoretical model with firm-level data accessed using the newly developed European microdata infrastructure (Bartelsman and MDI-Team (2024)), which harmonizes firm-level data across multiple countries. Each country's firm panel comprises linked data sources such as business registers, structure business statistics, firm-level product prices and quantities (Prodcom), customs data, and more. These data are harmonized for several European countries. The present paper focuses on France, with some cross-country comparisons with the Netherlands. However, the analysis can soon be replicated for all other countries in the MDI. Thanks to microdata, hence, we can estimate firm-level pricing equations that aggregate to the macro-level Phillips curve.

To estimate firms' pricing equations, we cluster the firms in our sample that have similar production technology and face similar demand curves within each cluster but are heterogeneous in supply and demand characteristics across clusters. We implement a clustering algorithm that provides the best fit for production function and price pass-through regression equations. To our knowledge, we are the first to implement such clustering to simultaneously control for both production and demand heterogeneity while analyzing firm pricing behaviour.

Our findings show that the most productive firms actually feature flatter supply curves. When they face a shock in demand, they respond modestly regarding prices. Moreover, they are found to exhibit higher volatility in output growth, implying a higher response in terms of output to industry- or firm-specific demand shocks. This results in less inflationary pressure at the macro level. We show, finally, that firms' pricing behaviour is at the foundation of macro estimates of the Phillips curve. Our micro results are also supported by micro-aggregated industry panels of representative firms for each productivity quintile of the TFP distribution for a range of 21 European countries from 2004 to 2020, available through the CompNet database.

Finally, our results can explain why market concentration is related to the flattening of the Phillips curve, given that the most productive firms are the ones gaining market shares after demand shocks. Moreover, our findings explain why, at the aggregate level, marginal costs are less elastic to increase in output, since the more productive firms are the ones meeting most of the demand shock. In addition to have lower marginal costs, the more productive firms are also characterized by higher markups. Therefore, our production technology explanation can shed light on the fact that high markup firms react less to output shocks in terms of prices.

The rest of the paper is outlined as follows: Section 3.2 describes the theoretical framework; Section 3.3 presents the first micro-based stylized facts from the CompNet database, while Section 3.4 illustrates the MDI microdata; then, Section 3.5 describes our clustering algorithm, and Section 3.6 reports our empirical strategy and the micro results; finally, Section 3.7 concludes.

3.2 The Theoretical Framework

3.2.1 The Economic Environment

Our analysis is based on a New Keynesian framework, the benchmark model for macro analysis and monetary policy forecasting. The model is extended to allow for heterogeneity in supply and demand characteristics of firms making dynamic pricing decisions.

Disaggregating the Phillips curve is becoming an important tool in recent literature (e.g., see Gagliardone et al. (2023)). However, we provide a framework to aggregate the effects of shocks to heterogeneous firms through their individual pricing decisions and market interactions into a macro Phillips curve.

The economy in our model is populated by a representative consumer who consumes final output that is composed of a continuum of produced goods [0,1]. Each good is produced in a (symmetric) industry populated by N firms that compete à la Bertrand in monopolistic competition. In this market structure, firms internalize the effect of their pricing decision on the industry price since the number of firms is limited to N. By contrast, firms take the aggregate price level as given.

The model focuses on the response of firms to aggregate demand shocks and to firm-specific demand or supply shocks. Firm i, in sector s, at time t, knows its own production technology and takes as given a residual demand curve for its output, $D_{ist}(p_{ist})$. Firms are constrained in their ability to make continuous price adjustments, à la Calvo.

We assume the following heterogeneous Cobb-Douglas firm production functions:

$$Y_{ist} = A_i(K_{ist}^{\alpha_i} L_{ist}^{(1-\alpha_i)})^{\gamma_i} \tag{3.1}$$

where Y_{ist}, K_{ist}, and L_{ist} are output, capital, and labour, respectively, of firm i, in industry s and time t. As will be derived below, the level of a firms' marginal costs depends on A_i and its slope on γ_i. As shown in Section 3.5, empirical support exists for a positive correlation between productivity and returns to scale – more productive firms have flatter marginal cost curves. With heterogeneity in marginal cost curves across firms, there is no symmetry in steady state, and firms have different market shares, while at the margin, they will feature different responses to shocks.

In this paper, we do not take a stand on a particular functional form or parameterization for industry demand. Instead, as advocated by Mrázová and Neary

(2017), we consider the "firm's eye view" of demand, where the residual demand curve facing a firm can be sufficiently characterized by its elasticity and convexity, which will be estimated. In particular, the firms' cost markup and pass-through decisions depend on these demand characteristics.

Owing to the "Calvo fairy", and subject to the expected residual demand D_{ist}, firms choose a "reset price" P^o_{ist} to maximize the present discounted value of real profits:

$$\max_{P^o_{ist}} E_t\left\{\sum_{k=0}^{\infty}\theta^k\left[\Lambda_{t,k}\left(\frac{P^o_{ist}}{P_{st+k}}D_{ist+k}-TC(D_{ist+k})\right)\right]\right\}$$

denoting $\Lambda_{t,k}$ as the stochastic discount factor and P_{st} as the industry price, while $TC(D_{ist})$ are the real total costs. Therefore, the FOC of this problem can be represented as:

$$E_t\left\{\sum_{k=0}^{\infty}\theta^k\Lambda_{t,k}D_{ist+k}\left[\frac{P^o_{ist}}{P_{st+k}}-(1+\mu_{ist+k})\frac{MC^n_{ist+k}}{P_{st+k}}\right]\right\}=0 \tag{3.2}$$

where MC^n_{ist} are nominal marginal costs. In monopolistic competition, the log markup μ_{ist} is an inverse function of the firm residual demand elasticity $\eta_{ist} = -\frac{\delta ln(D_{ist})}{\delta ln(P^o_{ist})}$ that firms are facing at the margin, which in turn depends on the elasticity of substitution for the firm good and the price reaction of competitors. Therefore, the log markup can be expressed as the usual Lerner index $ln\left(\frac{\eta_{ist}}{\eta_{ist}-1}\right)$, and the firm residual demand elasticity as:

$$\eta_{ist} = \eta_{ist}\left(\zeta_{ist}, \eta_d\right)$$

where $\zeta_{ist} = \frac{\delta p^{-i}_{st}}{\delta p^o_{ist}}$ is the price response of competitors to firm reset price and η_d the parameters defining the demand elasticity substitution for the firm good, which could differ among firms due to firm or industry characteristics. It is important to stress that the relationship between markups and residual demand elasticity is a general result of simply assuming monopolistic competition. Hence, markups are directly related to firm-specific production technology.

The residual demand elasticity is a negative function of the price response of competitors to firm i optimization. To see it analytically, we derive markups as a function of demand parameters and competitors' price behaviour in the case of a nested CES function, considering that the statements will still have a general scope.

In the case of a nested CES function, where ϵ is the elasticity of substitution across industries and σ within industries (and $\sigma > \epsilon$), η_{ist} becomes:

$$\eta_{ist} = -\frac{\delta ln(D_{ist})}{\delta ln(P^o_{ist})} = \sigma - (\sigma - \epsilon)\zeta_{ist}$$

Industry price can be, then, decomposed into the firm price and the rivals' price, as follows (ω_{ist} being a firm-specific demand shock):

$$P_{st} = \left[\frac{N-1}{N}(P^{-i}_{st})^{1-\sigma} + \frac{1}{N}(P^o_{ist}\omega^\sigma_{ist})^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$$

Hence, the elasticity of industry price relative to firm i price can be written as:

$$\frac{\delta p_{st}}{\delta p^o_{ist}} = \underbrace{\frac{\omega^\sigma_{ist}}{N}\left(\frac{P^o_{ist}}{P_{st}}\right)^{1-\sigma}}_{s_{ist}} + \underbrace{\frac{N-1}{N}\left(\frac{P^{-i}_{st}}{P_{st}}\right)^{1-\sigma}}_{1-s_{ist}}\zeta_{ist}$$

In steady state, firms are in Nash-Bertrand equilibrium and do not have an incentive to change prices given the competitors' optimization. This implies that $\zeta_{is} = 0$ in steady state, and the markup is log linearized as follows:

$$\hat{\mu}_{ist} = \mu_{ist} - \mu_{is} = -\Gamma_{is}(\hat{p}^o_{ist} - p^{-i}_{st}) + u^\mu_{ist}$$

where Γ_{is} denotes the markup elasticity with respect to firm price (where $\bar{x}$ stands for steady state value of x):

$$\Gamma_{is} = \frac{(\sigma-\epsilon)(\sigma-1)(N-1)\bar{p}_s^{-i1-\sigma}\bar{p}_{is}^{1-\sigma}}{\eta_{is}(\eta_{is}-1)N^2}$$

and

$$u^\mu_{ist} = \frac{(\sigma-\epsilon)(1-s_{is})}{\eta_{is}(\eta_{is}-1)}\zeta_{ist} + \frac{(\sigma-\epsilon)\sigma\bar{p}_{is}^{1-\sigma}}{\eta_{is}(\eta_{is}-1)N}\left(1 - \frac{\bar{p}_{is}^{1-\sigma}}{N}\right) ln(\omega_{ist})$$

Similar functional forms for markups can be obtained with different demand specifications (for example, Kimball preferences), and parameters could be specific to the firm i residual demand. In an environment of production heterogeneity, it is important to notice that each profit-maximizing firm sets a lower price as its productivity and output elasticity increase and, hence, features a higher market revenue share s_{is}. Moreover, markups μ_{is} can be higher for more productive firms in steady state if they are also located in different segments of the market and, hence, face different η_d parameters that lower demand elasticity. We will see in Section 3.5 that this seems to be the case, and firms with a higher production technology level face lower demand elasticity. In any case, markups are dynamically higher for the more productive firms due to strategic interaction. In fact, more productive firms react less in terms of price with respect to their competitors, and η_{ist} is an inverse function of ζ_{ist}.

As far as marginal costs are concerned, they are characterized as a function of input prices, output level, and firm technology, which, in the case of the Cobb-Douglas production function, can be expressed after cost minimization as:

$$MC^{n}_{ist} = \frac{C_{ist}}{A_i^{\gamma_i}} Y_{ist}^{\frac{1}{\gamma_i}-1} \tag{3.3}$$

where

$$C_{ist} = \left(\frac{W_t}{(1-\alpha)\gamma_i}\right)^{(1-\alpha)} \left(\frac{R_t}{\alpha\gamma_i}\right)^{\alpha}$$

Marginal costs are also directly related to production technology, becoming lower with an increase in firm production technology. This delivers a distribution of firm productivity in a similar shape as in Melitz (2003). Therefore, heterogeneity in production technology delivers different pricing behaviour across firms due to lower marginal costs and strategic interaction with competitors.

We want to stress that the only necessary condition for this is a monopolistic competitive market where firms face a decreasing residual demand. A particular functional form (CES) is just used here to provide the explanation with an analytical form and to derive an analytical aggregation to the macro level in the following subsection.

Hence, A_i and γ_i are sufficient statistics to describe the level of marginal costs and the slope of marginal costs, given input market prices and the output level. In equilibrium, output is also determined by those parameters, and we assume that the single firm takes input prices as given.

Log-linearizing the FOC of equation 3.2 around the steady state, the reset price equals the discounted value of desired markups and expected marginal costs (where $\hat{x}$ stands for x log deviation from steady state):

$$\hat{p}^o_{ist} = (1-\beta\theta)E_t \sum_{k=0}^{\infty} (\beta\theta)^k (\hat{\mu}_{ist+k} + \hat{mc}^n_{ist+k}) \tag{3.4}$$

Given the above specifications, equation 3.4 can be rewritten in the following way:

$$\hat{p}^o_{ist} = (1-\beta\theta)E_t \sum_{k=0}^{\infty} (\beta\theta)^k [(1-\Omega_{is})\hat{mc}^n_{ist+k} + \Omega_{is} p^{-i}_{st+k} + (1-\Omega_{is}) u^{\mu}_{ist+k}] \tag{3.5}$$

where $\Omega_{is} = \frac{\Gamma_{is}}{1+\Gamma_{is}}$, which is increasing with the firm production technology level.

From the formula of MC^n_{ist}, log marginal costs are:

$$\hat{mc}^n_{ist} = \hat{c}_{ist} + v_i \hat{y}_{ist}$$

where the slope of the marginal costs relative to output is decreasing with production output elasticity:

$$v_i = \frac{1-\gamma_i}{\gamma_i} \tag{3.6}$$

while $\hat{c}_{ist}$ is not firm-specific in our model, but it just depends on the market cost of labour and capital, which is given from the point of view of a single firm, as we assumed above. Therefore, the price equation for each firm becomes:

$$\hat{p}^o_{ist} = (1-\beta\theta)E_t \sum_{k=0}^{\infty} (\beta\theta)^k [(1-\Omega_{is})(\hat{c}_{ist+k} + v_i \hat{y}_{ist+k}) + \Omega_{is} p^{-i}_{st+k} + (1-\Omega_{is}) u^{\mu}_{ist+k}] \tag{3.7}$$

From the derivations above, it can be noticed that firm production technology is the crucial component of the firm supply curve, implying flatter marginal costs and competition mechanisms decreasing price pass-through for more productive firms. Even the competition mechanism results from higher production technology: lower marginal costs let the more productive firms grow larger and face less elastic residual demand. This implies that, at the occurrence of a demand shock, firms with a higher level of production technology react less in terms of prices and, consequently from monopolistic competition, more in terms of output.

Then, leveraging the Calvo pricing mechanism:

$$E_t[p_{ist}|p_{ist-1}, p^o_{ist}] = (1-\theta)p^o_{ist} + \theta p_{ist-1}$$

and

$$\hat{p}_{ist} = (1-\theta)\hat{p}^o_{ist} + \theta\hat{p}_{ist-1} + \nu_{ist}$$

Consequently, the firms' pricing equation can be rewritten as:

$$\hat{p}_{ist} = (1-\theta)(1-\beta\theta)E_t\sum_{k=0}^{\infty}(\beta\theta)^k[(1-\Omega_{is})(\hat{c}_{ist+k}+v_i\hat{y}_{ist+k})+\Omega_{is}\hat{p}^{-i}_{st+k}]+\theta\hat{p}_{ist-1}+\epsilon_{ist} \tag{3.8}$$

Given input prices and market structure, the higher the level of production technology at the firm, the flatter the firm supply curve. In fact, v_i decreases with productivity and output elasticities and denotes the lower increase in firm inputs needs after a demand increase. v_i is the slope of the firm marginal cost curve or supply curve. Moreover, $(1-\Omega_{is})$ denotes the strategic interaction effect as in Andrés and Burriel (2018), and it delivers a lower cost pass-through for firms characterized by more advanced production technology.

For our empirical strategy, we rely on equation 3.8 and estimate it for heterogeneous firms clustered according to their production technology. As stated above, the slope of firms' supply curve can also be affected by firm-specific demand elasticities.

Hence, we will control for it as well in our clustering analysis. Moreover, since we employ annual data as described in Section 3.4, the weight on future streams of output and related expectations becomes negligible. In fact, given standard estimated Calvo price stickiness parameters, firms are mostly free to adjust prices within one year. The same implication could be derived from agents' beliefs about effective monetary or fiscal policy responses to shocks in order to keep output on a balanced growth path.

3.2.2 Aggregating to the Phillips Curve

Finally, we show that the macro Phillips curve can be seen as an aggregation of heterogeneous firms' pricing equations, using the CES example. They are at the foundation of the economy-wide supply curve.

To derive the Phillips curve, we define the aggregate price index and the industrial prices as typical from a nested CES function:

$$P_t = \left(\int_0^1 \omega_{st}^{\epsilon} P_{st}^{1-\epsilon}\, ds \right)^{\frac{1}{1-\epsilon}}$$

$$P_{st} = \left[\sum_{i=1}^{N} \omega_{ist}^{\sigma} P_{ist}^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$$

where ω_{st} and ω_{ist} are possible industry-specific and firm-specific demand shocks, respectively.

To aggregate, we recover the equations for prices in log deviations around the steady state (omitting the shocks for ease of notation):

$$p_t = \int_0^1 p_{st} ds$$

$$p_{st} = \frac{1}{N} \sum_{i=1}^{N} \bar{p}_{is}^{1-\sigma} \hat{p}_{ist}$$

The firm price equation in recursive form can be written as follows:

$$\hat{p}_{ist}^{o} = (1-\beta\theta)[(1-\Omega_{is})(\hat{c}_{ist} + v_i \hat{y}_{ist}) + \Omega_{is} p_{st}^{-i} + (1-\Omega_{is}) u_{ist}^{\mu}] + \beta\theta E_t \hat{p}_{ist+1}^{o}$$

It is important to notice that, from CES specification, $\frac{\bar{p}_{is}^{1-\sigma}}{N} = s_{is}$. Hence, our aggregation is a weighted average of prices by steady-state firm revenue shares. It can be further shown that (thanks to Calvo iid draws and the law of large numbers):

$$p_t = \theta p_{t-1} + (1-\theta)\hat{p}_t^o$$

where

$$\hat{p}_t^o = \int_0^1 \left(\frac{1}{N} \sum_{i=1}^{N} \bar{p}_{is}^{1-\sigma} \hat{p}_{ist}^o \right) ds$$

This way, aggregating recursive firm price equations, we obtain:

$$\hat{p}_t^o = \beta\theta E_t \hat{p}_{t+1}^o + (1-\beta\theta)p_t + (1-\Omega)(1-\beta\theta)\hat{c}_t^r + (1-\beta\theta)v\hat{y}_t + u_t \tag{3.9}$$

where

$$(1-\Omega) = \int_0^1 \left(\frac{1}{N} \sum_{i=1}^{N} \bar{p}_{is}^{1-\sigma}(1-\Omega_{is}) \right) ds$$

and

$$v\hat{y}_t = \int_0^1 (\frac{1}{N} \sum_{i=1}^{N} \bar{p}_i^{1-\sigma}(1-\Omega_{is})v_i \hat{y}_{ist})ds$$

From equation 3.9, it is then straightforward to compute the Phillips curve:

$$\pi_t = \beta E_t \pi_{t+1} + (1-\Omega)(1-\beta\theta)\hat{c}_t^r(\hat{y}_t) + (1-\beta\theta)v\hat{y}_t + u_t \tag{3.10}$$

The slope of the Phillips curve, given expectations and input prices, is a weighted average of each firm's supply curve and is flatter when the market share of more productive firms is higher. The Phillips curve can flatten even if the steady-state share of the more productive firms does not increase as long as these firms are the ones responding the most to temporary demand shocks. It is important to notice that we would find the same result if we used an atomistic basic NK model with heterogeneity in production technology. In atomistic monopolistic competition, $\zeta_{is} = 0$ and $s_i = 0$ for each firm i, and this would eliminate strategic interaction (Ω_{is} would be zero for all firms). However, our model predicts heterogeneous pricing curves beyond competition effects due to flatter marginal cost curves for more productive firms.

Furthermore, the aggregation to the macro-level Phillips curve shows us that it is not necessary to aggregate by industry. What matters is the production structure of firms and the residual demand they face, with v being the weighted average across firms. In our empirical analysis, therefore, we consider only heterogeneity across technology and demand elasticity dimensions rather than heterogeneity across industries as defined by statistical agencies.

Finally, it must be noticed that the macro Phillips curve in equation 3.10 is characterized by a real input costs component c_t^r since we do not assume constant returns to scale in production technology. At the aggregate level, they are a function of the output gap, however they are driven by tightness in input markets. In any case, the higher the share of more productive firms with flatter derived input demand, the flatter the slope of the aggregate Phillips curve.

3.3 Stylized Facts

Building on the previous section's theoretical framework, we first report some stylized facts about the effect of production technology heterogeneity on the slope of the Phillips curve. To perform this analysis, we rely on micro-aggregated data from the 9^{th} vintage of the CompNet database.

