Bocconi

Bachelor of Science in International Economics and Finance

The Phillips Curve — Identification Challenges, Expectations and the Role of Central Banks

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0 Introduction

In 1958, A. W. Phillips postulated an inverse relationship between unemployment and wage growth (*Phillips, 1958*). The theoretical justification of the unveiled correlation rested on the simple idea that supply and demand dynamics in the labor market operate no differently than in markets for normal goods. For ordinary goods, prices are expected to rise when demand exceeds supply; likewise in the labor market, the cost of labor (wages) is then expected to increase if labor demand exceeds labor supply. In line with this reasoning, when unemployment is low, employers are expected to bid wage rates up, and vice versa; when the market is slack, downward price pressure is foreseen to mount. However, if workers are reluctant to accept wages below the prevailing rate during deflation, while they favorably accept wage increases during upsurges, wage rigidities counter the downward pressure generated by slackness giving rise to a nonlinear downward relationship between unemployment and inflation. While the proposed reasoning may sound convincing, empirically estimating the Phillips curve has been challenging for decades. The literature has obtained many conflicting results on the basis of the variables used, the periods considered, and the assumptions used to build the model. Many of these issues will be explored in the following chapters of this work. In this work, I will proceed as follows: in Chapter 1, I will briefly introduce the idea on which the Phillips curve is built and present the standard model used to describe the curve, providing empirical evidence on it. I will also document the flattening of the Phillips curve through a historical analysis of the Impulse Response Functions derived from a BVAR model I developed. 3D plots will depict how the reduced-form estimate of the coefficient on unemployment has evolved in magnitude and length across the last 50 years. In Chapter 2, I will describe the identification challenges that characterize the literature on the Phillips curve. In this context, I describe why the unemployment rate is an imperfect measure of real economic slackness and why alternative indicators may over-perform it by covering its flaws. In Chapter 3, I will focus on disentangling internal and external inflation components through a Phillips curve-driven approach. Subsequently, I will also show how BVAR models allow inflation decomposition by computing relative shock contributions based on shock identification and sign restrictions. Chapter 4 discusses how inflationary expectations bias the estimates of the Phillips curve relation and how central banks' endogenous monetary policy confounds estimates. In Chapter 5, I will focus on using regional data, its advantages, and the results obtained through this methodology. In Chapter 6, I will discuss how non-linearities are expected to emerge in low-inflation economies during periods of economic slackness. I will present some works that try to estimate a piece-wise Phillips Curve. To conclude, I will consider what the themes discussed in the previous chapters imply for central banks, analyze the Federal Reserve's recent review of its monetary policy strategy, and underline the importance of forward guidance.

1 New Keynesian formulation of the Phillips curve

1.1 Fundamental idea and standard formulation of the Phillips curve

At its core, the PC represents a relationship between inflation and economic slack. The unemployment rate has been traditionally employed as the default proxy for slackness. When unemployment is low, labor is scarce, and wages, which are the price of labor, are expected to increase. Since the price of labor is a key input cost, firms will seek to adjust their prices and production to optimize profit margins. Slackness affects prices in proportion to firms' pricing power, that is, their ability to pass input costs to consumers. This pass-through effect is significant as wage growth and CPI inflation correlate highly (Figure 1). In basic models, with some degree of simplification required, the firm's profit adjustment is modeled with Calvo pricing (*Calvo, 1983*). In this framework, firms are assumed to adjust their prices with a certain probability each period. This implies that the price level is a function of the expected future price level, the output gap, and a cost-push shock. The slope of the PC is determined by the degree of price stickiness, that is, how much firms can adjust their prices in response to changes in costs.