The CompNet datasets draw from various administrative, statistical, and public firm-level sources across numerous European countries and are constructed to be highly comparable across countries. CompNet data comprises firm-level indicators that are aggregated to different levels, e.g., 2-digit industry or industry by size class. The 9^{th} vintage includes 21 European countries for the period 2004-2020 and covers most of the private non-farm business sector, including activities trade and services[1]. A very useful feature of the CompNet database is the so-called *joint distribution* tables. These datasets aggregate firm-level indicators along the distribution of a specific variable, creating "representative firms" for each quintile of the distribution of the specific variable by country, sector, and year. For each of these "representative firms" defined by their quintile location in the within-industry productivity (TFP) distribution, we have data on output, productive inputs, and wages, by 2-digit industry, country and year. At the firm level, TFP is estimated through OLS regressions with year fixed effects assuming the Cobb-Douglas production function, as in our theoretical model.

As we showed in Section 3.2, productivity and costs are inversely related: if demand in an industry rises, and this demand is disproportionately supplied by the highest productivity/lowest cost firms, industry prices may well rise less than if low productivity firms, ceteris paribus, meet the demand.

Given that there is no information about firm prices in CompNet, we first test our theoretical model on the input prices side. In particular, we estimate wage equations as follows:

$$\delta w_{csqt} = \alpha x_{csqt} + \beta \delta w_{csqt-1} + \gamma \pi_{ct-1} + \delta_{csq} + \delta_t + \varepsilon_{csqt} \tag{3.11}$$

where δw_{csqt}, x_{cst}, and $\pi_{c,t}$ are real wage growth rate, output gap in log-points, and country inflation, respectively, in country c, industry s, productivity quintile q, and year t. Inflation is taken from Eurostat[2]. Furthermore, δ_{csq} and δ_t are country-industry-quintile and year fixed effects, respectively. This panel regression is shaped to mimic the formula of marginal costs in equation 3.3 of the theoretical model, controlling for trends in industry input prices. Potential output and output gap are also measured for the representative firms at each productivity level [3].

[1]For more details, please see Haug et al. (2022).

[2]Available at https://ec.europa.eu/eurostat/databrowser/view/tec00118/default/table.

[3]We measure potential output as the estimated maximum production in each country, 2-digit

Table 3.1: Real wage growth on output gap

	(1)	(2)
	δw_{csqt}	δw_{csqt}
x_{csqt}	0.136***	0.123***
	(0.004)	(0.004)
δw_{csqt-1}	-0.311***	-0.313***
	(0.005)	(0.006)
π_{ct-1}		0.119***
		(0.025)
Constant	0.0548***	0.0481***
	(0.010)	(0.011)
Country-Industry-Quintile FE	Yes	Yes
Year FE	Yes	Yes
Observations	35,600	27,611
R-squared	0.167	0.163

Source: CompNet 9^{th} vintage and Eurostat.
Notes: panel regressions at the country-industry-productivity quintile level of real wage growth on output gap, lagged real wage growth, lagged country-level inflation (model 2), and year fixed effects. Standard errors clustered at industry-country level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

At the aggregate level, the resulting wage Phillips curve is reported in Table 3.1. On average, for a 1 percentage point increase in output gap, wages increase by 0.13%. These findings are not directly comparable to macro estimates, given that the focus

industry, productivity quintile, and year, by a standard stochastic frontier model. The output gap is, then, measured as the log difference between actual real sales and potential output.

is on real wages and not on inflation. However, they are in line with estimates of the Phillips curve at the macro level. Recently, Ball and Mazumder (2021) report estimations of basic Phillips curve for the euro area around 0.22. Moreover, the slope of the Phillips curve in the ECB-BASE semi-structural model is estimated to be 0.12 (see Eser et al. (2020)).

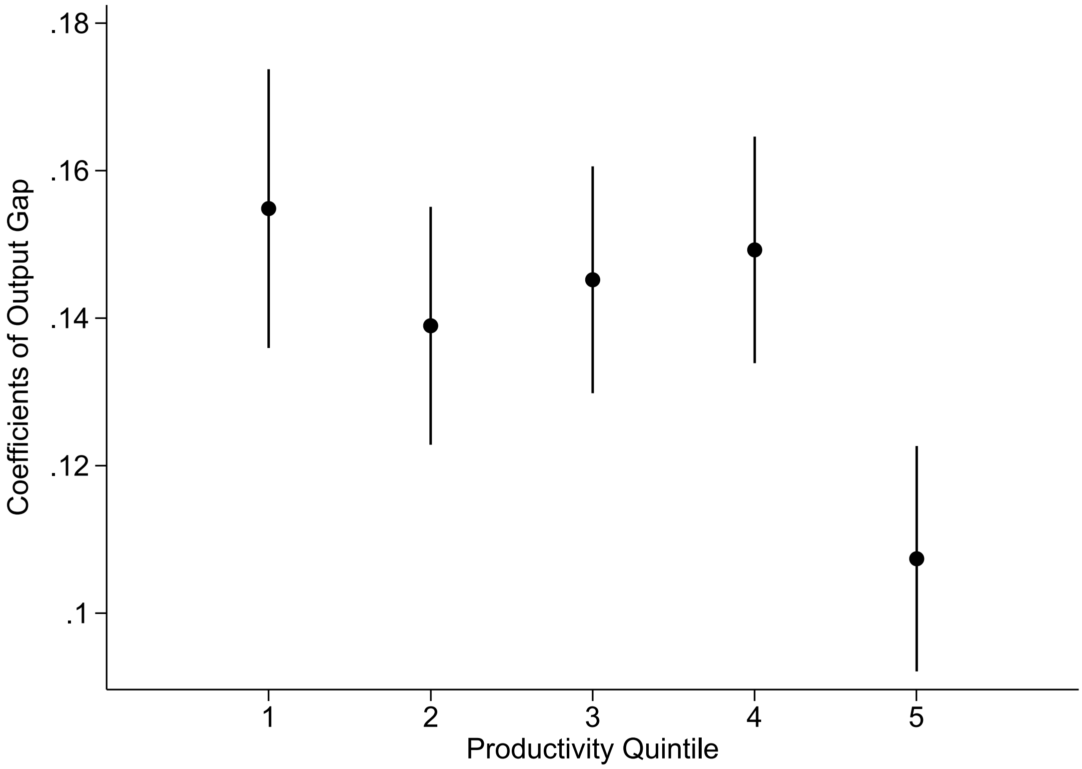


Figure 3.1: Slope of the firms' wage equation along the TFP distribution.

Source: CompNet 9^{th} vintage and Eurostat.

Note: Coefficients of the output gap, derived from panel regressions at the country-industry-productivity quintile level of real wage growth on the output gap, lagged real wage growth, lagged country-level inflation, labour market power, and year fixed effects for the period 2004-2020. Regressions are taken separately for each productivity quintile group of firms. All available industries and countries are pooled. 90% confidence intervals are included.

The most intriguing finding, however, emerges when performing estimations of firms' pricing behaviour along the productivity distribution. We estimate our wage-to-output relation 3.11 for each quintile of firms along the TFP distribution, controlling for labour market power as well[4]. As shown in Figure 3.1, the most productive firms are characterized by a less responsive wage increase when their available production capacity shrinks.

In a related reduced-form equation, we regress real sales growth by industry-quintile on industry aggregate real sales growth, interacted with productivity quintile dummies. As Figure 3.2 reports, the most productive quintile responds more intensively in terms of production to aggregate output increase. This is consistent with our theoretical model, which implies a lower slope of the Phillips curve for this group of firms.

This reduced-form empirical evidence, leveraging cross-country micro aggregated data, suggests that the marginal firm responding to demand shocks or, more generally, to an increase in aggregate demand, is the most productive firm with the lowest marginal costs. Hence, heterogeneous productivity, combined with lower price response and higher demand response from more productive firms, implies a flatter aggregate supply curve.

Unfortunately, the evidence remains from reduced-form regressions of quintile wage changes on output gaps or from quintile market share changes on industry output change, and the interpretation relies on consistency with comparative statics from a postulated model. To truly bring our model to the data, we would like to estimate the firm output price (and quantity) response to exogenous shifts in demand (or cost) for firms that differ by technology residual demand.

[4]Labour market power is defined as the ratio between firms' markup over labour and markup over intermediate input (markdown). For reference, please see Dobbelaere and Mairesse (2013) and Mertens (2019).

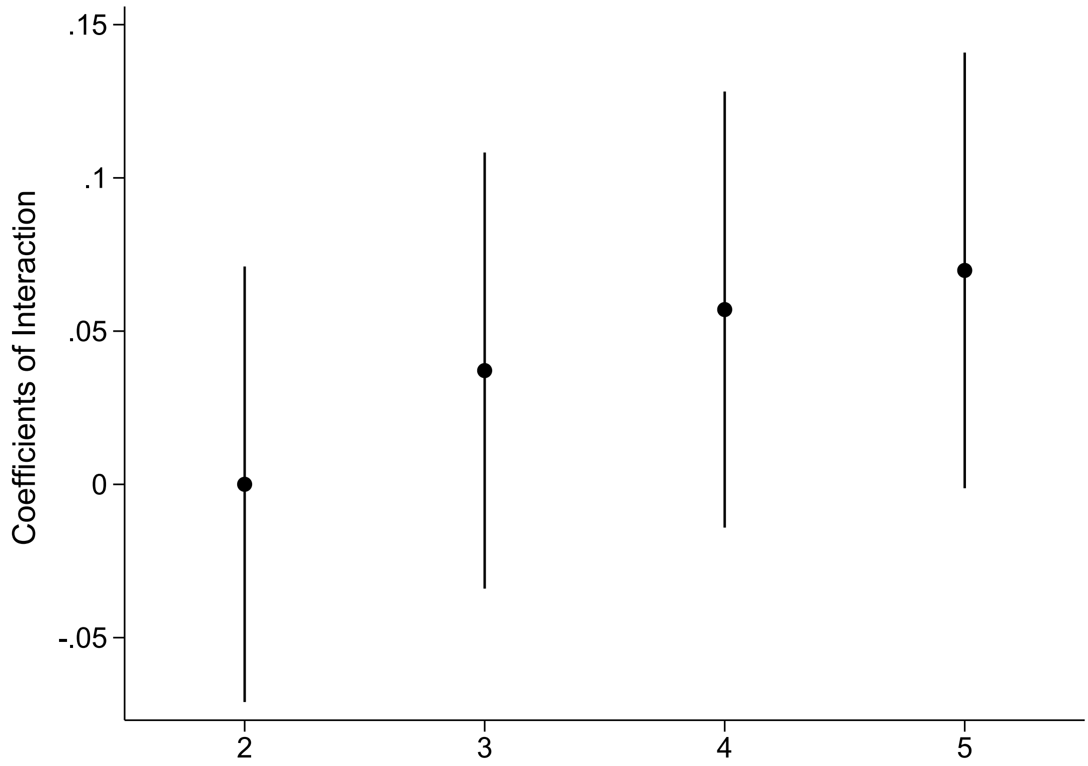


Figure 3.2: Increase in production along the TFP distribution. Year-on-year changes, TFP quintile 1 as reference.

Source: CompNet 9^{th} vintage.

Note: Coefficients of interaction between aggregate real sales growth and productivity quintile dummies, derived from panel regressions at the country-industry-productivity quintile level of real sales growth on country-industry production growth dummy (1 if growth rate is positive, 0 otherwise), interaction of the dummy with productivity quintiles, and year fixed effects, for the period 2004-2020. All available industries and countries are pooled. 90% confidence intervals are included.

3.4 Data Description

In the main empirical analysis, we make use of the newly built micro data infrastructure (MDI), that harmonizes firm-level data on output, inputs, and prices at EU statistical agencies. Further, we employ national statistical institute (NSI) data for industry price deflators, as well as OECD input-output tables and UN Comtrade data for the construction of exogenous demand indicators.

The MDI dataset is created under the EU *Technical Support Instrument* project[5], which involves the direct participation of NSI for data construction and harmonization, while national productivity boards (NPB) and several research institutes are data users and partners. A wide range of datasets are available at NSI, harmonized through the MDI, and linked in each country through a unique firm identifier.

MDI provides access to harmonized annual firm-level data for several European countries. Currently, we can access only French data directly. So, in what follows, our main analysis will be related to France. However, we are also provided with remote execution for the Netherlands[6]. Hence, we can implement some cross-country comparisons at the end of our empirical research. The MDI harmonization will come with the enormous advantage of letting researchers implement cross-country analysis on confidential firm-level data feasibly and efficiently, and we will be able to extend our analysis to more countries in the near future.

At the core of the MDI database is the *Statistical Business Register* (BR), which contains information on identifying firm characteristics. In MDI, the BR is the "backbone" or connection between various surveys and administrative datasets. In addition, the following datasets are available: *Balance Sheet and Income Statement* (BS), *Structural Business Statistics* (SBS), the *Community Innovation Survey* (CIS), the *ICT usage/E-Commerce Survey* (ICTEC), the *International Trade in*

[5]The MDI received funding from the H2020 project grant *Microprod*, 2019-222, and the EU TSI project, European Commission, Directorate-general for Structural Reform Support under grant agreement No. 101101853 and No. 101140673 (Austria). For more details, see the CompNet website at the following link: https://www.comp-net.org/eu-technical-support-instrument-tsi/overview/.

[6]Microdata are also under construction in Austria, Germany, Italy, Portugal, and Slovenia. Moreover, remote execution is available for Finland.

Goods Statistics (ITGS) and *International Trade in Services Statistics* (ITS), the *Foreign Affiliate Statistics* (FATS), *Firm Production Statistics* (Prodcom), and *Firm Energy Use* (ENER). For more details about each dataset, please see Appendix C.1.

The MDI allows harmonizing the linked panels in each country to have common classifications: for example, the same variable names and definitions, the same industry and product codes, and so on. Consequently, the researcher's code can run unchanged in each country to generate output datasets with, for example, moments and regression parameters, that can be analyzed jointly in a multi-country setting.

In our empirical analysis, we use mainly two datasets from the MDI environment: Prodcom and SBS. Prodcom data report revenues and quantities by firm and 8-digit product, covering the economic activities of mining and quarrying, manufacturing, and materials recovery. The Prodcom datasets are relatively harmonized owing to Eurostat regulation. In the specific case of France, the survey covers a wider set of products, but we restrict the analysis to the common set of products included in Prodcom for cross-country comparison purposes[7]. The production dataset, SBS, covers the business economy's activities, including industry, construction, distributive trade, and services. Harmonization of the SBS is more difficult because only aggregated statistical output is harmonized at the EU level (Commission Regulation (EC) No 250/2009) and countries have some discretion on how to collect the underlying information. MDI harmonization takes place regarding the detail of coverage of size-class, sector (now NACE 2.1), and the statistical definition of the transmitted indicators. The following analysis is undertaken on the selection of firms that report information in both datasets.

[7] In France, INSEE undertakes a wider survey than Prodcom, called ProdFra (acronym for *Production Française*). The ProdFra headings are usually coded on 10 digits, the first eight repeating the Prodcom code if it exists. Furthermore, we exclude invoices relating to subcontracted orders in the computation of revenues and sales.

We employ SBS to collect information about firms' revenues and production inputs, particularly labour and intermediate material expenses, as well as wages. As for capital and interest paid by firms, we derive these indicators from the BS data that have been disaggregated from the enterprise group to firm level[8]. These data are used to implement our clustering analysis on firm production and costs pass-through, as we explain in Section 3.5.

Prodcom data are used to create prices at the firm level. We define the yearly price for each firm and product as the ratio between product revenues and quantities. Then, we define the firm-product price change as the ratio between the price in year t and $t-1$, and we aggregate to the firm level using a Törnqvist index, weighting over product revenue shares within each firm[9]. The resulting firm price change is, hence, as follows[10]:

$$\frac{P_{it}}{P_{it-1}} = \prod_{g \in i_g} \left(\frac{P_{git}}{P_{git-1}} \right)^{s_{git}}$$

In the expression above, P_{git} is the price index for product g, firm i, and year t, and s_{git} is the average firm revenue share of that product between year t and year $t-1$. This way, we create a firm price index: we normalize $P_{i,2010} = 1$ for all firms, and we cumulate forward an backward by the annual price change[11].

[8] Labour is defined as full-time equivalent and capital as tangible plus intangible fixed assets.

[9] To construct the price change we need to harmonize the Prodcom codes across years. We do so thanks to official conversion tables provided by INSEE, the French NSI, and leveraging the firm-level data. In particular, we concord all one-to-one (the vast majority) and many-to-one matches. Also, we concord most of the one-to-many and many-to-many matches: in fact, if the concordance tables refer to a one-to-many or many-to-many match, but the single firm is producing only one good in year $t-1$ and t, we concord such codes straightforwardly. This way, we can concord up to more than 99% of the sample.

[10] We aggregate at the firm level products that are produced both in year $t-1$ and t, for which quantity unit of measure is comparable.

[11] For the years where firms are missing in the data, we fill the gap with 2-digit industry deflator change to complete the firm price series, and then we remove such observations from the final dataset.

Table 3.2: Descriptive statistics from the Prodcom dataset

	Average	5^{th} Pc	25^{th} Pc	Median	75^{th} Pc	95^{th} Pc
Revenue	20275.99	96.68	507.42	1884.74	6788.90	55784.14
Employees	58.85	1	3	11	33.84	203.25
Market Share within Manufacturing	0.004%	0.00002%	0.0001%	0.0004%	0.001%	0.012%
Market Share within 2-digit industry	0.089%	0.0005%	0.003%	0.098%	0.035%	0.262%
Market Share within 4-digit industry	0.811%	0.004%	0.026%	0.071%	0.276%	2.709%
Consecutive years	6.96	2	3	7	11	12
Number of industries	1.20	1	1	1	1	2
Within firm revenue share of main industry	96.27%	65.82%	100%	100%	100%	100%

Note: Firm descriptive statistics from Prodcom. The final number of observations from the Prodcom dataset is 260368. Employees are measured in full-time equivalents. Revenue is in thousands of Euros.

Similarly, we also create a price change variable for competitors, i.e., all the firms except firm i in a given 4-digit industry, which is required by our firm pricing equation estimation. In this case, we use firm market share as Törnqvist index weight. The choice of the 4-digit industry as the market size is given by Table 3.2, which reports descriptive statistics from the Prodcom dataset. As it can be noticed, only at the 4-digit level do firms have a meaningful share of the market (0.8% of the market on average), and it is reasonable, hence, to assume strategic interaction[12]. From Table 3.2 it can also be seen that the distribution of firms is skewed to the right in terms of sales and labour, and that firms are operating mostly in one 4-digit industry, and more than half of our sample produces more than one good.

Furthermore, it is instructive to test to what extent the pricing behaviour of firms reflects the aggregate price index. To do that, we aggregate our firm-level price changes, constructed as explained above, at the manufacturing level, again implementing a Törnqvist index weighting over market shares. We then compare our micro-based aggregate measure with the manufacturing gross output deflator from EU Klems[13].

As it can be seen in Figure 3.3, microdata manage quite well to replicate macro figures. On the one hand, this reveals the robustness of microdata. On the other hand, it also confirms that the aggregate price index consists of firms' pricing decisions.

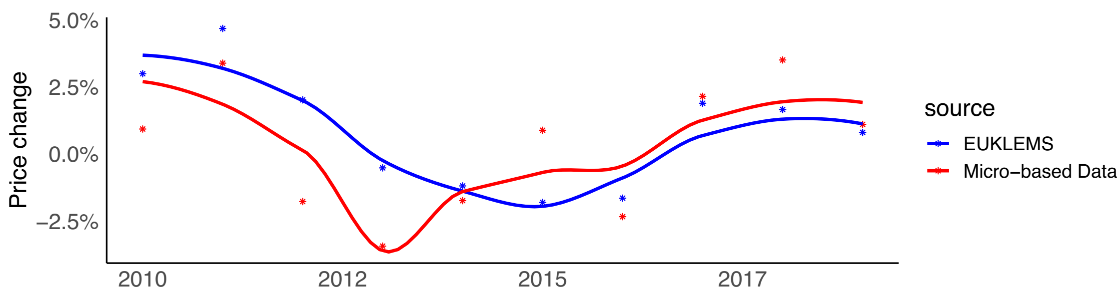


Figure 3.3: Aggregate price change in manufacturing: MDI and EU Klems.

In our estimation of firm-level price decision and supply curve slopes, we need exogenous measures of demand shocks. We create two typologies of downstream

[12] Similar results are provided for Belgium by Gagliardone et al. (2023).

[13] EU Klems data are available at https://euklems-intanprod-llee.luiss.it.

demand indicators. The first one is constructed using the Inter-Country Input-Output (IO) Tables from the OECD[14]. These tables report intermediate expenses and output for 76 countries and the rest of the world at the 2-digit sectoral level or aggregation of sectors (NACE Rev.2 classification).

Revenues from the IO tables are in millions of US dollar Therefore, we firstly convert units into national currencies and, then, we deflate activities by industry deflators (or country GDP deflator, when sectoral deflators are not available)[15]. Afterwards, we calculate the downstream indicator for each country-sector as the weighted average of the annual percentage change in input expenses of its destination partners. The average is weighted over the previous year's shipment shares to each destination partner. From the computation are excluded the destinations whose input expenses in the country-sector shipments are more than 5%, as well as the destinations that represent more than 5% of the country-sector input expenses (Boehm and Pandalai-Nayar (2022) suggests this further condition)[16]. Consequently, our measure of downstream demand is robust to concerns of endogeneity regarding supply shocks in one industry affecting the partner industry. Our first instrument is, hence, a version of the Shea's instrument (Shea (1993a), Shea (1993b)) of both domestic and foreign direct downstream demand:

$$DS_{st}^{Shea} = \sum_{j \in J_{st-1}} s_{jst-1} \Delta ln M_{jt}$$

where s_{jst-1} denotes the sales shares of industry s to destination j in year $t-1$, and $\Delta ln M_{jt}$ represents the aggregate growth rate of destination j's input expenses between years t and $t-1$.

[14] Available at https://www.oecd.org/sti/ind/inter-country-input-output-tables.htm.

[15] Sectoral deflators are taken by Eurostat, the OECD Structural Analysis Database (STAN), or EU Klems; GDP deflators and exchange rates are provided by the World Bank.

[16] We also exclude domestic destination partners, to increase the exogeneity of the instrument. However, to improve predictive power, for each of the bottom 50% sectors in terms of export, we include the downstream shock of the domestic top 50% exporters, weighted by the shipment shares from the bottom exporter sector to the top exporter.

Our second measure of demand shock is calculated as the world import growth rate, following the strategy of Dhyne et al. (2022). Export and import data are available in the UN Comtrade dataset[17] at the country-product level. Products are reported in millions of US dollars at the Harmonized System (HS) 6-digit level. Hence, we can construct the downstream indicator for each product as the total growth rate in world imports net of the imports from France. Imports are deflated by US GDP, which is a reasonable measure as a world import deflator (see, e.g., Gopinath et al. (2020)). This way, we can measure export-driven demand shock for each product in France. We then calculate a firm-specific shock weighting the product-level demand shocks with the firm revenue shares of such products, leveraging information from Prodcom:

$$DS_{it}^{wid} = \sum_{p \in \mathcal{P}_{pt-1}} s_{ipt-1} \Delta lnWID_{pt}$$

where s_{ipt-1} is the firm revenue share of product p for firm i in year $t-1$, and $\Delta lnWID_{pt}$ denotes the world demand growth rate for product p between years t and $t-1$.

We link the DS_{it}^{wid} instrument to our final firm-level dataset thanks to concordance tables between 8-digit Prodcom codes and 6-digit HS codes provided by Eurostat[18]. Instead, the DS_{st}^{Shea} is more easily linked since the first 4 digits of the Prodcom codes are identical to the NACE classification. After including all the relevant variables and cleaning data, the final firm-level annual dataset includes 200227 firm-level observations from 2011 to 2020.

Thanks to these demand instruments, which are standard in the literature, we

[17]Available at https://comtradeplus.un.org/.

[18]Eurostat provides concordance tables between Prodcom and the Combined Nomenclature 8-digit codes, which are equal to the HS classification for what concerns the first six digits. We take the average export demand shock in case of a one-to-many match.

can deal with endogeneity and estimate the supply curve for heterogeneous firms along the production technology distribution. Moreover, such shocks are different in nature. DS_{st}^{Shea} is closer to being an aggregate shock (at the industry level). All firms in the same industry are affected by the same shock coming from foreign downstream industries[19]. Hence, this indicator captures a global trend in demand for a particular domestic industry, directly affecting the industry demand for exporters and domestic firms. It is also correlated with domestic downstream indicators, proving it detects a general trend in demand for the whole industry. DS_{it}^{wid}, instead, is more firm-specific. In fact, it is again a foreign downstream indicator but specific to a particular product, and, as stated above, we weigh each product shock with a firm revenue share of that product. This way, we link the global trend directly to the firm basket of products and increase the micro-level variability of our demand shocks.

3.5 Clustering Analysis

Our study aims to estimate the supply curves of heterogeneous firms along the production technology distribution. Our objective is to estimate the coefficient v_i in equation 3.8 and, hence, the heterogenous firm output elasticity component γ_i governing the slopes of the supply curves. Such a parameter can be derived by estimating the coefficients of the output component and the competitors' price in equation 3.8. However, the strategic component $(1 - \Omega_{is})$ could, in principle, be affected by firm-specific demand elasticity, as we explain in Section 3.2, and this could bias our estimates of the firm supply curve. Therefore, before implementing our empirical analysis, we cluster firms along the production technology distribution and according to similar demand characteristics. This way, we aim to increase the precision in estimating v_i. The related literature is becoming increasingly aware of the need to consider the heterogeneity in the demand side while computing produc-

[19]For the few firms operating in different industries, DS_{st}^{Shea} is also weighted by the firm revenue shares. However, as shown by Table 3.2, even firms producing in different industries are mostly concentrated in the main one.

tion functions (see, e.g., Forlani et al. (2023)).

Hence, we propose an algorithm to cluster firms according to a supply and a demand dimension. Some recent methodologies allow cluster observations across membership of multi-dimensional regression parameters. For example, Cheng et al. (2023) estimate multiple memberships in non-linear panel data and compute heterogeneous parameters across groups. Instead, we want to assign each firm membership according to two different regression models. As for the supply dimension, we run production function estimations for five possible groups and cluster each firm according to the best fit, assigning firms to their production technology level, from the least productive firms in the first group progressively to the most productive firms in the fifth group. Firms are considered to feature higher technology level when they are characterized by larger TFP and output elasticities. On the demand side, given the focus on the margin of the residual demand curve, we estimate a cost pass-through equation and, again, we cluster firms according to the best fit (in the case of demand, we cluster in three possible groups, from the lowest level of pass-through, meaning higher demand elasticity, to the highest one).

For the production estimation, consistent with the model, we regress a Cobb-Douglas production function with time fixed effects, as follows:

$$y_{it} = \alpha + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 m_{it} + \delta_t + \epsilon_{it}$$

where y_{it}, k_{it}, l_{it}, and m_{it} are firm output, capital, full-time equivalent, and intermediate expenses, respectively, while δ_t are time fixed effects[20]. All variables are in real log terms. We deflate firm output thanks to the firm price index computed as described in Section 3.4. This way, we can reduce firm markup and product quality estimation bias. Capital and intermediate inputs are, instead, deflated by 2-digit

[20] We do not include firm fixed effect since the production function literature theorizes that these could amplify the highly-persistent measurement error noise in capital stock; see, for example, Ackerberg et al. (2015).

sector-specific deflators. Given the relatively short period in our sample, characterized by low inflation levels, the possible input price bias is also assumed to be negligible.

For the demand estimation, we follow Mrázová and Neary (2017), who show that in monopolistic competitive markets, the cost pass-through is a function of demand elasticity and convexity[21]. Therefore, we cluster firms according to the following equation:

$$\delta p_{it} = \beta_0 + \beta_1(\eta_d, \rho_d)\delta mc_{it} + \delta_t + \epsilon_{it}$$

where δp_{it} is the log difference of firm price, while mc_{it} are residuals from a regression of firm log marginal costs on our downstream demand shocks to mimic a supply cost shock. According to theory, the resulting β_1 from the demand side clustering is a function of the elasticity η_d and convexity ρ_d of firms' residual demand. This way, we can cluster firms according to similar characteristics regarding the demand side. From our theoretical framework (equation 3.3), marginal costs are proportional to unit variable costs, and, hence, mc_{it} can be proxied by a counterpart in the data. We measure unit variable costs as the ratio between the sum of wages, paid interest, and intermediate expenses, and real output (nominal sales deflated by firm-specific price).

This procedure allows the clustering of firms according to these two dimensions in a reasonable span of time[22] and without the need for a huge amount of data information. Moreover, we do not a-priori divide firms according to industry, but we focus only on similarities among firms as detected by production estimation and

[21]The authors, unlike us, assume constant marginal costs as well. However, at the margin, it can still be a good approximation, and again, we are interested in detecting similarities among firms with respect to the residual demand they face. Therefore, a cost pass-through equation in a fashion similar to Mrázová and Neary (2017) reaches the purpose.

[22]In the case of our dataset, which includes 203363 observations for the clustering algorithm, it took around 13 hours to run the full process.

demand characteristics. Initial clusters are homogenous in size, while each firm can be clustered in any group without restriction. If a firm is assigned a cluster, it will be part of such a group for all the years it appears in the data: this is consistent with the idea of persistent production characteristics and makes the algorithm faster. For more details on the algorithm, please see Appendix C.2.

Since we are interested in classifying firms along the production technology distribution and according to demand characteristics, the initial clustering is based on ranking firms in same-sized bins along labour productivity and the ratio between the log difference of prices and marginal costs as indicators of production technology and demand, respectively. Then, our algorithm will detect the clustering that minimizes the residual sum of squares (RSS) for each bin along both production and demand dimension[23]. To our knowledge, this study is the first to explicitly consider both production and demand heterogeneity while estimating firms' supply curves.

Table 3.3 reports the result of the clustering analysis. The algorithm delivers a skewed distribution of firms along the production technology distribution, with around 70% of observations in the second and third production groups, and a long right tail of more productive firms.

As for the demand side clustering, cost pass-through estimates align with available empirical evidence, suggesting a less than 100 percent price-cost transmission (e.g., Gopinath and Itskhoki (2010), De Loecker et al. (2016)). Moreover, it is interesting to notice that firms are mostly located in the third demand cluster, where demand is the most rigid and pass-through higher. However, many firms also face higher demand elasticity (the first demand cluster), and this group is comprised of

[23]The adopted procedure detects the local minimum in terms of RSS and delivers the same classification when initializing with other ranking proxies for production technology, such as capital intensity or size. A suggested rule of thumb is to replicate the algorithm with several reasonable initial clusters and choose the initialization that best fits the data after implementing the algorithm.

Table 3.3: Firm-years observations by technology and demand groups

	Demand 1	Demand 2	Demand 3
Technology 1	5522	1699	18180
Technology 2	32544	4370	52709
Technology 3	10362	6365	38714
Technology 4	1045	5039	17595
Technology 5	339	2524	6356
Cost pass-through	0.177	0.826	0.914

Note: *Cost pass-through* indicates the estimated coefficient for the demand side clustering.

less productive firms for the large majority, while the most productive firms mainly face the third and second types of demand. Therefore, the clustering result suggests a negative correlation between production technology and residual demand elasticity. This can be partly because the most productive firms are also larger, as shown below. Our model's strategic interaction in monopolistic competition predicts that their competitors react strongly to their reset price increase, hence maintaining the residual demand more rigid.

To better acknowledge the differences among clusters, Table 3.4 shows descriptive statistics along the estimated technology distribution and the results from the production function estimation in the last round of the clustering algorithm. As it can be seen, estimated TFP is positively correlated with the sum of capital and labour output elasticities. This result is robust to different production function estimation specifications, including one-order and two-order lagged inputs as instruments for current inputs and the implementation of the Ackerberg et al. (2015) (ACF) methodology on value-added estimation[24]. This confirms the theoretical framework where TFP is supposed to be positively correlated with capital and labour output elasticity. Furthermore, the sum of capital and labour output elasticity positively correlates with labour productivity, measured as sales deflated by the firm price index over labour (full-time equivalent).

Table 3.4: Descriptive statistics by technology group

Technology	firms	TFP	oe_{k+l}	$\text{oe}_{k+l,\text{ACF}}$	lprod	size	markup_m	marg. costs
1	4593	1.470	0.187	0.881	4.44	8370.33	1.19	2.38
2	14397	1.389	0.195	0.895	5.10	12857.79	1.25	1.05
3	8442	1.684	0.229	0.917	5.44	19788.32	1.37	0.73
4	3428	1.744	0.240	0.937	6.01	22721.60	1.43	0.55
5	1371	2.324	0.412	0.961	6.92	24991.31	1.81	0.27

Note: *Firms* refers to the number of firms, *TFP* is total factor productivity which, together with the sum of output elasticities of capital and labour (oe_{k+l}), is computed through the production function estimation by group in the cluster analysis; $oe_{k+l,ACF}$ is the sum of output elasticities from a value-added production function estimation with ACF methodology; *lprod* means labour productivity in logs; *size* is sales in thousands of euros; $markup_m$ is markup over intermediate inputs estimated as in Loecker and Warzynski (2012); *marg. costs* are marginal costs proxied by unit variable costs as computed in the main analysis.

[24]The literature on production estimation is concerned about possible bias due to unobserved productivity shocks. However, in this context, the focus is not on estimating output elasticities but on ranking firms according to such parameters. Productivity shocks would correlate with the estimated output elasticities, delivering the same technology ranking. Moreover, the fact that productivity could affect output elasticities matches the idea of ranking firms according to production technology. In any case, robustness estimations are implemented, as stated in the main text.

The model predictions regarding size, markups, and marginal costs are also confirmed. As the firm increases production technology, it is found to be larger, with higher markups and lower marginal costs. In addition to that, from the CIS data, we find that only 52% of employees in firms from technology groups 1 and 2 use ICT, while the share increases to 62% for groups 3 and 4 until a percentage of ICT intensity among employees of 70% for technology group 5.[25].

Table 3.5: Growth in market shares and volatility of output change by production group

	Δs	$se(\Delta_y)$
Production 1	-1.40%	3958.62
Production 2	-1.55%	4468.83
Production 3	-1.50%	7598.99
Production 4	+3.80%	8174.57
Production 5	+0.65%	12515.39

Note: Δs is the change in market shares between 2013 and 2019, while $se(\Delta_y)$ is the volatility of output change, respectively.

Finally, Table 3.5 reports the growth rate in market shares between 2013 and 2019 and the volatility of output change during the sample period by technology group. As can be seen, even in a short period, we detect a reallocation of around 4.45% of market shares from the least productive to the most productive firms. Even more interestingly, the volatility of the output change is the highest for the most productive firms. This hints that demand shocks are mostly met by the firms at the technology frontier, meaning that these are the main suppliers at the margin,

[25]However, the statistics from the CIS data are based only on around 5% of the sample.

as predicted by theory and with deep implications for the aggregate supply curve slope. The more demand shocks are met by the most productive firms, the flatter the Phillips curve becomes.

3.6 Micro Results

The clustering analysis implemented in the previous section allows us to group firms according to their production technology level and detect differences in the residual demand they face. It delivers a population of firms classified only according to these two dimensions.

Based on such division, it is now possible to test whether firms' supply curves are heterogeneous across the production technology distribution, controlling for demand characteristics as well. To do that, we estimate firms' pricing equation 3.8 considering firm heterogeneity on these two dimensions. In particular, leveraging on the New Keynesian framework we described in Section 3.2, and considering we are employing annual data (for which firms can be considered allowed to optimize prices and, hence, weigh future streams negligibly), in our main analysis we estimate the following pricing equation:

$$\delta p_{it} = \beta_1 \delta y_{it} + \beta_{1c} \delta y_{it}{}^* D_c + \beta_2 \delta p^{-i}_{st-1} + \beta_{2c} \delta p^{-i}_{st-1}{}^* D_c + \beta_3 \delta p_{it-1} + \delta_{st} + \delta_i + \epsilon_{it} \quad (3.12)$$

where we implement 2SLS regressions to instrument firm real output increase δy_{it} by the downstream demand indicators we described in Section 3.4; δp_{it} and δp^{-i}_{st} are the log difference of firm and competitors' price at 4-digit industry level, respectively. We also add industry-year fixed effects δ_{st} to control for trends in industry input prices, and, this way, we want to mimic the component $\hat{c}_{ist}$ from the model pricing equation. Results are qualitatively similar when controlling at the 2-digit or 4-digit industry level. Moreover, we include firm fixed effects δ_i and lagged firm price log difference to control for the possibility that the firm pricing behaviour is outside the balanced growth path (which is implicitly assumed by the theoretical framework). We also instrument competitors' prices with their lagged value to avoid the risk of endogeneity in the case of industry shocks affecting both firm and competitors' pricing decisions.

Finally, $\beta_{xc}D_c$ for $x \in \{1, 2\}$ represents all the interaction coefficients with different cluster membership specifications. Cluster membership interacts with demand shocks and, as a robustness check, also with competitors' prices. The main parameter of interest is β_1 (and its interactions with cluster membership), which represents $(1 - \Omega_{is})v_i$ for each cluster from the theoretical model. The strategic competition effect Ω_{is} can be subtracted from the estimated coefficient of competitors' prices. Consequently, we can estimate our parameter of interest v_i for different groups of firms along the production technology distribution, net of the effect of strategic competition and controlling for residual demand characteristics. In all our regression specifications, observations are weighted by the revenue share to better mimic an aggregate supply curve slope.

We first analyze firms' pricing behaviour by comparing supply curves along the production technology distribution, without taking into account residual demand differences. Therefore, in this case, cluster interactions refer solely to the technology distribution.

Table 3.6 reports the results for the first stage of the demand instruments in the case of this first specification. Both types of downstream indicators are employed to increase the predictive power about firm sales increase. As it can be noticed, the DS_{st}^{Shea} instrument has a larger, though varying, impact on firm-specific demand increase (a 1% increase in aggregate demand raises firm output by 5.8% for the reference group). This is due to its aggregate nature, and this high variability makes it mostly insignificant. DS_{it}^{wid}, instead, manages to capture more firm-level variability and results highly significant. It is interesting to notice that in the case of an aggregate shock, the most responding firms in terms of sales are the firms at the top of the production technology estimation, implying a certain degree of reallocation within

Table 3.6: First stage of firm pricing equation by technology group

	δy_{it}		
DS_{st}^{Shea}	5.855	DS_{it}^{wid}	0.176***
	(8.411)		(0.032)
×tech$_2$	-4.168**		-0.026
	(1.912)		(0.033)
×tech$_3$	-4.597**		-0.003
	(2.050)		(0.035)
×tech$_4$	-2.529		-0.061
	(2.595)		(0.049)
×tech$_5$	11.426***		0.035
	(3.248)		(0.042)
Other regressors included		Yes	
Sector*Year fixed effects		Yes	
Firm fixed effects		Yes	
Obs		200227	
F-statistics		11.26***	
R^2		0.54	

Note: Observations weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p<0.01, ** $p < 0.05$, * $p < 0.1$, $^+ < 0.15$.

the industry from the least to the most productive firms. For the following price equation specifications, we report the first stage results in Appendix C.3. Here, it must be noticed that the effect of the instruments turns out to be mostly insignificant for the reference group, but this is due to the high number of interactions terms of the instruments with the cluster memberships, which are significant in some cases.