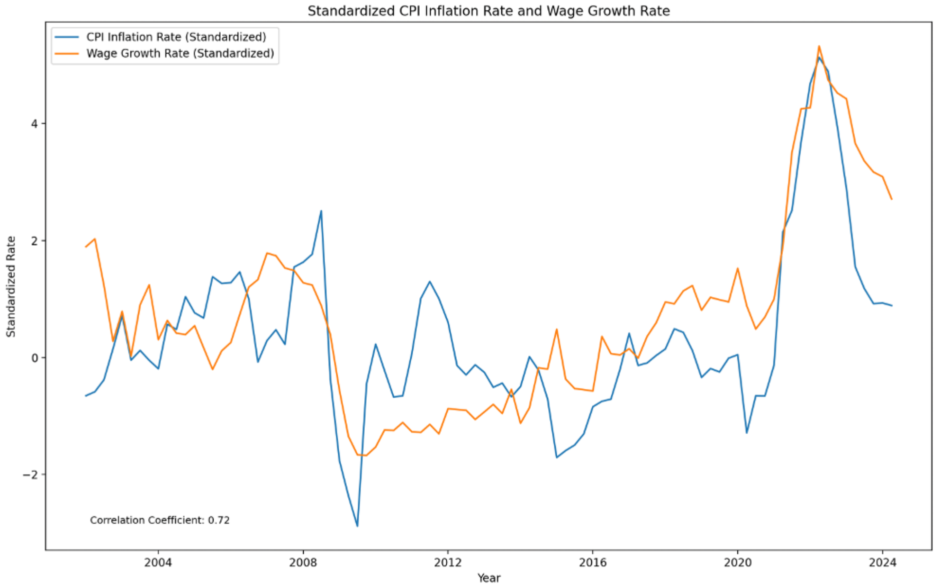


Figure 1: Inflation and Wage Growth

Note: The figure shows the evolution of the standardized rates of CPI inflation and wage growth over time in the US, indicating a positive correlation between the two variables. Source: Author's calculation

In its standard and best-known specification, the Phillips curve is written as:

$$\pi_t = \beta E_t \pi_{t+1} - \kappa(u_t - u_t^n) + \nu_t. \tag{1}$$

In this formulation, inflation π_t is determined by three factors: the expected inflation $E_t\pi_{t+1}$, the output gap -the difference between the unemployment rate u_t and the natural rate of unemployment u_t^n- and cost-push shocks ν_t. The slope of the Phillips curve κ describes how sensitive inflation is to the output gap, that is, how much a variation in slackness affects inflation. The higher the value of κ, the steeper the Phillips curve. The parameter β is the discount factor determining how much weight is given to future inflation. The higher the value of β, the more future future inflation expectations influence current inflation. The term ν_t represents cost-push shocks, shocks that affect the price level independently of slackness. As this standard specification of the Phillips curve has been particularly criticized in recent decades, many authors have developed augmented versions of this equation. For example, expected inflation can be modeled in many ways, more sophisticated measures of slackness can be used to circumvent the many flaws the unemployment rate presents, and a plethora of controls can be introduced to control for related sources of bias. A simple way of modeling expected inflation is using adaptive expectations, $\beta E_t \pi_{t+1} = \pi_{t-1}$, equation 1 simplifies to the "accelerationist" form:

$$\Delta \pi_t = -\kappa (u_t - u_t^n) + \nu_t. \tag{2}$$

As will be discussed later, this formulation is too simplistic as it reduces expected inflation to equal the previous year's inflation.

1.2 Criticism

This standard specification of the Phillips curve has been widely criticized in recent decades. Many authors have, in fact, observed a progressive flattening of the PC. During Volcker's years, the relationship between the unemployment gap and inflation had been estimated to be steep. As the FED tightened monetary policy in the early 80s, unemployment rose markedly, and inflation fell significantly. In fact, most of the papers, such as *Stock and et al (2019)*, *Ball and et al (2011)*, *Kiley (2015a)*, and *Blanchard (2016)* find the κ coefficient to be large and significant in that period. Figure 2 visually represents the PC flattening across the last five decades. Overall, the PC has also been criticized for its poor forecasting performance. Even simple models using only past inflation data to forecast future inflation can outperform more sophisticated ones based on the PC relationship. *Atkeson et al. (2001)* showed how predictions based on Phillips curve models were not better than random guesses. *Dotsey and et al (2018)* presented how AR, RW, and VAR models can outperform PC models; comparable results are found by *Stock and Watson (2007)*, *Ciccarelli and Osbat (2017)* and *Forbes et al. (2017).* This hints the standard model may be flawed.