Table 3.7 shows the estimation results for the firm pricing equation by production technology cluster, where the first group is taken as reference. This first specification strongly points out a flattening supply curve along the production technology distribution. In fact, the least productive firms turn out to feature a steep curve, where a 1% increase in demand impacts prices by around 0.33%, while this slope decreases as the production technology increases until the most productive are characterized by a completely flat (and possibly even negative) supply curve. This result is robust to the inclusion of interaction with the competitors' price change and 4-digit industry-year fixed effects. The columns *Slope* report the significance from a t-test of the difference between cluster c and cluster $c-1$ coefficients, where $c = \{1, 2, 3, 4, 5\}$, and confirm the significant flattening of the supply curves as production technology rises. Finally, it is interesting to notice that strategic competition does not seem to have a huge impact on the flattening of the supply curve once heterogeneity in production technology is taken into account. The coefficient of competitors' price is found to be less than 0.08%, and the interactions with cluster membership do not reveal any significant pattern. This differs from, for example, Gagliardone et al. (2023), who find a flattening of the supply curves of around 50% due to competition interaction. This is, however, expected given the lower number of competitors in Belgium (on which the authors implement their empirical strategy) than in France.

This first result, hence, supports the theoretical framework in which the most productive firms have flatter supply curves. However, as we discussed above, the firm-specific residual demand could differ for firms located at different levels of production technology. This is the case as shown in Section 3.5. We, hence, leverage multi-dimensional clustering, and the main pricing equation specification includes interaction with all the production-demand groups delivered by the clustering algorithm. This way, the heterogeneity in supply curves can be assessed while keeping

Table 3.7: Firm pricing equation by technology group

	δp_{it}	Slope	δp_{it}	Slope
δy_{it}	0.335***		0.338***	
	(0.014)		(0.015)	
$\delta y_{it} \times \text{tech}_2$	-0.090***	***	-0.090***	***
	(0.010)		(0.010)	
$\delta y_{it} \times \text{tech}_3$	-0.147***	***	-0.144***	***
	(0.010)		(0.010)	
$\delta y_{it} \times \text{tech}_4$	-0.200***	***	-0.201***	***
	(0.012)		(0.012)	
$\delta y_{it} \times \text{tech}_5$	-0.507***	***	-0.505***	***
	(0.012)		(0.013)	
δp^{-i}_{st-1}	0.056***		0.079***	
	(0.007)		(0.022)	
δp_{it-1}	-0.253***		-0.255***	
	(0.005)		(0.004)	
δp^{-i}_{st-1}-Technology group fixed effects	No		Yes	
2 digit Industry-Year fixed effects	Yes		Yes	
Firm fixed effects	Yes		Yes	
Obs	200227		200227	
R^2	0.22		0.23	

Note: 2sls regression at the firm level, weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, $^+ < 0.15$. *Slope* column indicates whether there is a significant flattening of the pricing equation along the productivity distribution.

demand characteristics fixed.

Table 3.8: Firm pricing equation by technology - demand group

	δp_{it}			Slope		
	demand$_1$	demand$_2$	demand$_3$			
$\delta y_{it} \times$ tech$_1$	0.200***	0.129**	0.152***			
	(0.032)	(0.061)	(0.032)			
$\delta y_{it} \times$ tech$_2$	0.044	-0.028	0.059*		***	***
	(0.032)	(0.039)	(0.031)			
$\delta y_{it} \times$ tech$_3$	0.064*	-0.044	-0.006		***	***
	(0.035)	(0.036)	(0.031)			
$\delta y_{it} \times$ tech$_4$	-0.092$^+$	-0.154***	-0.046$^+$	***	***	***
	(0.057)	(0.045)	(0.032)			
$\delta y_{it} \times$ tech$_5$	-0.087	-0.277***	-0.350***		***	***
	(0.090)	(0.034)	(0.031)			
δp^{-i}_{st-1}	0.055***					
	(0.007)					
δp_{it-1}	-0.227***					
	(0.004)					
2 digit Industry-Year fixed effects		Yes				
Firm fixed effects		Yes				
Obs		200227				
R^2		0.22				

Note: 2sls regression at the firm level, weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p<0.01, ** $p < 0.05$, * $p < 0.1$, $^+ < 0.15$. Reference group is $prod_1 \times demand_1$. *Slope* column indicates whether there is a significant flattening of the pricing equation along the productivity distribution for each demand cluster.

The results from the main specification are presented in Table 3.8. Now, three columns are reported for each demand cluster, and interaction coefficients are in comparison with the technology 1 - demand 1 group. The results still provide strong evidence of firms' supply curve flattening along the production technology distribution. In particular, for demand groups 2 and 3, where demand is more rigid, the slope of the supply curves is significantly decreasing as production technology improves, as stated by the *Slope* columns reporting t-test for the difference between each consecutive production cluster within the same demand group. The most productive firms (i.e., technology groups 4 and 5), which are present mostly in these demand groups featuring less elastic residual demands, have the flattest supply curves. Technology group 5 is also characterized by an average slope that is not significantly different from zero.

As for demand cluster 1, instead, there is no significant flattening of the supply curve along the production distribution, except for technology group 4. This demand group features a more elastic demand curve, as shown in Table 3.3. Therefore, it is expected to deliver less variability in firms' price response since it features a demand much more sensitive to price change. Particularly, the least productive firms appear to decrease their price response when residual demand becomes more elastic. In addition to that, it is also possible that the insignificant results for demand group 1 are due to a smaller number of productive firms in such a cluster.

The results presented in Table 3.8 can now be considered cleaned from possible variability in terms of the residual demand firms face, and be caused by the sole heterogeneity in production technology. Again, the results are robust to different industry fixed effects specifications and to the inclusion of interactions between competitors' prices and cluster membership. Strategic competition turns out to have a similar effect as in the previous specification, with a flattening impact of around 5.5% and no significant patterns among clusters.

Figure 3.4 summarizes the dynamics of the supply curves along the production technology distribution for the three demand clusters. The average pricing equation coefficient for each technology group across demand clusters and the relative confidence interval are presented in the graph, which shows a clear flattening of the firm price response as its productivity increases. Figure 3.4 is the firm-level counterpart of our aggregate empirical evidence in Figure 3.1, which supports our micro findings for a broader set of countries and sectors (included services).

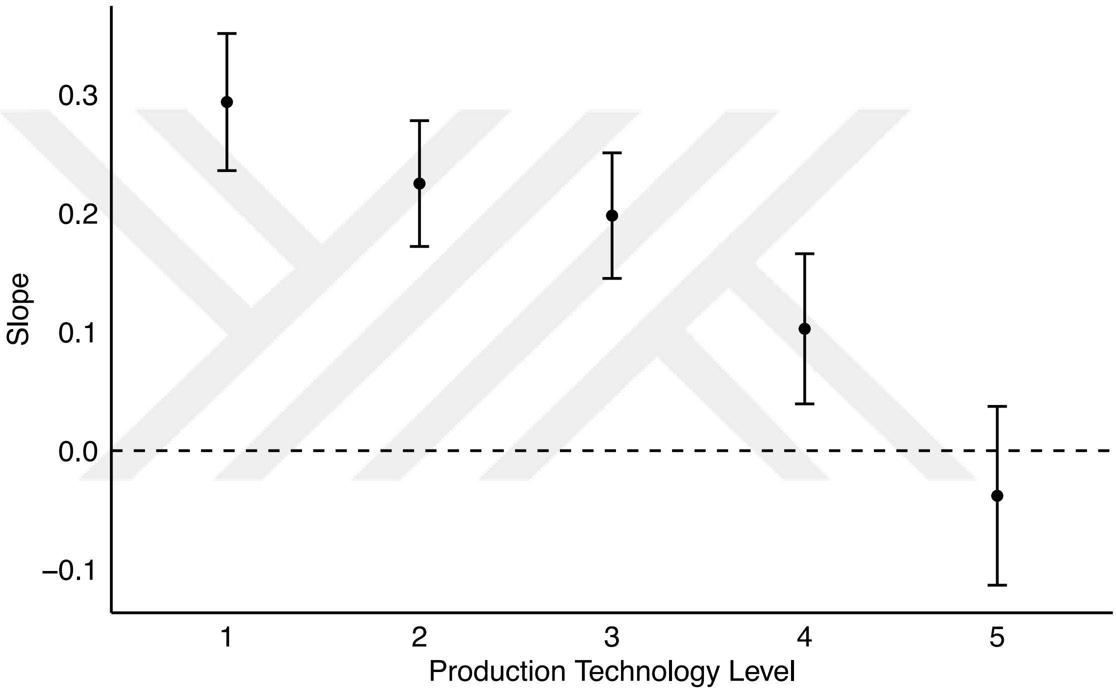


Figure 3.4: Slope of pricing equations by technology group.

Note: Average coefficients by production technology group from regression in Table 3.8. 95% confidence intervals constructed based on variance-covariance matrix of coefficients.

We further check the flattening of the supply curves along the production technology distribution with the following specification: we aggregate the production technology groups to separate the least productive firms (groups 1, 2, and 3) from the most productive firms (groups 4 and 5). We then regress our pricing equation clustering according to these aggregated groups, always controlling for demand characteristics. Results are presented in Appendix Table C.3. In this last specification, we detect a flattening of the supply curves in all demand groups.

To summarize our findings, heterogeneity in production technology significantly impacts firms' pricing behaviour. Even after controlling for strategic competition and residual demand characteristics, the distribution of production technology predicts a flattening of the supply curves. From a price response of around 0.3% for the least productive firms, the supply curve flattens along the production technology distribution until it reaches a slope that is not significantly different from zero.

Furthermore, from the estimations of our main specification in Table 3.8, we can derive an average parameter v_i for each cluster of production technology. To this aim, we take the average slope coefficient of the pricing equation for each production technology cluster across demand groups, net of the strategic competition effect detected from the coefficient of competitors' price[26]. This way, the computed heterogeneous slopes of the supply curves result in 0.356, 0.261, 0.2, 0.145, 0.001 from the least to the most productive firms, with the γ_i parameter being 0.737, 0.793, 0.833, 0.875, 0.999, respectively[27]. Hence, the heterogeneous supply curves along the production technology distribution can be represented in Figure 3.5. In the graph, the supply curves are calibrated around each cluster's mean marginal costs and sales, whose data are taken from Table 3.4. As can be seen, the higher the production technology, the lower the marginal costs, and the flatter the supply curve. This is expected from the model, where marginal costs are a function of productivity A_i and the output elasticity γ_i.

Given that the most productive firms are also larger and with higher markups,

[26] We multiply the average slope coefficient of the pricing equation by (1-0.06) in each production technology cluster. This factor represents $(1 - \Omega_{is})$ from the theoretical model, and it is not found to differ across clusters significantly (it is slightly smaller for the more productive firms, as would be expected).

[27] Actually, for the most productive firms (technology group 5), the mean slope would be -0.18, with γ_i equal to 1.22. However, it is not found to be significantly different from zero. Hence, we do not abandon this assumption.

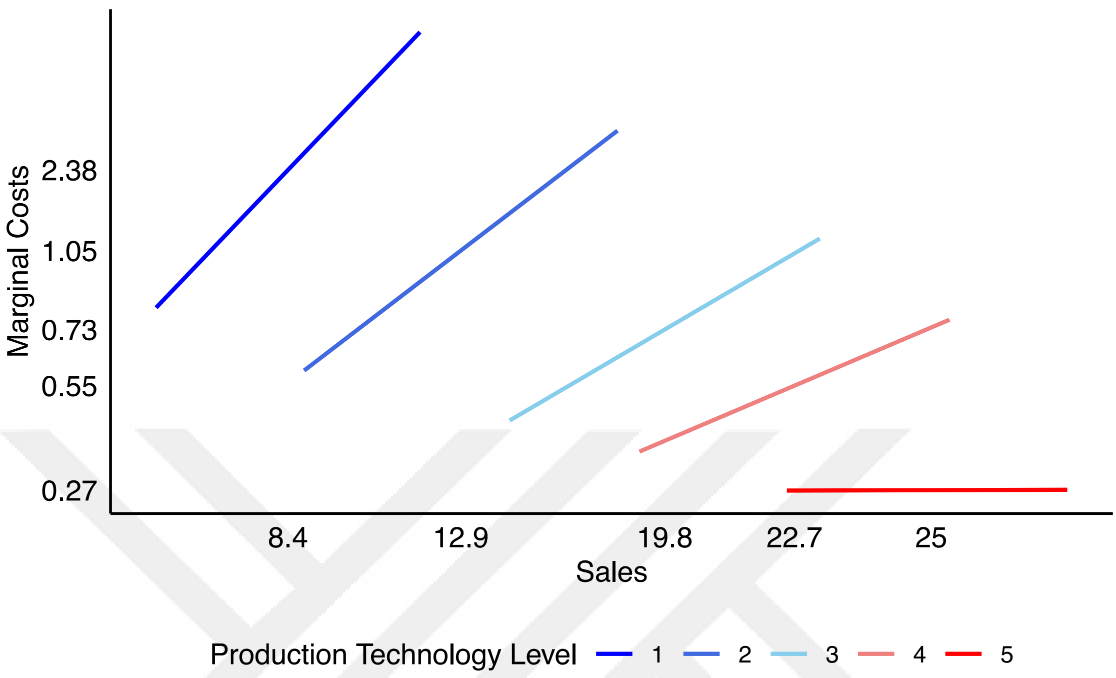


Figure 3.5: Heterogeneous Phillips curves.

Note: Calibrated firms' supply curve for each production technology cluster. Marginal costs and sales are data from table 3.4.

our results can also explain why a lower price response characterizes high markup firms and more concentrated markets (see, e.g., Fujiwara and Matsuyama (2022)).

Finally, we show microdata's power in replicating the Phillips curve's macro estimates. In Section 3.2, we explained that the macro Phillips curve is the weighted average of each firm supply curve, and it is, therefore, a weighted curve along firms' heterogeneity in production technology. Hence, an aggregate Phillips curve can be computed from micro evidence and compared with typical macro estimates.

We estimate a macro Phillips curve employing EU Klems data for the French manufacturing industry: the slope of the Phillips curve is computed through rolling regressions of sectoral price change on the output gap, controlling for lagged country

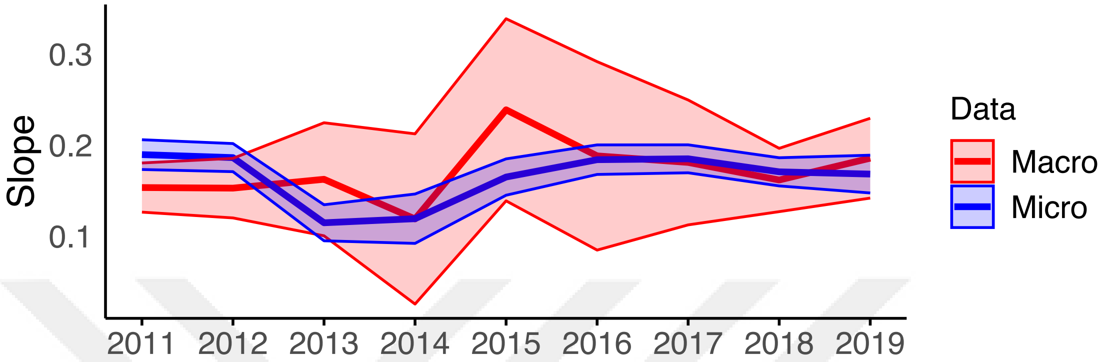


Figure 3.6: Slope of aggregate Philips curve, micro vs macro.

Note: Macro Phillips slope derived from rolling regressions of inflation on output gap, based on EU Klems French manufacturing data, controlling for lagged country inflation. Micro-based Phillips curve slope is computed as the weighted average of the estimated slopes of firms' pricing equations from Table 3.8, with yearly change in cluster sales as weight.

inflation. Each regression spans five years, and the slope of the macro Phillips curve is estimated from 2011 to 2019 (the last available year from EU Klems). Then, an estimate of the macro Phillips curve is derived from our micro results. Again, the average coefficients for each production technology cluster are taken from Table 3.8 and weighed by the cluster share of output change in each year. The comparison between the macro and the micro-based Phillips curve can be seen in Figure 3.6. When aggregated at the manufacturing level, micro-based estimates can predict the macro Phillips curve slope quite well and are included in its confidence interval for most of the estimation period.

The comparison suggests that now-casting the slope of the aggregate Phillips curve using microdata is an insightful exercise, where macro data analysis seems like a needlessly difficult task (e.g., see Bartelsman and Wolf (2014)).

3.6.1 Cross-Country Comparison

To widen the perspective of this study, some cross-country results from the MDI data are reported in this subsection. In particular, firms' pricing equation 3.8 is estimated in the case of the Netherlands for the same period as for France.

Each manufacturing firm is divided according to the productivity distribution. We construct firm total factor productivity (TFP), estimating a Cobb-Douglas production function for each 2-digit manufacturing industry, and then, firms are grouped in TFP quantile groups from the least productive to the most productive. This way, the following base equation can be estimated for each group:

$$\delta p_{ist} = \alpha + \beta x_{ist} + \delta_s + \delta_t + \epsilon_{ist}$$

where for each firm i, in industry s and year t, the price change is regressed on firm output gap x_{ist}, constructed as in Section 3.3, including industry and time fixed effect to control for sectoral differences and trends in input prices.

Table 3.9 shows that the increase in output gap does not have inflationary consequences among the most productive firms (column 4), while the supply curve is steeper for the other quantiles representing less productive enterprises. Hence, at the aggregate level, the higher the share of these most productive firms, the flatter the Phillips curve becomes. This result is graphically shown in Figure 3.7, where the average supply curve slope is taken among the least productive firms.

Finally, as for the case of France, Dutch firms are clustered according to production technology and demand characteristics, as explained in Section 3.5. Then, the firm pricing equation 3.8 is estimated for each technology-demand group, as in our

Table 3.9: Estimation of firm pricing equations - Netherlands

	(1)	(2)	(3)	(4)
	δp_{ist}	δp_{ist}	δp_{ist}	δp_{ist}
x_{ist}	0.02*	0.03***	0.03**	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
constant	0.15***	0.06***	0.07***	0.08***
	(0.05)	(0.02)	(0.02)	(0.03)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	19,828	19,967	15,638	14,015
R-squared	0.065	0.035	0.033	0.01

Note: OLS regression at the firm level, from the least productive (column 1) to the most productive firms (column 4). Standard error clustered by 2-digit sector in parenthesis. *** p<0.01, ** p $<$ 0.05, * p $<$ 0.1, $^{+}$ $<$ 0.15.

main empirical analysis. The summary of the results is presented in Figure 3.8. As can be noticed, the flattening of the firms' supply curves also characterizes Dutch firms, although they present a generally flatter marginal costs curve than in France.

The empirical findings in the Netherlands confirm the main analysis and hints, together with the multi-country results in Section 3.3, that the production technology effect on firms' pricing behaviour has a general scope across countries and sectors.

Microdata, therefore, helps understand the relationship between price changes and market tightness. Firm heterogeneity can lead to different inflationary pressures due to varying marginal costs along the productivity distribution. Hence, under-

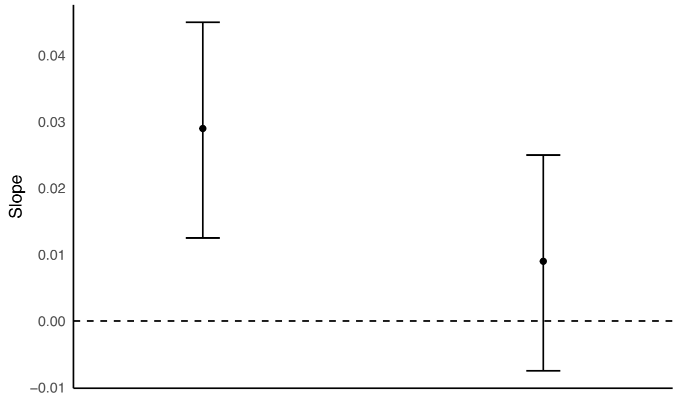


Figure 3.7: Coefficients of output gap in micro pricing equations - Netherlands.

Note: on the left is the average coefficient for the least productive firms, while on the right is the coefficient of the most productive ones.

standing how individual firms respond to demand shocks provides insight that can lead to better inflation forecasts.

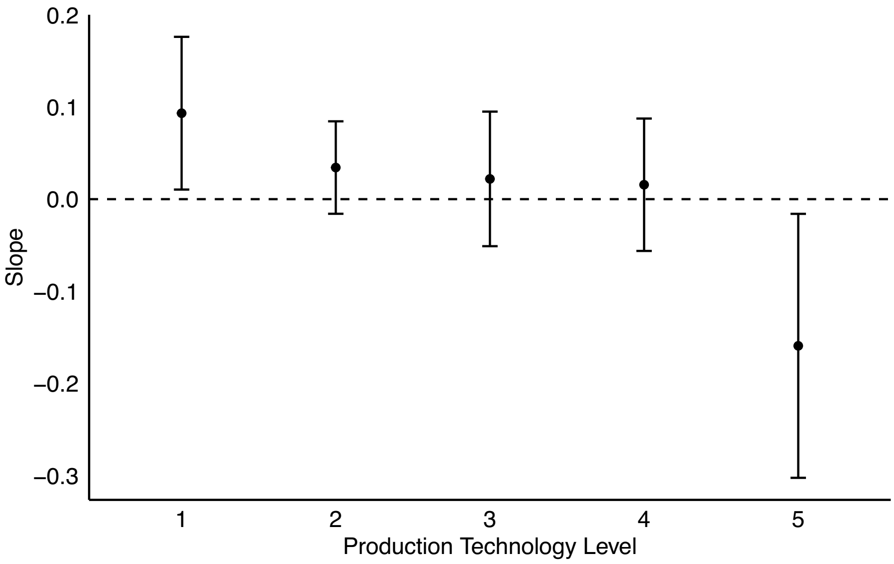


Figure 3.8: Slope of pricing equations by technology group - Netherlands.

Note: Average coefficients by production technology group from pricing equation in the Netherlands. 95% confidence intervals constructed based on variance-covariance matrix of coefficients.

3.7 Conclusion

Production technology matters for price pass-through. We estimated firms' pricing equations in the context of a New Keynesian model and documented that the most productive firms have flatter supply curves, even after controlling for differences in firm residual demand and net of strategic competition.

The Phillips curve slope, then, turns out to be well represented by a weighted average of the slopes of these firm supply curves. This has important implications for the possibility to forecast better future inflation on the base of current firms' production technology distribution.

The more productive firms are also larger and characterized by higher volatility in the output growth rate. As a consequence, the slope of the Phillips curve is mostly affected by the pricing behaviour of the most productive firms, which are the main suppliers at the margin. These firms also exhibit lower marginal costs and higher markups, hence connecting the high markup firms' pricing behaviour with a production technology explanation beyond market competition interaction.

The empirical findings rely on French firm-level data regarding mining, quarrying, manufacturing, and materials recovery. Also, they are supported by a similar analysis of the Dutch industry, covering the same set of economic activities, and by cross-country analysis of micro-based data regarding several European countries for the entire business economy (including services).

Our study, therefore, shows that firm heterogeneity can lead to different inflationary pressures due to varying marginal costs along the production technology distribution. A better understanding of how individual firms respond to demand shocks is then crucial to provide insight that can lead to better inflation forecasts and, thus, a better gauging of measures aimed at taming the current price pressures.

It is important to note that we employ aggregate demand measures to instrument firm demand shock. They work sufficiently well, but finding a closer measure of a firm-specific demand shock would be very effective and better track demand-driven increases in firm sales. Future research should work on a robust instrument for this aim.

Finally, our findings mostly relate to the manufacturing sector, although CompNet data help make more general statements about firms' pricing behaviour. It is, hence, a natural further step in this field to include a larger part of the economy, in particular, services. Currently, data are mostly available for firm input prices. Although this can already shed light on the heterogeneity in marginal cost curves, price statistics should become essential information in European data collection.

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Appendix A

APPENDIX FOR CHAPTER 1

A.1 All Detrended Equations of the RBC Model

Given investment specific technological progress γ, the model has a deterministic balanced growth path. Labour n_j for $j = [1, T-1]$ and n_P, and vintages p_j are stable. Capital k_{jt} and P increase at rate $\gamma^{\frac{1}{1-\alpha}t}$. Relative price of capital decreases at rate $\frac{1}{\gamma^{t+1}}$. Consequently, given the resource constraint, consumption c grows at the rate $\gamma^{\frac{\alpha}{1-\alpha}t}$, as well as the exogenous process λ. Finally, given the envelope theorem equations, $V_j(.)$ are also stable, while $V_T(.)$ decreases at the rate $\gamma^{-\frac{1}{1-\alpha}t}$.

Therefore, the model equations are detrended, dividing each variable by γ^{xt}, the specific growth rate of that variable. The full set of equations representing the stationary RBC model, which are then loglinearized in the main analysis, are reported below.

FOC with respect to consumption c:

$$\frac{\gamma^{\frac{\alpha}{1-\alpha}}}{c - \frac{\Theta}{1+\theta}(\sum_{i=1}^{T-1} p_i(n_i + m_i) + n_P)^{1+\theta}} = \beta E V_1(p_1^{'}, ..., p_{T-1}^{'}, P^{'}, z^{'})$$

FOCs with respect to labour n_j:

$$\left[\frac{1-\delta}{\gamma^{\frac{1}{1-\alpha}}}\right]^{\alpha(j-1)} z\mu_j(1-\alpha)n_j^{-\alpha} = \Theta(\sum_{i=1}^{T-1} p_i(n_i + m_i) + n_P)^{\theta}$$

FOC with respect to labour n_P:

$$zP^{\alpha}(1-\alpha)n_P^{-\alpha} = \Theta(\sum_{i=1}^{T-1} p_i(n_i + m_i) + n_P)^{\theta}$$

Constraints:

$$c + p_1^{'}\gamma^{\frac{\alpha}{1-\alpha}} = \sum_{j=1}^{T-1} p_j z\mu_j n_j^{1-\alpha}\left[\frac{1-\delta}{\gamma^{\frac{1}{1-\alpha}}}\right]^{\alpha(j-1)} + zP^{\alpha}n_P^{1-\alpha}$$

$$p_{j+1}^{'} = p_j \quad \text{for } 1 \leq j \leq T-2$$

$$P^{'}\gamma^{\frac{1}{1-\alpha}} = (1-\delta)P + (1-\delta)p_{T-1}\left[\frac{1-\delta}{\gamma^{\frac{1}{1-\alpha}}}\right]^{T-2}$$

Productivity process:

$$z^{'} = z^{\rho_z} e^{\epsilon_z^{'}}$$

Envelope Theorem equations for $j = [1, T-2]$:

$$\begin{aligned} V_j(p_1, ..., p_{T-1}, P, z) = &-\frac{\Theta(\sum_{i=1}^{T-1} p_i(n_i + m_i) + n_P)^{\theta}(m_j + n_j)}{c - \frac{\Theta}{1+\theta}(\sum_{i=1}^{T-1} p_i(n_i + m_i) + n_P)^{1+\theta}} + \beta V_{j+1}(p_1^{'}, ..., p_{T-1}^{'}, P^{'}, z^{'}) \\ &+ \beta V_1(p_1^{'}, ..., p_{T-1}^{'}, P^{'}, z^{'})\gamma^{-\frac{\alpha}{1-\alpha}}\left[z\mu_j n_j^{1-\alpha}\left[\frac{1-\delta}{\gamma^{\frac{1}{1-\alpha}}}\right]^{\alpha(j-1)}\right] \end{aligned}$$

Envelope Theorem equations for $j = T-1$:

$$\begin{aligned} V_{T-1}(p_1, ..., p_{T-1}, P, z) = &-\frac{\Theta(\sum_{i=1}^{T-1} p_i(n_i + m_i) + n_P)^{\theta}(m_{T-1} + n_{T-1})}{c - \frac{\Theta}{1+\theta}(\sum_{i=1}^{T-1} p_i(n_i + m_i) + n_P)^{1+\theta}} \\ &+ \beta V_T(p_1^{'}, ..., p_{T-1}^{'}, P^{'}, z^{'})(1-\delta)\left[\frac{1-\delta}{\gamma^{\frac{1}{1-\alpha}}}\right]^{T-2}\gamma^{-\frac{1}{1-\alpha}} \\ &+ \beta V_1(p_1^{'}, ..., p_{T-1}^{'}, P^{'}, z^{'})\gamma^{-\frac{\alpha}{1-\alpha}}\left[z\mu_{T-1} n_{T-1}^{1-\alpha}\left[\frac{1-\delta}{\gamma^{\frac{1}{1-\alpha}}}\right]^{\alpha(T-2)}\right] \end{aligned}$$

Envelope Theorem equations for P:

$$\begin{aligned} V_T(p_1, ..., p_{T-1}, P, z) = &\beta V_T(p_1^{'}, ..., p_{T-1}^{'}, P^{'}, z^{'})(1-\delta)\gamma^{-\frac{1}{1-\alpha}} \\ &+ \beta V_1(p_1^{'}, ..., p_{T-1}^{'}, P^{'}, z^{'})\gamma^{-\frac{\alpha}{1-\alpha}}\left[z\alpha P^{\alpha-1} n_T^{1-\alpha}\right] \end{aligned}$$

A.2 RBC Model without Vintage Capital Structure

In the case of neither vintage capital structure nor learning by doing (i.e., $T = 1$), the model boils down to a classical RBC framework and reduces to the following maximization problem:

$$\max_{c_t,n_t} \sum_{t=0}^{\infty} \beta^t ln \left[c_t - \lambda_t \Theta \frac{n_t^{1+\theta}}{1+\theta} \right]$$

subject to

$$c_t + q_t P_{t+1} = z P_t^{\alpha} n_t^{1-\alpha} + (1-\delta) q_t P_t$$

$$0 < n_t < 1$$

It can be solved, then, through the same procedure as for the main vintage capital model, loglinearizing the detrended FOCs and constraint equations.

A.3 All Detrended Equations of the NK Model

Given investment specific technological progress γ, the model has a deterministic balanced growth path. Labour n_j for $j = [1, T-1]$ and n_S, and vintages s_j are stable, as well as inflation and interest rate. Capital k_j and S increase at rate $\gamma^{\frac{1}{1-\alpha}t}$, and relative price of capital decreases at rate $\frac{1}{\gamma^{t+1}}$. Given the plant first order conditions, wages W growth at rate $\gamma^{\frac{\alpha}{1-\alpha}t}$. Consequently, consumption c also grows at rate $\gamma^{\frac{\alpha}{1-\alpha}t}$, from budget constraint. Hence, λ grows at the rate $\gamma^{\frac{\alpha(1-\sigma)}{1-\alpha}t}$. y and x grow at rate $\gamma^{\frac{\alpha}{1-\alpha}t}$ as well, from market clearing. Finally, given the envelope theorem equations, $W_j(.)$ grow at rate $\gamma^{\frac{\alpha}{1-\alpha}t}$, while $W_T(.)$ decreases at the rate γ^{-t}.

To deal with stationary variables, each model variable is detrended by γ^{xt}, its own growth rate. The full set of equations representing the stationary NK model, which are then loglinearized in the main analysis, are reported below.

FOC with respect to consumption c:

$$\beta E \left[\frac{c^{\sigma}}{c'^{\sigma}} \right] = \frac{\gamma^{\frac{\sigma\alpha}{(1-\alpha)}} P'}{P(1+R')}$$

FOC with respect to labour l:

$$\Theta l^{\theta} = \frac{Wc^{-\sigma}}{P}$$

Optimal price setting:

$$\sum_{k=0}^{\infty}(\theta_c \gamma^{\frac{\alpha}{1-\alpha}})^k E\{Q_k y_k(\frac{P^*}{P_{-1}} - \mu\frac{P_{H,k}}{P_k}\Pi_{-1,k})\} = 0$$

Inflation:

$$\Pi^{1-\epsilon} = \theta_c + (1-\theta_c)\left(\frac{P^*}{P_{-1}}\right)^{1-\epsilon}$$

Aggregate price:

$$P = [\theta_c P_{-1}^{1-\epsilon} + (1-\theta_c)P^{*1-\epsilon}]^{\frac{1}{1-\epsilon}}$$

FOC with respect to labour n_j:

$$P_H(1-\alpha)z\mu_j n_j^{-\alpha}\left[\frac{1-\delta}{\gamma^{\frac{1}{1-\alpha}}}\right]^{\alpha(j-1)} = W$$

FOC with respect to labour n_s:

$$P_H(1-\alpha)zS^{\alpha}n_S^{-\alpha} = W$$

Investment efficiency condition:

$$P_H = E\left[\frac{W_1(s_1^{'}, ..., s_{T-1}^{'}, S^{'}, z^{'})}{1+R}\right]$$

Constraints:

$$s_{j+1}^{'} = s_j$$

$$S^{'}\gamma^{\frac{1}{1-\alpha}} = (1-\delta)S + (1-\delta)s_{T-1}\left[\frac{1-\delta}{\gamma^{\frac{1}{1-\alpha}}}\right]^{(T-2)}$$

Envelope Theorem equations for $j = [1, T-2]$:

$$W_j(s_1, ..., s_{T-1}, S, z) = P_H z \mu_j n_j^{1-\alpha} \left[\frac{1-\delta}{\gamma^{\frac{1}{1-\alpha}}}\right]^{\alpha(j-1)} - W(n_j + m_j) + \frac{\gamma^{\frac{\alpha}{1-\alpha}} W_{j+1}(s_1^{'}, ..., s_{T-1}^{'}, S^{'}, z^{'})}{1+R}$$

Envelope Theorem equations for $j = T-1$:

$$W_{T-1}(.) = P_H z \mu_{T-1} n_{T-1}^{1-\alpha} \left[\frac{1-\delta}{\gamma^{\frac{1}{1-\alpha}}}\right]^{\alpha(T-2)} - W(n_{T-1} + m_{T-1}) + \frac{W_T(.^{'})(1-\delta)\gamma^{-1}}{1+R} \left[\frac{1-\delta}{\gamma^{\frac{1}{1-\alpha}}}\right]^{(T-2)}$$

Envelope Theorem equations for $j = T$:

$$W_T(s_1, ..., s_{T-1}, S, z) = P_H \alpha z S^{\alpha-1} n_S^{1-\alpha} + \frac{W_T(s_1^{'}, ..., s_{T-1}^{'}, S^{'}, z^{'})(1-\delta)\gamma^{-1}}{1+R}$$

Market clearing:

$$c_t = y_t$$

$$\int_0^1 y_t(i)\, di = \int_0^1 x_t(h)\, dh$$

$$x_t = \int_0^1 y_t(i)\, di = \int_0^1 \left(\frac{P_t(i)}{P_t}\right)^{-\epsilon} y_t\, di = P_t^{\epsilon} y_t \int_0^1 P_t(i)^{-\epsilon}\, di = P_t^{\epsilon} y_t [(1-\theta_c) P_t^{*-\epsilon} + \theta_c P_{t-1}^{-\epsilon}]$$

$$x_t = \sum_{j=1}^{T-1} s_j z \mu_j n_j^{1-\alpha} \left[\frac{1-\delta}{\gamma^{\frac{1}{1-\alpha}}}\right]^{\alpha(j-1)} + z S^{\alpha} n_S^{1-\alpha} - s_1^{'} \gamma^{\frac{\alpha}{1-\alpha}}$$

$$l_t = \sum_{j=1}^{T-1} s_j (n_j + m_j) + n_S$$

Productivity process:

$$z^{'} = z^{\rho_z} e^{\epsilon_z^{'}}$$

Monetary policy rule:

$$\frac{R_t}{\bar{R}} = \left(\frac{\Pi_t}{\bar{\Pi}}\right)^{\phi_\Pi} \left(\frac{y_t + s_{1t+1}\gamma^{\frac{\alpha}{1-\alpha}}}{\bar{y} + \bar{s}_1 \gamma^{\frac{\alpha}{1-\alpha}}}\right)^{\phi_Y}$$

A.4 NK Model without Vintage Capital Structure

In the case of neither vintage capital structure nor learning by doing (i.e., $T = 1$), the model boils down to a standard NK framework. The model is the same as in the case of $T > 1$, with the exception of the intermediate firms' problem, which becomes as follows.

$$W(S, z) = \max_{I, n_S} \left\{ P_H z S^{\alpha} n_S^{1-\alpha} - W n_S - P_H I + E\left[\frac{W(S^{'}, z^{'})}{1+R}\right] \right\}$$

where

$$I = q(S^{'} - (1-\delta)S)$$

and

$$x_H + I = z S^{\alpha} n_S^{1-\alpha}$$

The efficiency conditions are:

$$P_H(1-\alpha) z S^{\alpha} n_S^{-\alpha} = W$$

$$P_H q = E\left[\frac{W_1(S^{'}, z^{'})}{1+R}\right]$$

The Envelope Theorem equation is:

$$W_1(S, z) = P_H \alpha z S^{\alpha-1} n_S^{1-\alpha} + \frac{W_1(S^{'}, z^{'})(1-\delta)}{1+R}$$

The system of detrended equations is, hence, the same as in the case of $T > 1$, with the following differences regarding the intermediate firms' equations:

Efficiency conditions:

$$P_H(1-\alpha) z S^{\alpha} n_S^{-\alpha} = W$$

$$P_H = E\left[\frac{W_1(S^{'}, z^{'})}{1+R}\right]$$

Constraints:

$$I = S^{'} \gamma^{\frac{\alpha}{1-\alpha}} - (1-\delta) S \gamma^{-1}$$

$$x_H + I = zS^{\alpha}n_S^{1-\alpha}$$

Envelope Theorem equation:

$$W_1(S,z) = P_H \alpha z S^{\alpha-1} n_S^{1-\alpha} + \frac{W_1(S', z')(1-\delta)\gamma^{-1}}{1+R}$$

Labour market clearing:

$$l_t = n_{St}$$

Monetary policy rule:

$$\frac{R_t}{\bar{R}} = \left(\frac{\Pi_t}{\bar{\Pi}}\right)^{\phi_\Pi} \left(\frac{y_t + S'\gamma^{\frac{\alpha}{1-\alpha}} - (1-\delta)S\gamma^{-1}}{\bar{y} + \bar{S}\gamma^{\frac{\alpha}{1-\alpha}} - (1-\delta)\bar{S}\gamma^{-1}}\right)^{\phi_Y}$$

A.5 NK Model with Output Gap Imperfect Measurement

It is further assumed that the central bank is not aware of the learning needs and productivity level among vintages. Hence, it cannot measure perfectly potential output and it will estimate a larger potential output during expansions (positive productivity shocks) and otherwise in contractions (negative productivity shocks). Therefore, the main model is extended with a different monetary policy rule to take into account this bias in central bank estimation of potential output.

Such an equation, in detrended form, is the following:

$$\frac{R_t}{\bar{R}} = \left(\frac{\Pi_t}{\bar{\Pi}}\right)^{\phi_\Pi} \left(\frac{y_t + s_{1t+1}\gamma^{\frac{\alpha}{1-\alpha}}}{(\bar{y} + \bar{s}_1\gamma^{\frac{\alpha}{1-\alpha}})z^{\frac{\gamma^{\phi\mu}}{\mu_1}-1}}\right)^{\phi_Y}$$

Now the steady state level of output, as measured by the central bank, is positive correlated with the productivity shock through a function of the technological progress parameters. The higher the technological progress, the higher the bias, and the more price moderation due to monetary policy imperfect measurement is detected.