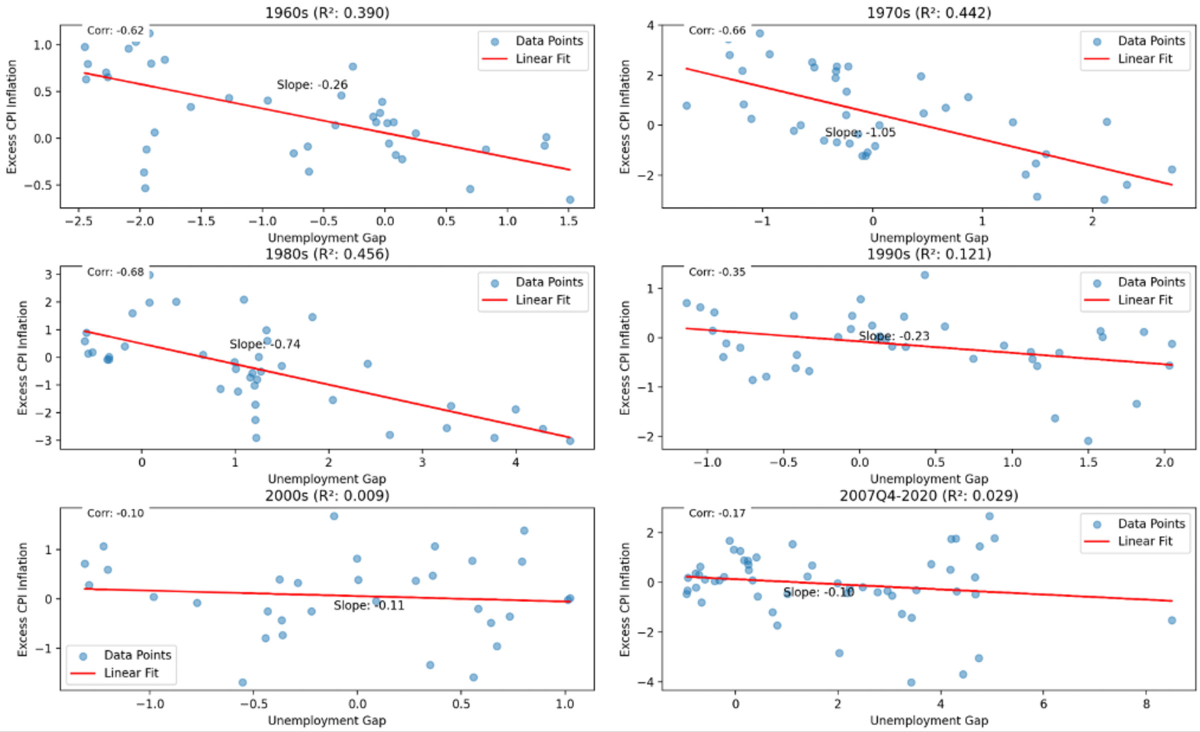


Figure 2: The Phillips curve in the last 50 years

Note: The figure illustrates the Phillips curve across six decades, showing the relationship between the unemployment gap and excess CPI inflation in the US. Each panel represents a different decade, with the slope of the linear fit and the correlation coefficient indicated. The correlation weakens over time, with steeper curves in earlier decades (e.g., 1970s) and flatter curves in more recent decades (e.g., 2000s and 2007Q4-2020), suggesting a flattening Phillips curve. Source: Author's calculation.

1.3 Evidence

We can see how the slope coefficient on the Phillips curve has been decreasing over time: in the 60s, in the 70s, and in the 80s, the slope was markedly negative. However, several puzzles started to emerge in the following years. In the 90s, a considerably strong labor market did not seem to create much inflation, and as illustrated in the plot, the slope became less steep. Later, during the 2008 recession, unemployment soared to strikingly high levels without generating the expected disinflationary pressures; in the same period, the coefficient estimate on the unemployment gap flattened to almost zero. Overall, the last thirty years, read through the lenses of PC models, are marked by periods of missing inflation and disinflation. This has led to the idea the PC was hibernating or even disappearing. More in-depth, it is possible to analyze through the lenses of a BVAR model how the sensibility of inflation to a 1% change in unemployment changed across the last fifty years (Figure 3). BVAR models are a class of linear multivariate time series models estimated using Bayesian methods. They estimate the inter-temporal effect of a shock in one variable on another variable. The model is built on the MATLAB toolkit provided by *Canova and Ferroni (2021)* and estimated using monthly data from 1960 to 2020. I used data from the FRED database on the US CPI, unemployment rate, and Fed funds for the analysis. It is possible to appreciate how the effect of a 1% increase in unemployment evolved markedly across time. In the 80s, during Volker's disinflation, unemployment increased and led to a strong deflationary response. Not only was the magnitude of the short-term effect more significant, but the shock also lasted longer in the long run (Figure 4). In the 90s, the effect of a rise in unemployment on inflation was less pronounced, and the shock was shorter. In the early 2000s, the impact of an increase in unemployment on inflation was almost zero. However, in the aftermath of the 2008 recession, the effect of an increase in unemployment on inflation was positive before flattening again up to 2020. As is typical with these formulations of the Phillips curve, this plot captures only a reduced-form relationship between unemployment and inflation. It is essential to address the biases associated with the analysis to achieve a more structural interpretation of the parameters estimated from the BAR. The following sections will first assess the challenges and biases related to estimating the Phillips curve and then focus on mitigating these factors.

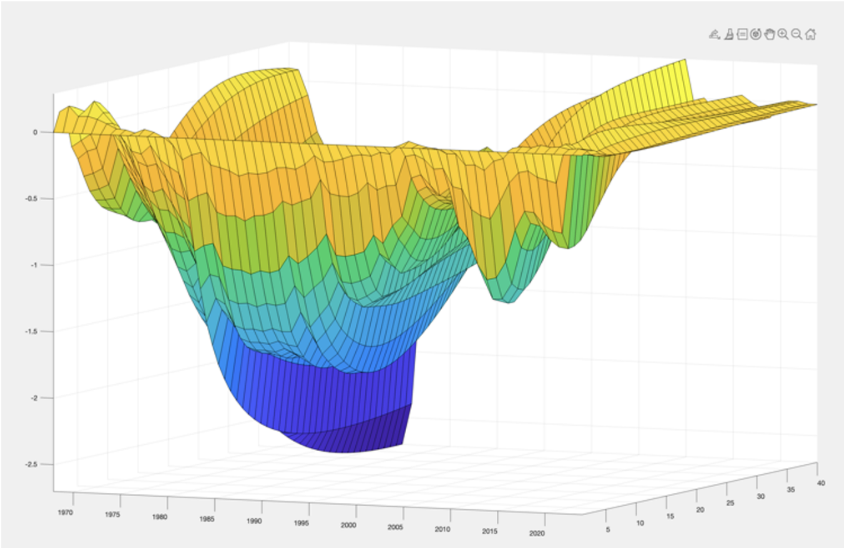


Figure 3: Magnitute of the IRFs derived from the BVAR model

Note: The figure depicts the magnitude of Impulse Response Functions (IRFs) derived from the BVAR model over time. The variables used are the US CPI, unemployment rate, and Fed funds (monthly data from 1960 to 