A.6 Additional Empirical Results

In this appendix, additional graphs and tables are reported regarding the empirical results discussed in Section 1.6.

A.6.1 Graphs

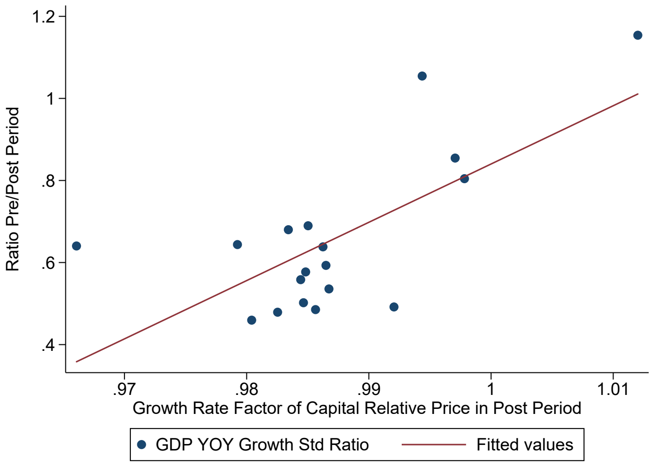

Figure A.1: Relative price of capital and the Great Moderation.

Source: PWT and OECD.

Note: Ratio of real GDP y-o-y growth rate standard deviation between pre- and post-Great Moderation, and relative price growth factor of other assets in the period 1984-2007.

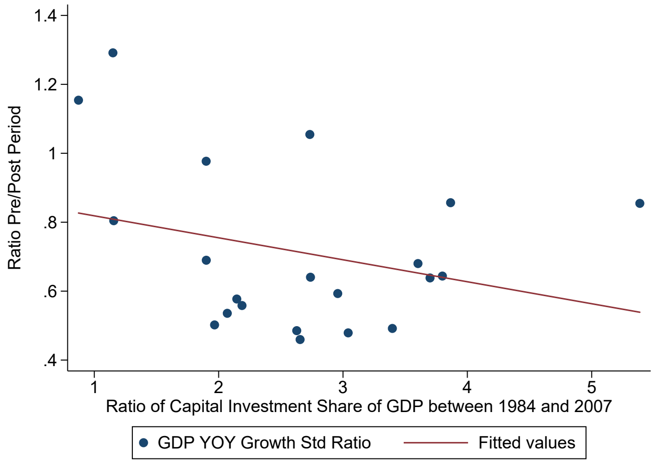

Figure A.2: GDP share of investment in other assets and the Great Moderation.

Source: PWT and OECD.

Note: Ratio of real GDP y-o-y growth rate standard deviation between pre- and post-Great Moderation, and ratio of investment in other assets over GDP between 1984 and 2007.

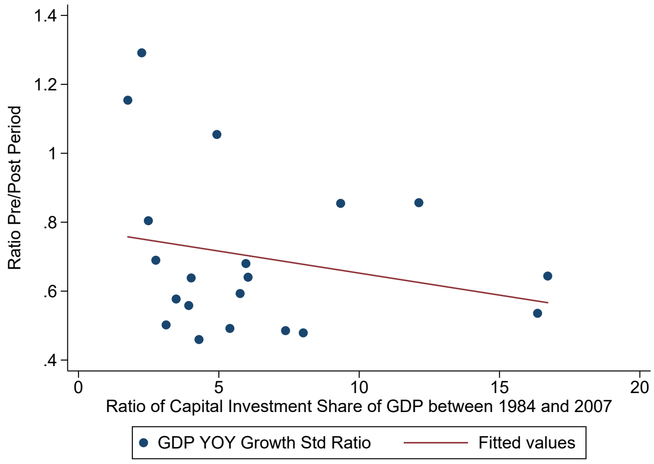

Figure A.3: GDP share of investment in other assets and the Great Moderation.

Source: PWT and OECD.

Note: Ratio of real GDP y-o-y growth rate standard deviation between pre- and post-Great Moderation, and ratio between 1984 and 2007 of GDP share of investment (in efficiency units) in other assets.

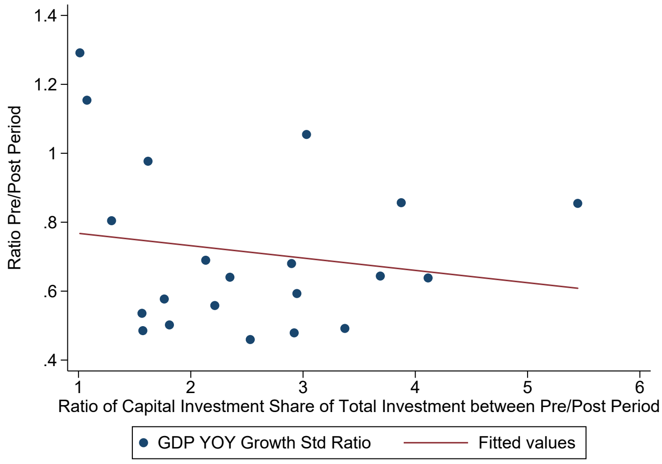

Figure A.4: Investment in other assets as share of total investment and the Great Moderation.

Source: PWT and OECD.

Note: Ratio of real GDP y-o-y growth rate standard deviation between pre- and post-Great Moderation, and ratio of investment (in efficiency units) in other assets over total investment between 1984 and 2007.

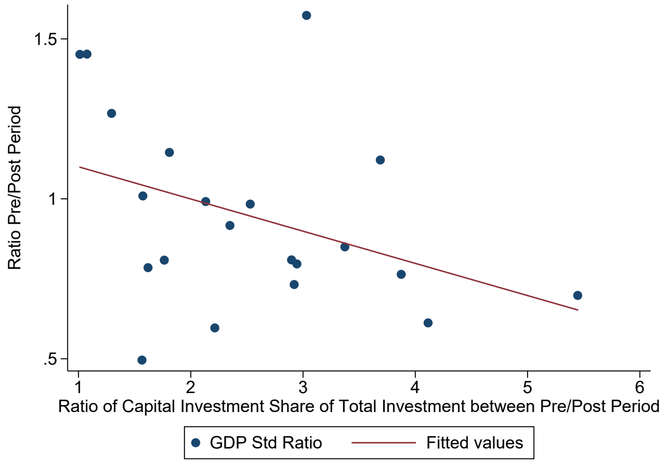

Figure A.5: Investment in other assets as share of total investment and the Great Moderation.

Source: PWT.

Note: Ratio of real GDP standard deviation between pre- and post-Great Moderation, and ratio of investment (in efficiency units) in other assets over total investment between 1984 and 2007.

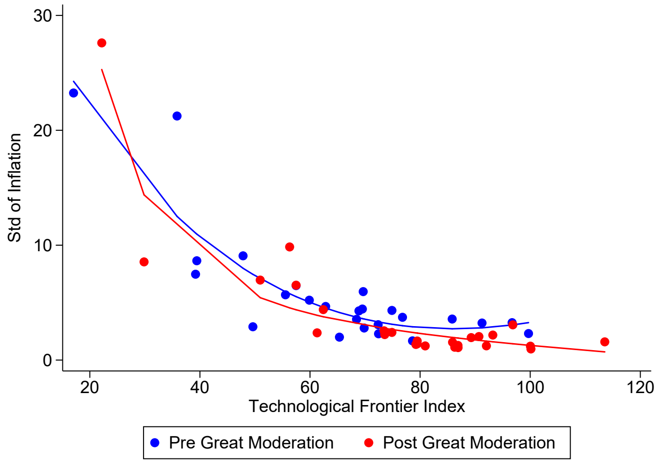

Figure A.6: Technological Frontier Index and Inflation Volatility, pre- and post-Great Moderation.

Source: PWT, OECD, and World Bank.

Note: Standard deviation of Inflation and Technological Frontier Index in pre- and post-Great Moderation periods.

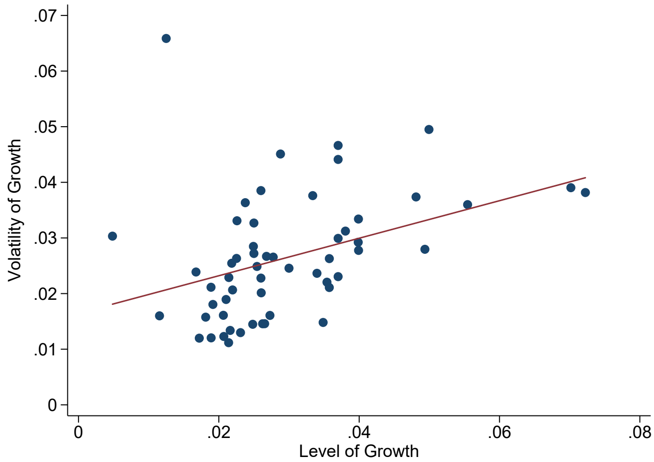

Figure A.7: Level and Volatility of Growth.

Source: PWT.

Note: Level and standard deviation of real GDP y-o-y growth rate in pre- and post-Great Moderation periods.

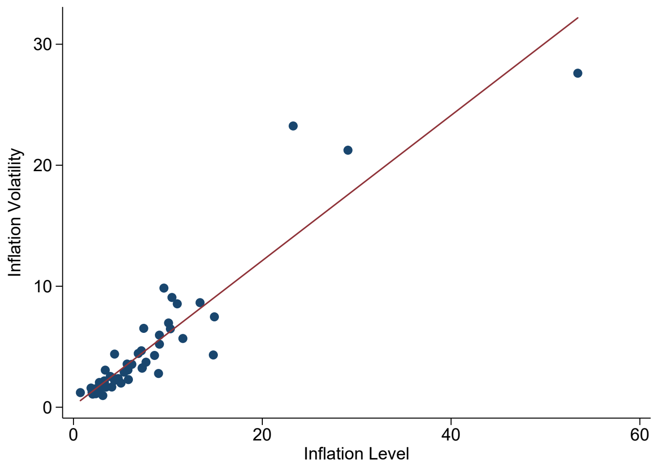

Figure A.8: Level and Volatility of Inflation.

Source: OECD.

Note: Level and standard deviation of CPI inflation in pre- and post-Great Moderation periods.

A.6.2 Tables

Table A.1: GDP share of investment in other assets and the Great Moderation

	GDP Std Ratio					
Investment over GDP	-0.13**	-0.12*	-0.13**	-0.13*	-0.15*	-0.09
	(0.056)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)
GDP capita		5e-06	5e-06	6e-06	3e-06	6e-06
		(5e-06)	(5e-06)	(6e-06)	(7e-06)	(7e-06)
Open Std			0.49	0.50	0.58	0.93
			(0.83)	(0.86)	(0.88)	(0.86)
HC Std				0.13	0.31	-1.31
				(1.91)	(1.96)	(2.08)
CPI Std					-0.01	-0.02
					(0.01)	(0.011)
Int Std						0.11+
						(0.06)
Constant	1.29***	1.07***	1.03***	1.01**	1.12**	0.68
	(0.16)	(0.27)	(0.28)	(0.43)	(0.47)	(0.51)
Obs	21	21	21	21	21	21
R^2	0.23	0.27	0.28	0.28	0.30	0.42

Note: OLS regressions of real GDP standard deviation ratio between pre- and post-Great Moderation on the ratio of GDP share of investment in other assets between 1984-2007, progressively controlling for the mean of real GDP per capita, trade openness, human capital index, CPI standard deviation, and nominal interest standard deviation. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10, + p<0.15.

Table A.2: GDP share of investment in other assets and the Great Moderation

	GDP Std Ratio					
Investment (EU) over GDP	-0.028*	-0.03	-0.03	-0.03	-0.09**	-0.07**
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
GDP capita		1.99e-06	1.89e-06	1.91e-06	2.24e-06	3.31e-06
		(8e-06)	(8e-06)	(9e-06)	(7e-06)	(7e-06)
Open Std			-0.12	-0.12	0.76	0.96
			(0.89)	(0.92)	(0.87)	(0.79)
HC Std				0.017	2.04	0.32
				(2.22)	(2.07)	(2.07)
CPI Std					0.18**	0.09
					(0.07)	(0.08)
Int Std						0.12*
						(0.06)
Constant	1.13***	1.05**	1.07**	1.07*	0.67	0.51
	(0.11)	(0.36)	(0.41)	(0.50)	(0.46)	(0.43)
Obs	20	20	20	20	20	20
R^2	0.16	0.16	0.16	0.16	0.42	0.56

Note: OLS regressions of real GDP standard deviation ratio between pre- and post-Great Moderation on the ratio of GDP share of investment in other assets (in efficiency units) between 1984-2007, progressively controlling for the mean of real GDP per capita, trade openness, human capital index, CPI standard deviation, and nominal interest standard deviation. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$, + $p<0.15$.

Appendix B

APPENDIX FOR CHAPTER 2

B.1 Further Details about the Model

In the following, we derive the true data generation process of the theoretical model.

As shown in equation 2.1 of the main text, the aggregate supply is:

$$\pi_t - \gamma\pi_{t-1} = \mu_t + \hat{E}_t \sum_{t=0}^{\infty} (\alpha\beta)^t [\xi s_t + (1-\alpha)\beta(\pi_{t+1} - \gamma\pi_t)]$$

Taking out s_t from the summation and substituting it with the central bank policy rule, as well as inserting expectations about future policy rules in the summation:

$$\begin{aligned}\pi_t - \gamma\pi_{t-1} =& \frac{\lambda}{\lambda+\xi}\mu_t + \frac{\xi}{\lambda+\xi}\phi_t + \frac{\xi\lambda}{(\lambda+\xi)\bar{\lambda}_t}\hat{E}_t \sum_{t=0}^{\infty} (\alpha\beta)^t [\alpha\beta(\phi_{t+1} - (\pi_{t+1} - \bar{\pi}_t) \\ & + \gamma(\pi_t - \bar{\pi}_t))] + \frac{\lambda\beta(1-\alpha)}{\lambda+\xi}\hat{E}_t \sum_{t=0}^{\infty} (\alpha\beta)^t (\pi_{t+1} - \gamma\pi_t)\end{aligned}$$

Then, aggregating π_t on the left hand side, we get:

$$\begin{aligned}\left[1 - \frac{\alpha\beta\gamma\xi\lambda}{(\lambda+\xi)\bar{\lambda}_t} + \frac{(1-\alpha)\beta\gamma\lambda}{\lambda+\xi}\right]\pi_t - \gamma\pi_{t-1} =& \frac{\lambda}{\lambda+\xi}\mu_t + \frac{\xi}{\lambda+\xi}\phi_t + \frac{\xi\lambda}{(\lambda+\xi)\bar{\lambda}_t}\hat{E}_t \sum_{t=0}^{\infty} (\alpha\beta)^t \alpha\beta\phi_{t+1} \\ & + \frac{\lambda}{\lambda+\xi}\hat{E}_t \sum_{t=0}^{\infty} (\alpha\beta)^t \left[-(1-\alpha\beta\gamma)(\frac{\alpha\beta\xi}{\bar{\lambda}_t} - (1-\alpha)\beta)\pi_{t+1}\right] \\ & + \frac{\xi\lambda}{(\lambda+\xi)\hat{\lambda}_t}\hat{E}_t \sum_{t=0}^{\infty} (\alpha\beta)^t [\alpha\beta(1-\gamma)\bar{\pi}_t]\end{aligned}$$

Given that ϕ_t is a known AR(1) process, $\bar{\pi}_t$ is constant in expectations (anticipated utility solution), and substituting the expectation of future inflations π_{t+1}

with the imperfect knowledge forecast of agents, as shown below:

$$\hat{E}_t \sum_{t=0}^{\infty} (\alpha\beta)^t \pi_{t+1} = \hat{E}_t \sum_{t=0}^{\infty} (\alpha\beta)^t \left[\gamma\pi_t + (1-\gamma)\bar{\pi}_t + \frac{\xi}{\xi + \hat{\lambda}_t(1-\beta\rho)} \rho\phi_t \right]$$

$$\hat{E}_t \sum_{t=0}^{\infty} (\alpha\beta)^t \pi_{t+1} = \hat{E}_t \sum_{t=0}^{\infty} (\alpha\beta)^t (1-\gamma)\bar{\pi}_t + \hat{E}_t \sum_{t=0}^{\infty} (\alpha\beta\rho)^t \frac{\xi}{\xi + \hat{\lambda}_t(1-\beta\rho)} \phi_t + \sum_{t=0}^{\infty} (\alpha\beta)^t \gamma\pi_t$$

$$\hat{E}_t \sum_{t=0}^{\infty} (\alpha\beta)^t \pi_{t+1} = \hat{E}_t \sum_{t=0}^{\infty} (\alpha\beta)^t (1-\gamma)\bar{\pi}_t + \hat{E}_t \sum_{t=0}^{\infty} (\alpha\beta\rho)^t \frac{\xi}{\xi + \hat{\lambda}_t(1-\beta\rho)} \phi_t + \alpha\beta \sum_{t=0}^{\infty} (\alpha\beta)^t \gamma\pi_{t+1} + \gamma\pi_t$$

$$\hat{E}_t \sum_{t=0}^{\infty} (\alpha\beta)^t \pi_{t+1} = \frac{1}{1-\alpha\beta\gamma} \left[\gamma\pi_t + \frac{1-\gamma}{1-\alpha\beta} \bar{\pi}_t + \frac{\xi\rho}{(1-\alpha\beta\rho)(\xi + (1-\rho\beta)\hat{\lambda}_t)} \phi_t \right]$$

the true data generation process is found as in the main text.