2020). The The 3D plot shows how the response of inflation to unemployment shocks has evolved since the 1970s, with deeper responses in earlier periods and flattening responses in more recent years. Source: Author's calculations.

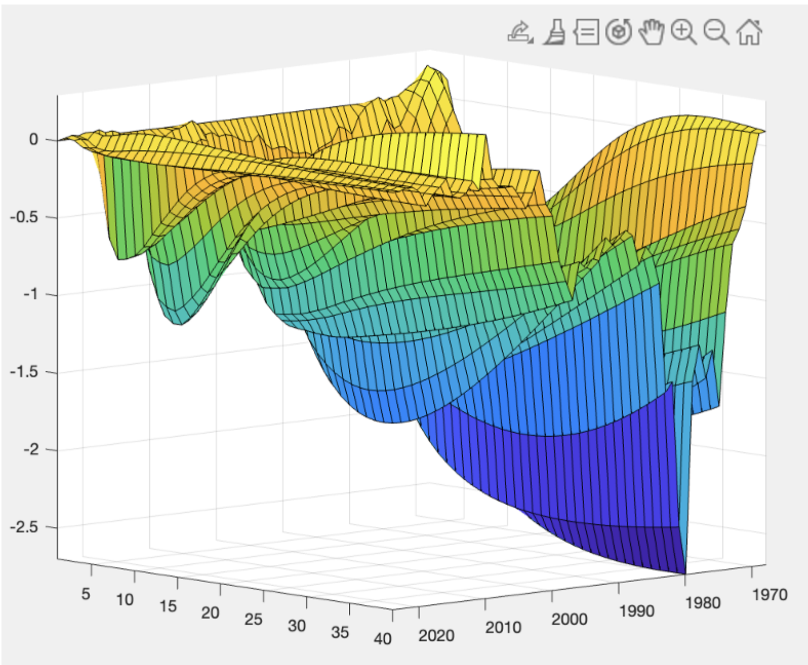
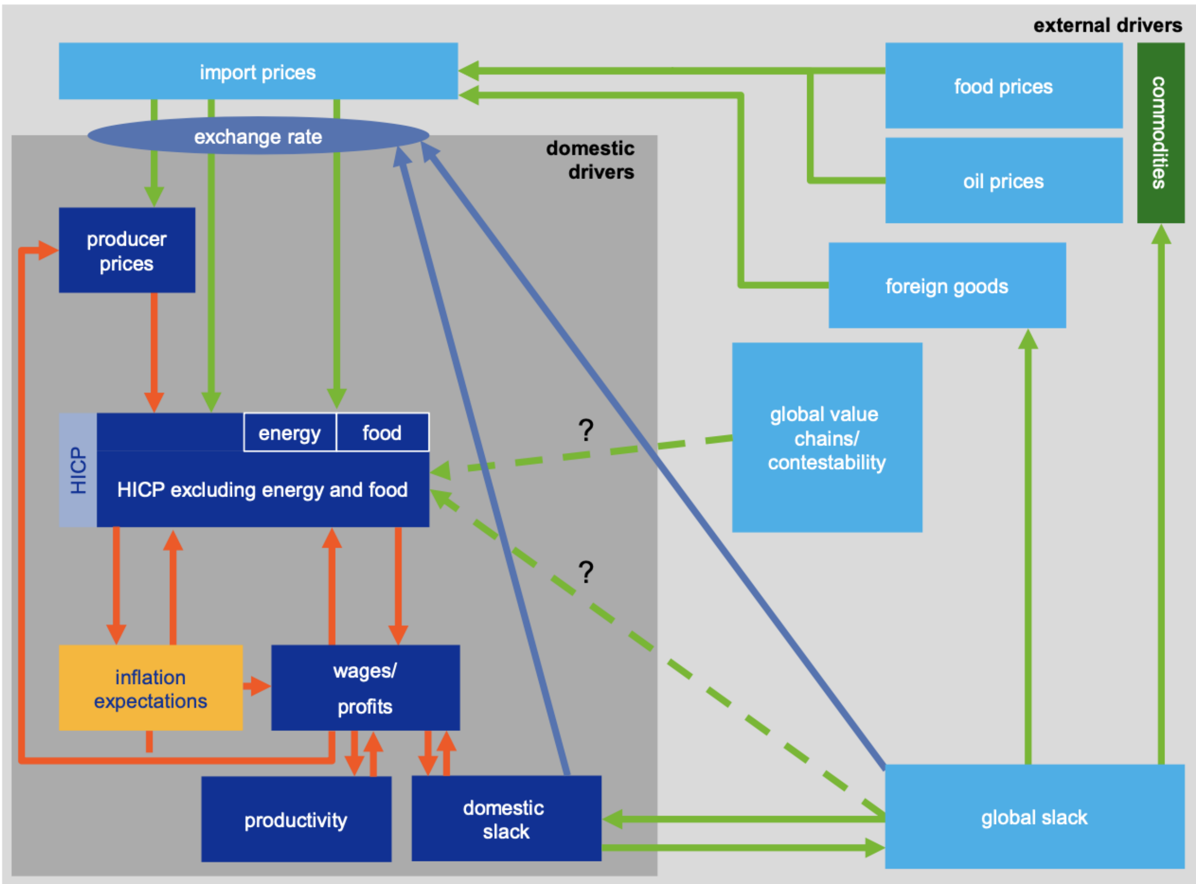


Figure 4: Long-term effect of the IRFs derived from the BVAR model

Note: The figure shows the long-term effects of Impulse Response Functions (IRFs) derived from the BVAR model. The variables used are the US CPI, unemployment rate, and Fed funds (monthly data from 1960 to 2020). It illustrates the sustained impact of unemployment shocks on inflation over time, highlighting the changing duration and magnitude of these effects across different decades. Source: Author's calculations.

2 Internal and External identification issues

Identifying the labor market effect on inflation is challenging as the relationship is blurred by many confounders (Figure 5). To guide the discussion, the article "Domestic and global drivers of inflation in the euro area" (*ECB, 2017*) is taken as a reference. This section will focus on the primary sources of bias affecting the estimation of the PC. To practically illustrate the presented theoretical exposition, I will use EU data on the post-2008 recession (*ECB, 2015a*).



Source: ECB illustration. The red arrows reflect domestic drivers of inflation, the green arrows external drivers. Blue arrows illustrate that global and domestic slack are important drivers of exchange rate developments. The dashed green lines reflect the hypotheses discussed in this article – namely that GVCs and global slack have a direct influence on euro area inflation.

Figure 5: Internal and external drivers of Inflation

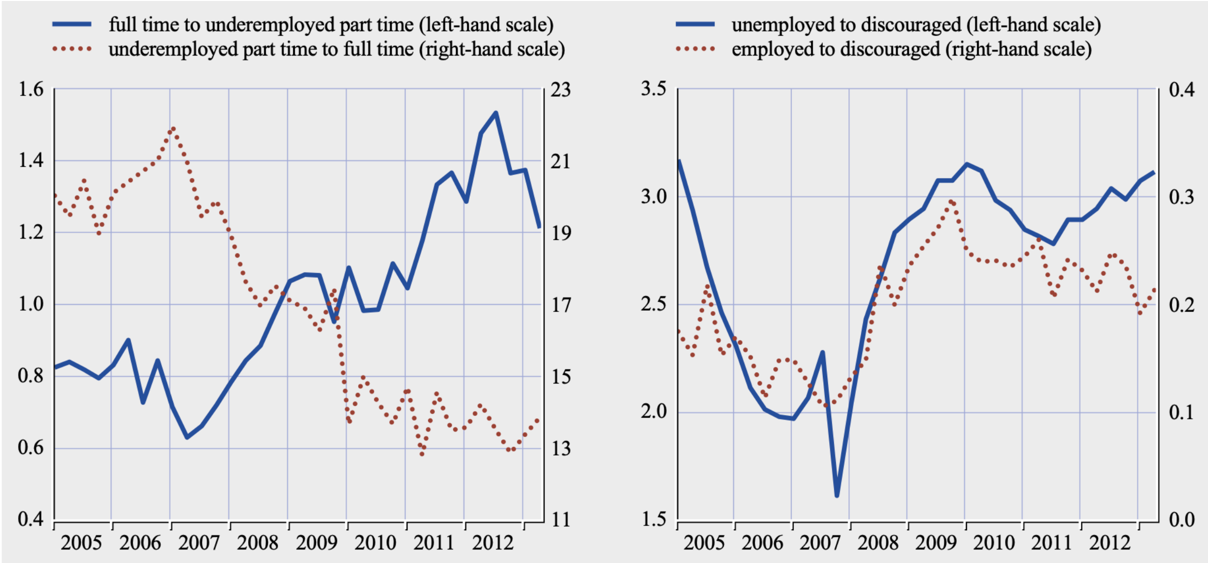
2.1 Internal Identification Issues

2.1.1 Discouraged workers, Unemployment and Job Switchers

Unemployment as a proxy for economic activity misses some crucial sources of slackness in the labor market.

First, Discouraged workers who have stopped looking for a job are counted in the unemployment statistics as inactive. As a consequence, ceteris paribus, an increase in the number of discouraged workers leads to a reduction in the unemployment rate. Paradoxically, this may lead to a reduction in the unemployment rate during recessions. For example, in the aftermath of the 2008 recession, discouraged workers increased from 5.2 to 7% in stressed countries, with many unemployed becoming discouraged.

Second, underemployed workers who work part-time but would like to work more hours are not given a differentiated weight. This means that the gross measure of the unemployment rate hinders the true slackness in the labor market by underestimating the number of workers who would like to work more hours. Also, in this case, in the 2008-2012 period, the change in the share of part-time workers increased significantly, with many full-time workers ending up in a part-time job (Figure 6).



Source: Authors' calculations based on the Labour Force Survey.
Notes: Underemployed are those working part-time for economic reasons, but willing to work more hours. Data are seasonally-adjusted using the Tramo-Seats method.

Source: Authors' calculations based on the Labour Force Survey.
Notes: Discouraged workers are inactive persons available to work but not seeking. Data are seasonally-adjusted using the Tramo-Seats method.

Figure 6: Discouraged workers and underemployment, evidence from the EU

Third, job switchers, those who already have a job and want to switch to a new one, are obviously not included in the unemployment rate as a potential measure of economic activity. However, they create pressure on the labor market as they are actively looking for jobs. As a side note, it is worth mentioning that during the pandemic the number of job switchers increased markedly, with many workers looking for a new job as the pandemic changed both people's preferences and the structure of the economy (Figure 7 by *Furman and Powell, 2021*).