B.2 The Estimation Algorithm

Model Notation

The model is estimated using Bayesian techniques based on US and Turkish data. Given the non-linearities in the model, marginalized particle filter and smoother are implemented. From the main text, the model equations are the following:

$$\pi_t = (1-\gamma)\Gamma\bar{\pi}_t + \gamma\pi_{t-1} + f(\bar{\lambda}_t)\phi_t + \tilde{\mu}_t$$

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k_t^{-1} \times f_{t-1}$$

$$k_t = (k_{t-1}+1)I(\bar{\pi}_{t-1}, \phi_{t-2}) + \bar{g}^{-1}(1 - I(\bar{\pi}_{t-1}, \phi_{t-2}))$$

$$f_t = (1-\gamma)(\Gamma-1)\bar{\pi}_t + g(\bar{\lambda}_t)\rho\phi_{t-1} + f(\bar{\lambda}_t)\epsilon_t + \tilde{\mu}_t$$

$$\phi_t = \rho\phi_{t-1} + \epsilon_t,$$

where the function $I(\bar{\pi}_{t-1}, \phi_{t-2})$ derives from the anchoring threshold:

$$I(\bar{\pi}_{t-1}, \phi_{t-2}) = \begin{cases} 1, & \text{if } |(1-\gamma)(\Gamma-1)\bar{\pi}_{t-1} + g(\bar{\lambda}_{t-1})\rho\phi_{t-2}| \leq \bar{\nu}\sigma \\ 0, & \text{otherwise} \end{cases}.$$

To better describe the estimation algorithmn subsequently, the model can also be written in matrix notation, separating linear and non linear variables as follows. The linear states are represented by ζ_t:

$$\zeta_t = f_\zeta(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2}) + A_\zeta(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2})\zeta_{t-1} + S_{\zeta,t}\begin{bmatrix}\epsilon_t\\ \mu_t\end{bmatrix},$$

where

$$\zeta_t = \begin{bmatrix}\eta_t\\ \phi_t\\ \phi_{t-1}\\ \pi_t\end{bmatrix}; \quad \eta_t = f(\bar{\lambda}_t)\epsilon_t + \tilde{\mu}_t;$$

and

$$f_\zeta(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2}) = \begin{bmatrix}0_{3\times 1}\\ (1-\gamma)\Gamma f_{\bar{\pi}}(.)\end{bmatrix};$$

$$A_\zeta(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2}) = \begin{bmatrix}0 & 0 & 0 & 0\\ 0 & \rho & 0 & 0\\ 0 & 1 & 0 & 0\\ (1-\gamma)\Gamma f_k(.)^{-1} & \rho & (1-\gamma)\Gamma f_k(.)^{-1} g(\bar{\lambda}_{t-1})\rho & \gamma\end{bmatrix};$$

$$S_{\zeta,t} = \begin{bmatrix}f(\bar{\lambda}_t) & 1\\ 1 & 0\\ 0 & 0\\ f(\bar{\lambda}_t) & 1\end{bmatrix};$$

while

$$f_k(.) = f_k(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2}) = (k_{t-1}+1)I(\bar{\pi}_{t-1}, \phi_{t-2}) + \bar{g}^{-1}(1 - I(\bar{\pi}_{t-1}, \phi_{t-2}));$$

$$f_{\bar{\pi}}(.) = f_{\bar{\pi}}(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2}) = \left[1 - (1-\Gamma)(1-\gamma)f_k(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2})^{-1}\right]\bar{\pi}_{t-1}.$$

Whereas the nonlinear states are the following functions:

$$k_t = f_k(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2})$$

and

$$\bar{\pi}_t = f_{\bar{\pi}}(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2}) + A_{\bar{\pi}}(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2})\zeta_{t-1},$$

where

$$A_{\bar{\pi}}(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2}) = \begin{bmatrix} f_k(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2})^{-1} \\ 0 \\ f_k(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2})^{-1} g(\bar{\lambda}_{t-1})\rho \\ 0 \end{bmatrix}'.$$

Finally, we can unify notation for both linear and nonlinear variables in a more compact way:

$$k_t = f_k(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2})$$

$$\begin{bmatrix} \bar{\pi}_t \\ \zeta_t \end{bmatrix} = f(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2}) + A(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2})\zeta_{t-1} + \begin{bmatrix} 0 \\ S_{\zeta,t} \end{bmatrix} \begin{bmatrix} \epsilon_t \\ \mu_t \end{bmatrix}$$

where

$$f(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2}) = \begin{bmatrix} f_{\bar{\pi}}(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2}) \\ f_{\zeta}(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2}) \end{bmatrix},$$

$$A(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2}) = \begin{bmatrix} A_{\bar{\pi}}(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2}) \\ A_{\zeta}(\bar{\pi}_{t-1}, k_{t-1}, g(\bar{\lambda}_{t-1})\rho\phi_{t-2}) \end{bmatrix},$$

and

$$\Sigma = E\left(\begin{bmatrix} \epsilon_t \\ \mu_t \end{bmatrix} \begin{bmatrix} \epsilon_t \\ \mu_t \end{bmatrix}' \right)$$

is the variance-covariance matrix of the exogenous shocks.

Algorithm of the Marginalized Particle Filter

Given that our CBC model is an extension of the imperfect knowledge New Keynesian model as described by Carvalho et al. (2023), we follow their marginalized particle filter methodology, applied to our model case. This procedure is based on

Schon et al. (2005) and Kitagawa (1996). The marginalized particle filter allows us to compute the probability of a sequence of states during the sample period and, based on that, the likelihood function and the posterior probability of the estimated parameters. As explained in the main text, to keep computation simpler, the updating sequence of $\bar{\lambda}_t$ is calibrated from the data, as well as α, β, and ξ are taken from the related literature. In the following, we describe the algorithm in the case of our CBC model. For more discussion and proofs, see Online Appendix of Carvalho et al. (2023).

For all the estimations, we set the number of particles $N = 2500$. As suggested by Carvalho et al. (2023) and discussed deeply in Fernández-Villaverde and Rubio-Ramírez (2007), we keep the following innovations constant, to avoid extra randomness in the likelihood calculation: initial conditions for the nonlinear state variables; draws to compute shocks in the nonlinear prediction step; and draws in the resampling step.

Algorithm:

1. Initialization. $\bar{\pi}_{1|0}^{(i)}, k_{1|0}^{(i)}$ are drawn from the normal distribution and $U(0, \bar{g}^{-1})$, respectively, while $\zeta_{1|0}^{(i)}$, $P_{1|0}^{(i)} = [\zeta_0, P_{1|0}]$, where $P_{1|0}$ denotes the initial precision matrix in the linear Kalman filter.

2. Measurement equation. For each $t = 1...T$, we compute:

   $$\Omega_t = H_t' P_{t|t-1} H_t + R_t$$

   and its inverse.

   It is important to note that H_t is time-varying not only due to possible missing values in the observed data but also because it is a function of $\bar{\lambda}_t$. For $i = 1, \ldots, N$, the importance weights are:

   $$q_t^{(i)} = p(y_t | \bar{\pi}_{t|t-1}^{(i)}, \zeta_{t|t-1}^{(i)}) = \mathcal{N}(h_{0,t} + h_{\bar{\pi},t}\bar{\pi}_{t|t-1}^{(i)} + H_t' \zeta_{t|t-1}^{(i)}, H_t' P_{t|t-1} H_t + R_t)$$

More precisely:

$$q_t^{(i)} = w_{t|t-1}^{(i)} |\Omega_t|^{-1/2} \times$$
$$\exp\left\{ -\frac{1}{2}\left(y_t - h_{0,t} - h_{\bar{\pi},t}\bar{\pi}_{t|t-1}^{(i)} - H_t'\zeta_{t|t-1}^{(i)}\right)' \Omega_t^{-1} \left(y_t - h_{0,t} - h_{\bar{\pi},t}\bar{\pi}_{t|t-1}^{(i)} - H_t'\zeta_{t|t-1}^{(i)}\right)\right\}$$

where $w_{t|t-1}^{(i)}$ denotes the particle weight from the previous period.

3. Re-sampling. If the effective sample size (ESS), computed as:

$$ESS = \frac{1}{\sum (w_t^{(i)})^2},$$

falls below the threshold ($ESS < 0.75 \times N$), we resample the nonlinear variable through a systematic re-sampling where:

$$p\left(\left[\bar{\pi}_{t|t}^{(i)}, k_{t|t}^{(i)}\right] = \left[\bar{\pi}_{t|t-1}^{(j)}, k_{t|t-1}^{(j)}\right]\right) = \frac{q_t^{(j)}}{\sum q_t^{(j)}}$$

After resampling, particles feature a discrete distribution with equal weights:

$$w_t^{(i)} = \frac{1}{N} \quad \text{for } i = 1, \ldots, N.$$

In case of not resampling, the weights are:

$$w_t^{(i)} = \frac{q_t^{(i)}}{\sum q_t^{(j)}}.$$

4. Linear Kalman filter. For $i = 1, \ldots, N$, we compute:

$$\zeta_{t|t}^{(i)} = \zeta_{t|t-1}^{(i)} + K_t\left(y_t - h_{0,t} - h_{\bar{\pi},t}\bar{\pi}_{t|t}^{(i)} - H_t'\zeta_{t|t-1}^{(i)}\right)$$

where

$$K_t = P_{t|t-1} H_t \Omega_t^{-1}$$

$$P_{t|t} = P_{t|t-1} - K_t H_t' P_{t|t-1}$$

5. Particle filter prediction. For $i = 1, \ldots, N$, we evaluate:

$$k_{t+1|t}^{(i)} = f_k(\bar{\pi}_{t|t}^{(i)}, k_{t|t}^{(i)}, g(\bar{\lambda}_t)\rho\zeta_{3,t|t}^{(i)})$$

and draw $\bar{\pi}^{(i)}_{t+1|t}$ from the distribution:

$$p(\bar{\pi}_{t+1} \mid Y_t, \bar{\pi}^{(i)}_{t|t}, k^{(i)}_{t|t}, g(\bar{\lambda}_t)\rho\zeta^{(i)}_{3,t|t}) = \mathcal{N}\Big(f_{\bar{\pi}}(\bar{\pi}^{(i)}_{t|t}, k^{(i)}_{t|t}, g(\bar{\lambda}_t)\rho\zeta^{(i)}_{3,t|t}) + f_k(\bar{\pi}^{(i)}_{t|t}, k^{(i)}_{t|t}, g(\bar{\lambda}_t)\rho\zeta^{(i)}_{3,t|t})^{-1}\eta^{(i)}_{t|t}$$
$$+ g(\bar{\lambda}_t)\rho\zeta^{(i)}_{3,t|t}, \quad f_k(\bar{\pi}^{(i)}_{t|t}, k^{(i)}_{t|t}, g(\bar{\lambda}_t)\rho\zeta^{(i)}_{3,t|t})^{-2} P^{[\eta,\eta]}_{t|t} \Big)$$

where $P^{[i,j]}_{t|t} = P_{t|t}(i,j)$.

6. Model prediction of linear states.

$$\tilde{\zeta}^{(i)}_{t|t} = \zeta^{(i)}_{t|t} + \tilde{K}^{(i)}_t \left(\bar{\pi}^{(i)}_{t+1|t} - f_{\bar{\pi}}(\bar{\pi}^{(i)}_{t|t}, k^{(i)}_{t|t}, g(\bar{\lambda}_t)\rho\zeta^{(i)}_{3,t|t}) - f_k(\bar{\pi}^{(i)}_{t|t}, k^{(i)}_{t|t}, g(\bar{\lambda}_t)\rho\zeta^{(i)}_{3,t|t})^{-1}\eta^{(i)}_{t|t} + g(\bar{\lambda}_t)\rho\zeta^{(i)}_{3,t|t} \right)$$

$$\zeta^{(i)}_{t+1|t} = f_\zeta(\bar{\pi}^{(i)}_{t|t}, k^{(i)}_{t|t}, g(\bar{\lambda}_t)\rho\zeta^{(i)}_{3,t|t}) + A_\zeta(\bar{\pi}^{(i)}_{t|t}, k^{(i)}_{t|t}, g(\bar{\lambda}_t)\rho\zeta^{(i)}_{3,t|t})\tilde{\zeta}^{(i)}_{t|t}$$

$$P_{t+1|t} = Q_{\zeta,t} + \tilde{P}_{t|t}$$

where

$$Q_{\zeta,t} = S_{\zeta,t}\Sigma S'_{\zeta,t}$$

$$\begin{aligned}\tilde{K}^{(i)}_t &= P_{t|t}A'_{\bar{\pi}}(\bar{\pi}^{(i)}_{t|t}, k^{(i)}_{t|t}, g(\bar{\lambda}_t)\rho\zeta^{(i)}_{3,t|t}) \left(A_{\bar{\pi}}(\bar{\pi}^{(i)}_{t|t}, k^{(i)}_{t|t}, g(\bar{\lambda}_t)\rho\zeta^{(i)}_{3,t|t}) P_{t|t} A'_{\bar{\pi}}(\bar{\pi}^{(i)}_{t|t}, k^{(i)}_{t|t}, g(\bar{\lambda}_t)\rho\zeta^{(i)}_{3,t|t}) \right)^{-1} \\ &= f_k(\bar{\pi}^{(i)}_{t|t}, k^{(i)}_{t|t}, g(\bar{\lambda}_t)\rho\zeta^{(i)}_{3,t|t}) \begin{bmatrix} 1 \\ \frac{P^{[\eta,\phi]}_{t|t}}{P^{[\eta,\eta]}_{t|t}} \\ 0 \\ \frac{P^{[\eta,\pi]}_{t|t}}{P^{[\eta,\eta]}_{t|t}} \end{bmatrix}\end{aligned}$$

and

$$\tilde{P}_t|_t = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & \iota_1\rho^2 & \iota_1\rho & \iota_1\rho^2 f_t(\bar{\lambda}_t) + \iota_2\rho\gamma \\ 0 & \iota_1\rho & \iota_1 & \iota_1\rho f_t(\bar{\lambda}_t) + \iota_2\gamma \\ 0 & \iota_1\rho^2 f_t(\bar{\lambda}_t) + \iota_2\rho\gamma & \iota_1\rho f_t(\bar{\lambda}_t) + \iota_2\gamma & \rho f_t(\bar{\lambda}_t)(\iota_1\rho f_t(\bar{\lambda}_t) + \iota_2\gamma) + \gamma(\rho f_t(\iota_2\bar{\lambda}_t) + \iota_3\gamma) \end{bmatrix}$$

where

$$\iota_1 = \left[P^{[\phi,\phi]}_{t|t} - \frac{\left(P^{[\eta,\phi]}_{t|t}\right)^2}{P^{[\eta,\eta]}_{t|t}} \right]$$

$$\iota_2 = \left[P_{t|t}^{[\phi,\pi]} - \frac{P_{t|t}^{[\eta,\pi]} P_{t|t}^{[\eta,\phi]}}{P_{t|t}^{[\eta,\eta]}} \right]$$

$$\iota_3 = \left[P_{t|t}^{[\pi,\pi]} - \frac{\left(P_{t|t}^{[\eta,\pi]}\right)^2}{P_{t|t}^{[\eta,\eta]}} \right]$$

$P_{t+1|t}$ would be particle dependent given that it is a function of $g(\bar{\lambda}_t)\rho\zeta_{3,t|t}^{(i)}$. However, since $g(\bar{\lambda}_t)$ takes values close to zero, we can approximate this element to zero when computing $P_{t+1|t}$ in the algorithm, to allow a fast evaluation of the likelihood and the posterior distribution without affecting the solution of the model close to the equilibrium where $g(\bar{\lambda}_t) = 0$.

7. The log-likelihood is then approximated by the particles weigths:

$$L(\cdot) = \sum_{t=1}^{T} \log p(y_t|Y_{t-1}) = \sum_{t=1}^{T} \log \left(\sum_{i=1}^{N} q_t^{(i)} \right)$$

Finally, it must be noticed that the algorithm is implemented with the constraint that $\zeta_{2,t} = \zeta_{3,t+1}$ since the current monetary policy state is the lagged monetary policy state in the following period.

Algorithm of the Marginalized Smoother

Also in the case of the particle smoother, we apply to our extended model a procedure similar to the one implemented by Carvalho et al. (2023), who apply joint backward simulation Rao-Blackwellised particle smoother as in Lindsten et al. (2013). The full distribution of states and parameters is computed using Carter and Kohn (1994).

We start drawing $\bar{\pi}_{T|T}^{(j)}$, $k_{T|T}^{(j)}$ from the empirical distribution of $\{\pi_{t|t}^{(k)}, k_{t|t}^{(k)}\}_{k=1}^{N}$ at the end of the above forward filter, where each particle has weight $w_t^{(k)}$. Moreover, conditional on the draw $\bar{\pi}_{T|T}^{(j)}$, $k_{T|T}^{(j)}$ and the constraint on $\zeta_{3,T|T}$, we draw the linear state $\zeta_{T|T}^{(j)}$ from the normal distribution $\mathcal{N}(\zeta_{T|T}^{(j)}, P_{T|T})$. Given such initialization, we compute the following algorithm.

Algorithm:

For $t = T-1$ to 1 (backward step):

For each $i = 1 \dots N$, the particle weight is

$$w_{t|t+1}^{(i,j)} = \frac{w_t^{(i)} p(\bar{\pi}_{t+1|t+1}^{(j)}, k_{t+1|t+1}^{(j)}, \zeta_{t+1|t+1}^{(j)} | \pi_{t|t}^{(i)}, k_{t|t}^{(i)}, \zeta_{3,t|t}^{(i)}, Y_t)}{\sum_k w_t^{(k)} p(\bar{\pi}_{t+1|t+1}^{(j)}, k_{t+1|t+1}^{(j)}, \zeta_{t+1|t+1}^{(j)} | \pi_{t|t}^{(k)}, k_{t|t}^{(k)}, \zeta_{3,t|t}^{(k)}, Y_t)}$$

The probability distribution above can be expressed as:

$$\begin{aligned} & p(\bar{\pi}_{t+1|T}^{(j)}, k_{t+1|T}^{(j)}, \zeta_{t+1|T}^{(j)} | \pi_{t|t}^{(i)}, k_{t|t}^{(i)}, \zeta_{3,t|t}^{(i)}, Y_t) = \\ & \quad p(\bar{\pi}_{t+1|T}^{(j)}, \zeta_{t+1|T}^{(j)} | \bar{\pi}_{t|t}^{(i)}, k_{t|t}^{(i)}, \zeta_{3,t|t}^{(i)}, Y_t) p(k_{t+1|T} | \bar{\pi}_{t|t}^{(i)}, k_{t|t}^{(i)}, \zeta_{3,t|t}^{(i)}, Y_t) \end{aligned}$$

where $k_{t+1|t} = f_k(\bar{\pi}_t, k_t, g(\bar{\lambda}_t)\rho\zeta_{3,t})$. We, hence, evaluate

$$\begin{aligned} & p(\bar{\pi}_{t+1|T}^{(j)}, \zeta_{t+1|T}^{(j)} | \bar{\pi}_{t|t}^{(i)}, k_{t|t}^{(i)}, \zeta_{3,t|t}^{(i)}, Y_t) \times \mathbf{1}_{k_{t+1}^{(j)} = f_k(\bar{\pi}_{t|t}^{(i)}, k_{t|t}^{(i)}, g(\bar{\lambda}_t)\rho\zeta_{3,t|t}^{(i)})} = \\ & \qquad \begin{cases} p_{t|t+1}^{j,i}, & \text{if } k_{t+1|T}^{(j)} = f_k(\bar{\pi}_{t|t}^{(i)}, k_{t|t}^{(i)}, g(\bar{\lambda}_t)\rho\zeta_{3,t|t}^{(i)}) \\ 0, & \text{otherwise} \end{cases} \end{aligned}$$

where

$$p_{t|t+1}^{j,i} \propto \exp\left\{-\frac{1}{2}\ln|\tilde{\Omega}_t^{(i)}| - \frac{1}{2}(\tau_{t+1}^{j,i})' \times (\tilde{\Omega}_t^{(i)})^{-1}(\tau_{t+1}^{j,i})\right\}$$

$$\tau_{t+1}^{j,i} = \begin{bmatrix} \bar{\pi}_{t+1|t+1}^{(j)} \\ \zeta_{t+1|t+1}^{(j)} \end{bmatrix} \left[f(\bar{\pi}_{t|t}^{(i)}, k_{t|t}^{(i)}, g(\bar{\lambda}_t)\rho\zeta_{3,t|t}^{(i)}) + A(\bar{\pi}_{t|t}^{(i)}, k_{t|t}^{(i)}, g(\bar{\lambda}_t)\rho\zeta_{3,t|t}^{(i)})\zeta_{t|t}^{(i)} \right]$$

$$\tilde{\Omega}_t^{(i)} = Q_t + A(\bar{\pi}_{t|t}^{(i)}, k_{t|t}^{(i)}, g(\bar{\lambda}_t)\rho\zeta_{3,t|t}^{(i)}) P_{t|t} A(\bar{\pi}_{t|t}^{(i)}, k_{t|t}^{(i)}, g(\bar{\lambda}_t)\rho\zeta_{3,t|t}^{(i)})'$$

$$Q_t = \begin{bmatrix} 0 & 0 \\ 0 & S_{\zeta,t}\Sigma S_{\zeta,t}' \end{bmatrix}$$

and

$$\begin{aligned} & \mathbf{1}_{k_{t+1}^{(j)} = f_k(\bar{\pi}_{t|t}^{(i)}, k_{t|t}^{(i)}, g(\bar{\lambda}_t)\rho\zeta_{3,t|t}^{(i)})} = \mathbf{1}_{k_{t+1}^{(j)} = \bar{g}} \times \mathbf{1}_{|(1-\gamma)(\Gamma-1)\bar{\pi}_{t|t}^{(i)} + g(\bar{\lambda}_t)\rho\zeta_{3,t|t}^{(i)}| > \bar{\nu}\sigma} + \\ & (1 - \mathbf{1}_{k_{t+1}^{(j)} = \bar{g}}) \times \mathbf{1}_{|(1-\gamma)(\Gamma-1)\bar{\pi}_{t|t}^{(i)} + g(\bar{\lambda}_t)\rho\zeta_{3,t|t}^{(i)}| \le \bar{\nu}\sigma} \times \mathbf{1}_{k_{t+1}^{(j)} - 1 = k_{t|t}^{(i)}} \end{aligned}$$

and taking into account the constraint on $\zeta_{2,t+1|T}$.

Therefore, we draw the nonlinear variables $\bar{\pi}^{(j)}_{t|T}, k^{(j)}_{t|T}$ from$\{\bar{\pi}^{(k)}_{t|t}, k^{(k)}_{t|t}\}^N_{k=1}$ using the newly computed set of weights $\{w^j_{t|t+1}(k)\}^N_{k=1}$. Conditional on this draw, we finally sample from (subject to the mentioned constraints):

$$p(\zeta_t|\bar{\pi}^j_{1:t}, k^j_{1:t}, \zeta_{t+1}, \bar{\pi}_{t+1}, Y_t).$$

In particular, we draw $\zeta^{(j)}_{t|T}$ from the distribution

$$\mathcal{N}(\zeta^{(j)}_{t|t} + \Delta^{(j)}_t \left(\left[\bar{\pi}^{(j)}_{t+1|T}, \zeta^{(j)}_{t+1|T}\right]' - f(\bar{\pi}^{(j)}_{t|T}, \zeta^{(j)}_{t|T}) - A(\bar{\pi}^{(j)}_{t|T}, \zeta^{(j)}_{t|T})\zeta^{(j)}_{t|t}), \Lambda^{(j)}_{t|t} \right)$$

where $\zeta^{(j)}_{t|t}$ corresponds to the same draw j from which the particles $\bar{\pi}^{(j)}_{t|T}$, $k^{(j)}_{t|T}$ are obtained, and where

$$\Delta^{(j)}_t = P_{t|t}A(\bar{\pi}^{(j)}_{t|T}, k^{(j)}_{t|T}, g(\bar{\lambda}_t)\rho\zeta^{(j)}_{3,t|T})'(Q_t + A(\bar{\pi}^{(j)}_{t|T}, k^{(j)}_{t|T}, g(\bar{\lambda}_t)\rho\zeta^{(j)}_{3,t|T})P_{t|t}A(\bar{\pi}^{(j)}_{t|T}, k^{(j)}_{t|T}, g(\bar{\lambda}_t)\rho\zeta^{(j)}_{3,t|T})')^{-1}$$

$$\Lambda^{(j)}_{t|t} = P_{t|t} - \Delta^{(j)}_t A(\bar{\pi}^{(j)}_{t|T}, k^{(j)}_{t|T}, g(\bar{\lambda}_t)\rho\zeta^{(j)}_{3,t|T})P_{t|t}.$$

B.3 Details on the Turkish Case

In Table B.1, the results of the Bayesian estimation procedure in the case of Turkey are reported. Model predictions in terms of one- and four-quarters ahead and inflation, compared to TCMB data, are presented in Figures B.1, B.2, and B.3, respectively. Even if Turkish data are very volatile, a model with CBC can fit these data pretty well.

Table B.1: Prior and posterior distribution of structural parameters - Turkey

	Prior distribution			Posterior distribution			
	Distribution	Mean	SD	Mode	Mean	5^{th} Pct	95^{th} Pct
π^*	Normal	18.800	2.000	18.817	19.108	15.790	22.425
$\bar{\nu}$	Gamma	0.200	0.040	0.189	0.186	0.127	0.245
$\bar{g}$	Gamma	0.800	0.090	0.768	0.796	0.651	0.938
γ	Beta	0.500	0.265	0.500	0.848	0.364	0.970
ρ	Beta	0.500	0.200	0.985	0.673	0.220	0.968
ω	Normal	0.900	0.020	0.903	0.906	0.873	0.944
λ	Gamma	2.000	0.200	2.006	2.002	1.740	2.318
σ_ϵ	InvGamma	1.000	2.000	1.326	2.245	0.339	7.807
$\sigma_{\tilde{\mu}}$	InvGamma	1.000	1.000	0.998	2.605	0.598	4.131
$\sigma_{o,1}$	InvGamma	5.000	1.000	4.402	4.449	3.558	5.394
$\sigma_{o,2}$	InvGamma	9.000	1.000	11.934	11.775	10.368	13.651
$\sigma_{o,3}$	InvGamma	8.000	1.000	8.732	8.648	7.104	10.294

Note: The posterior distribution is obtained using a Metropolis-Hastings algorithm. Moreover, the remaining parameters are calibrated according to the main New Keynesian literature: $\alpha = 0.66$, $\beta = 0.99$, and, hence, $\xi = 0.17$.

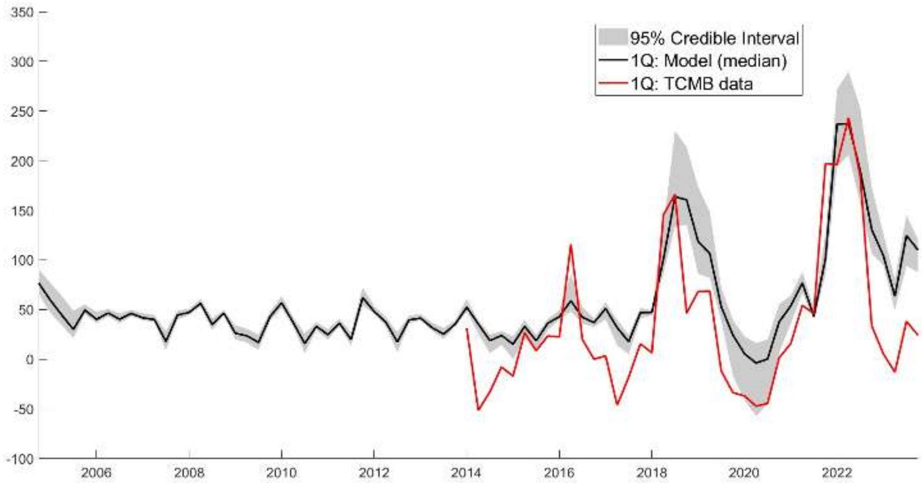

Figure B.1: Short-run inflation expectations: model vs data.

Note: The panel shows the evolution of one-quarter-ahead inflation expectations from TCMB, compared with model predictions.

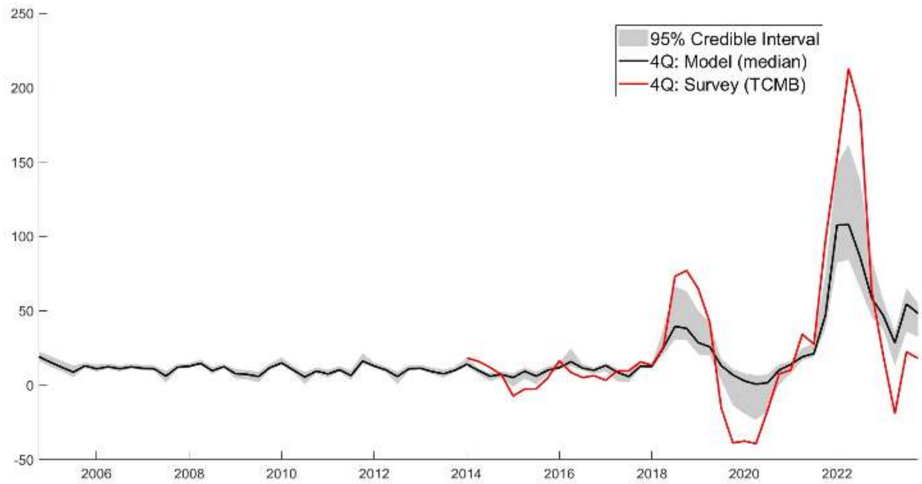

Figure B.2: Short-run inflation expectations: model vs data.

Note: The panel shows the evolution of four-quarters-ahead inflation expectations from TCMB, compared with model predictions.

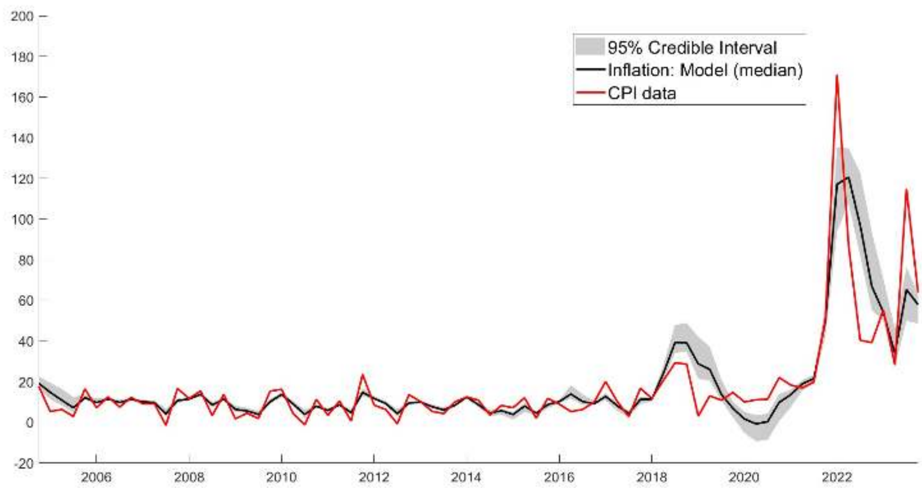

Figure B.3: Inflation: model vs data.

Note: The panel shows the evolution of inflation from TCMB, compared with model predictions.

Appendix C

APPENDIX FOR CHAPTER 3

C.1 Further Details about the MDI Database

The MDI database provides the following data[1]:

- *Statistical Business Register.* BR is central in producing business statistics and is the starting point for establishing statistical survey frames. The BR contains information on identifying characteristics such as ID numbers, names and addresses, demographic characteristics, economic activity, legal form, and institutional sector code, as well as information on control and ownership relations for enterprises, their local and legal units, and enterprise groups. In MDI, the BR serves as a "backbone" or connection between various surveys and administrative datasets.

- *Balance Sheet and Income Statement.* BS is generally sourced from the tax authority, leveraging compulsory tax declarations firms submit before paying their taxes. They normally cover the universe of companies, unless some small firms rely on personal taxes instead of corporate taxation, which is possible in most European countries. Data harmonization is provided by a standard reclassification of the most common items of the Balance Sheet/Income Statement developed by the CompNet team in its almost 10 years of work, in strong collaboration with the National Statistical Offices.

- *Structural Business Statistics.* SBS describes the economic activities within the business economy, including industry, construction, distributive trade, and ser-

[1] Information reported in this appendix is taken from the MDI manual, currently under drafting.

vices. SBS indicators at the detailed sector level are transmitted to Eurostat and published by all European Statistical System (ESS) members (EU Member States, Norway and Switzerland, some candidate and potential candidate countries). Harmonization of the SBS has taken place regarding the detail and coverage of the sectors (now NACE 2.1) and the statistical definition of the transmitted indicators (Commission Regulation (EC) No 250/2009). Generally, the SBS indicators in each country are collected at the level of individual enterprises engaged in economic activity.

- *Firm Production Statistics.* Prodcom provides statistics on the production of manufactured goods by enterprises in EU countries. These statistics are part of European business statistics and are collected by the national statistical institutes under the European business statistics regulation. Prodcom data cover the economic activities of mining and quarrying, manufacturing, and materials recovery. It delivers information about firm sales and sold quantity by product (at the 8-digit level).

- *Community Innovation Survey.* CIS is part of the EU science and technology statistics and provides mostly qualitative information on firms' innovative activity. Surveys are carried out every two years by EU member states and several ESS member countries voluntarily. The harmonized survey contains information on the types of innovation and various aspects of the development of an innovation, such as the type of funding and innovation expenditures. The CIS covers both innovation outputs and the innovative process and inputs (type of funding, R&D expenditure) and distinguishes four innovation types: process, product, organizational, and marketing, thus covering both innovative property as well as capabilities and organizational capital. Additionally, the CIS asks about the novelty of the innovation, i.e. whether it is new for the market, new to the country, developed by the firm or was adopted, and thus provides information about the innovative value.

- *ICT usage/E-commerce Survey.* ICTEC is an annual survey conducted since 2002, which collects information on the use of information and communication technology, the internet, e-government, e-business and e-commerce in enterprises. Like the CIS, the EC survey contains mostly qualitative data. The ICT use survey measures various dimensions of firm technology use. Besides software and databases being considered as an integral part of intangibles, the adoption of certain technologies also provides information about firms' organizational capital and ICT capabilities both in the firms' internal operations and regarding the firms' supplier and buyer relationships. The qualitative information in the survey can be used to construct an ICT intensity index which allows for variation in the underlying source variables, thereby overcoming the issue with changing survey questions and the saturation of certain variables over time.

- *International Trade in Goods Statistics* and *International Trade in Services Statistics.* ITGS measure the value and quantity of goods firms trade between EU Member States (intra-EU trade) and with non-EU countries (extra-EU trade) broken down by types of goods (Combined Nomenclature) and by partner countries. The providers of statistical information differ between intra and extra EU-trade. In the first case, they correspond to all taxable persons reporting transactions exceeding a certain threshold fixed by member states; in the second case, it corresponds to administrative data from the customs declarations lodged by natural or legal persons in the customs administration. ITS typically cover trade services, i.e., transactions paid for the services that have taken place between the residents and non-residents.

- *The Foreign Affiliate Statistics.* FATS are distinguished into inward FATS, i.e. the activity of foreign affiliates resident in the compiling country, and the outward FATS, that is, the activity of foreign affiliates abroad but controlled by the compiling country. FATS allows to qualitatively assess the degree of economic activity of a domestic enterprise abroad and identify foreign-controlled firms.

- *International Sourcing Survey.* ISS gathers data on international organizations and the sourcing of business functions in 16 European countries, covering the period 2014-2016 or 2015-2017, depending on the country. The survey results cover nearly 60,000 businesses with over 50 employees. However, since the survey is still in the pilot stage, the survey design varies across countries.

- Moreover, data on firm energy use (ENER) and demographics (FD) are also available from Eurostat for some countries. ENER provides data on expenditures and quantities of several renewable and non-renewable energy sources, whereas FD informs about firm entry-exit and mergers-acquisitions.

C.2 Clustering Algorithm

The computation details of the clustering algorithm are reported below. Firms are clustered according to the best fit in terms of RSS from a production function estimation and a cost pass-through regression.

Clustering Algorithm
Initialization, s = 0. Cluster firms into 5 bins according to labour productivity distribution and into 3 bins based on the ratio of price and marginal cost log difference.
Iterations, s = 1, 2, 3, ...:
1. Production function estimation in each cluster along the production technology distribution:
$\Rightarrow \hat{\alpha}_s$, $\hat{\beta}_{1,s}$, $\hat{\beta}_{2,s}$, $\hat{\beta}_{3,s}$.
2. Given the estimated parameters from the previous step, cluster each firm is the production technology bin that minimizes its $RSS_{prod,s}$.
3. Cost pass-through regression in each demand cluster:
$\Rightarrow \hat{\beta}_{1,s}(\eta_d, \rho_d)$.
4. Given the estimated parameters from the previous step, cluster each firm is the demand bin that minimizes its $RSS_{d,s}$.
5. Assess convergence: stop if $RSS_{prod,s-1} - RSS_{prod,s} \leq \epsilon$ and $RSS_{d,s-1} - RSS_{d,s} \leq \epsilon$, otherwise repeat from step 1, where ϵ is a tiny number (= 0.001 in our main analysis).

C.3 Additional Empirical Results

This appendix reports the first stage of the firm pricing equation based on production technology and demand group (Table 3.8 in the main text).

Moreover, the firm pricing equation by aggregate production technology and demand group is shown, with the related first stage. Aggregate production group 1 is the sum of the first three production clusters, while the two more productive clusters are merged in the aggregate production group 2. Results are qualitatively similar to the main specifications presented in the main text and, again, robust to the inclusion of different industry fixed effects or the interaction between competitors' price response and cluster membership. In particular, for this specification, we observe a flattening of the supply curve in all the demand clusters.

Table C.1: First stage of firm pricing equation by technology - demand group

	δy_{it}		
DS_{st}^{Shea}	5.310	DS_{it}^{wid}	0.106
	(11.095)		(0.114)
× tech_demand$_{1,2}$	-7.267		0.144
	(15.125)		(0.481)
× tech_demand$_{1,3}$	3.218		0.131
	(7.845)		(0.117)
× tech_demand$_{2,1}$	0.167		0.143
	(7.815)		(0.125)
× tech_demand$_{2,2}$	0.829		0.083
	(8.798)		(0.138)
× tech_demand$_{2,3}$	-3.253		0.095
	(7.718)		(0.117)
× tech_demand$_{3,1}$	-1.718		0.086
	(7.975)		(0.141)
× tech_demand$_{3,2}$	-3.800		0.145
	(8.853)		(0.150)
× tech_demand$_{3,3}$	-2.196		0.122
	(7.698)		(0.085)
× tech_demand$_{4,1}$	-4.283		0.145
	(10.644)		(0.333)
× tech_demand$_{4,2}$	-0.502		0.139***
	(9.447)		(0.024)
× tech_demand$_{4,3}$	-3.428		0.057
	(7.918)		(0.121)
× tech_demand$_{5,1}$	-6.029		0.315
	(23.741)		(0.334)
× tech_demand$_{5,2}$	35.786***		-0.029
	(10.717)		(0.136)
× tech_demand$_{5,3}$	10.676		0.144***
	(8.205)		(0.034)
Other regressors included		Yes	
Sector-Year fixed effects		Yes	
Firm fixed effects		Yes	
Obs		200227	
F-statistics		4.97***	
R^2		0.54	

Note: Observations weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p<0.01, ** $p < 0.05$, * $p < 0.1$, $^+ < 0.15$.

Table C.2: First stage of firm pricing equation by technology - demand aggregated group

	δy_{it}		
DS_{st}^{Shea}	3.770	DS_{it}^{wid}	0.110
	(8.346)		(0.070)
× aggtech_demand$_{1,2}$	-5.603		-0.036
	(3.272)		(0.080)
× aggtech_demand$_{1,3}$	-0.690		-0.002
	(1.476)		(0.040)
× aggtech_demand$_{2,1}$	-6.751		0.044
	(6.570)		(0.306)
× aggtech_demand$_{2,2}$	12.891***		0.039
	(4.666)		(0.168)
× aggtech_demand$_{2,3}$	1.268		0.005
	(1.207)		(0.045)
Other regressors included		Yes	
Sector-Year fixed effects		Yes	
Firm fixed effects		Yes	
Obs		200227	
F-statistics		7.64***	
R^2		0.54	

Note: Observations weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p<0.01, ** $p < 0.05$, * $p < 0.1$, $^{+} < 0.15$.

Table C.3: Firm pricing equation by technology - demand aggregated group

	δp_{it}			Slope		
	demand$_1$	demand$_2$	demand$_3$			
δy_{it} × agg_tech$_1$	0.130***	-0.091***	0.006			
	(0.026)	(0.018)	(0.009)			
δy_{it} × agg_tech$_2$	-0.070*	-0.180***	-0.230***	***	***	***
	(0.015)	(0.017)	(0.031)			
δp^{-i}_{st-1}	0.060***					
	(0.007)					
δp_{it-1}	-0.173***					
	(0.008)					
2 digit Industry-Year fixed effects		Yes				
Firm fixed effects		Yes				
Obs		200227				
R^2		0.22				

Note: 2sls regression at the firm level, weighted by the share of nominal revenue. Standard error clustered by 2-digit sector in parenthesis. *** p<0.01, ** $p < 0.05$, * $p < 0.1$, $^{+} < 0.15$. Reference group is $prod_1 \times demand_1$. *Slope* column indicates whether there is a significant flattening of the pricing equation along the productivity distribution for each demand cluster.