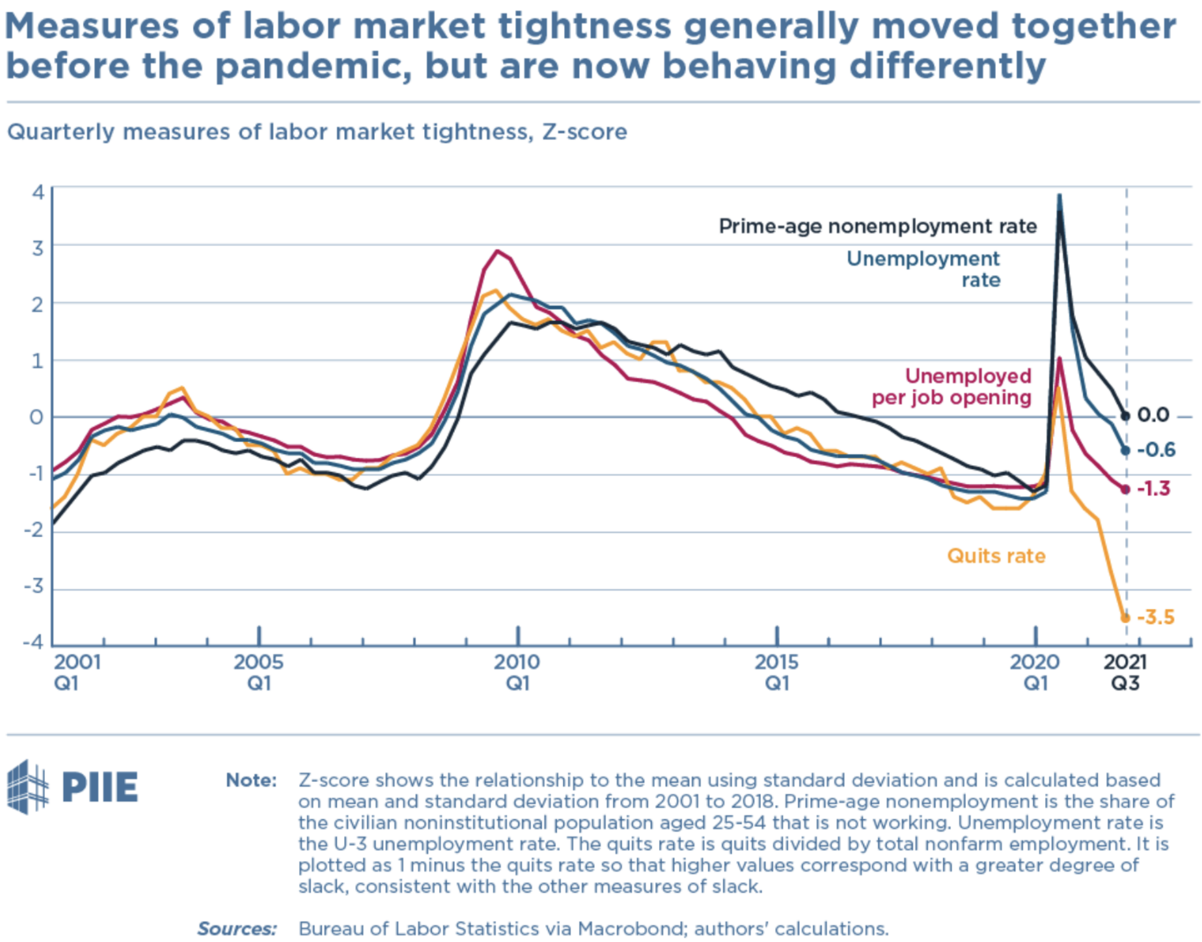


Figure 7: Quit rate shows the strongest labor market of the last two decades

While these issues may appear subtle, they are not. In fact, under some particular circumstances, using different measures of slackness has led to blatant contradictions that the general public has widely recognized. For example, during COVID, US and EU unemployment rates diverged massively. In the EU, temporary layoffs are given no weight, while in the US, they are considered to have the same relevance as long-term unemployment. The real amount of slackness was clearly somewhere in between these two estimations, however this case clearly suggests that a more nuanced proxy of real economic slackness must be found. This has crucial impacts on the estimation of the Phillips curve. As some measures may lead to an overestimation of slackness during recessions while others may underestimate the growth of economic activity during recoveries, Phillips curves built on different measures of slackness will lead to different estimations for the

k coefficient. This, in turn, will lead models to have lower or higher explanatory power. In this sense, picking the right measure of slackness is critical. For example, *Bell et al. (2018)* concludes that underemployment replaces unemployment as the primary measure of labor market slack in the post-recession years.

Empirically, the magnitude and significance of the coefficient on unemployment in the PC is highly sensitive to the measure of slackness used, and some indicators work more efficiently than others. To frame the issue it is possible to regress CPI inflation on different measures of slackness. Figure 8 presents three scatter plots examining the relationship between excess CPI inflation and different measures of labor market slackness: the unemployment rate, the unemployed per job opening, and quit rate slackness. The data are segmented into four distinct periods: 2002-2009, 2010-2018, 2019-2023, and a fit for the most recent period from 2019-2023. The fitted regression lines and R-squared values for each period provide insight into the evolving nature of this relationship across time. Overall, the results have significant variations, and the estimates are susceptible to the period analyzed.

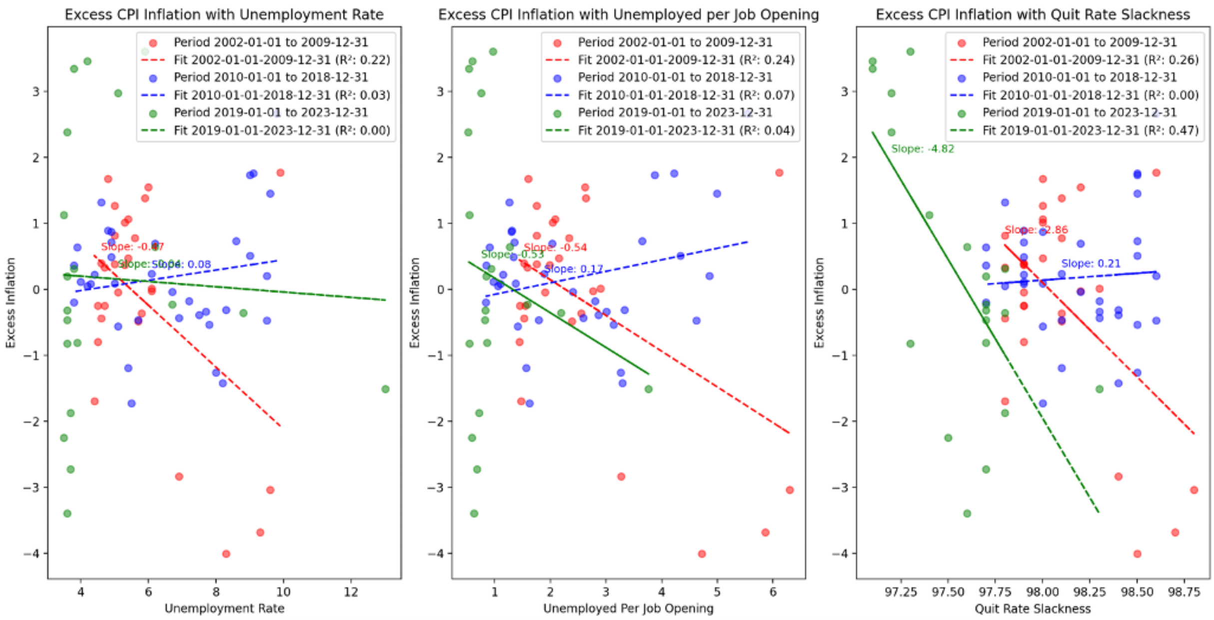


Figure 8: Underemployment in the Eu

Note: The figure presents the relationship between excess CPI inflation and three EU labor market slack measures: unemployment rate, unemployed per job opening, and quit rate slackness. Each panel shows data points and fitted lines for three distinct periods (2002-2009, 2010-2018, and 2019-2023). The slopes and R-squared values indicate varying degrees of correlation across periods, with quit rate slackness showing the strongest relationship to inflation during the 2019-2023 period. Source: Author's calculation.

Panel A depicts the relationship between excess CPI Inflation and the Unemployment Rate. The scatter points are color-coded by period, with each color corresponding to a specific period. The red dots representing the 2002-2009 period show a downward-sloping regression line and an R-squared value of 0.22. This moderately negative correlation indicates that higher unemployment rates during this period were associated with lower levels of excess inflation. The Blue dots correspond to the 2010-2018 period: the slope is moderately positive in these years and the R-square is very small. Green dots reflect data from 2019-2023, characterized by a flat slope and an R-squared of nearly zero.

Panel B presents the relationship between excess CPI Inflation and Unemployed per Job Opening. Red dots for the 2002-2009 period again show a negative slope, with an R-squared value of 0.24. The blue dots for 2010-2018 show a positive slope with an R-squared of 0.07. The green dots for 2019-2023 exhibit a steeper negative slope but with a meager R-squared value. Overall, the unemployment per job opening measure seemed slightly better than the unemployment one in capturing the relationship between unemployment and slackness.

Panel C illustrates how excess CPI Inflation and Quit Rate Slackness are related. The red dots (2002-2009) show a strong negative relationship, with a steeper slope and an R-squared of 0.26, suggesting that higher quit rates relative to slackness were linked to higher inflation. The slope is slightly positive for 2010-2018 (blue dots), but the R-squared is very low. The green dots for 2019-2023 reveal a return to a significant negative correlation between quit rate slackness and inflation, with a relatively high R-squared value of 0.47, the strongest fit among the three panels. It is interesting to note how the quit rate measure signaled a very strong labor market in 2021 and led to a very steep Phillips curve estimation.

Overall, the first two panels show a diminishing relationship between inflation and slackness since the financial crisis, consistent with the flattening of the Phillips Curve. However, the third panel, focusing on quit rate slackness, demonstrates a re-emerging solid relationship in the post-2019 period.

2.1.2 Building more nuanced measures of slackness

The crucial issue with these measures of economic activity is that each tells us just part of the full picture, and none of them can fully uncover the real amount of slackness of the economy. In turn, this hidden slackness may slow down recoveries or conceal losses during crises. For example, discouraged workers flowing back into the job market after a recession may slow down the reduction of the unemployment rate, hence lessening the apparent strength of the recovery. A solution to the issues above may be the approach described in *Trigari (2021)*, where a more sophisticated measure of labor market slackness is built by estimating search intensities for 22 categories of job seekers with heterogeneous characteristics. The measure is the product of the number of job seekers of type i times the estimated search intensity (Figure 9). After standardization, the developed measure seems to capture deeper slackness during recessions but raises more promptly during recoveries (Figure 10). This may lead to flatter s-based Phillips curves.

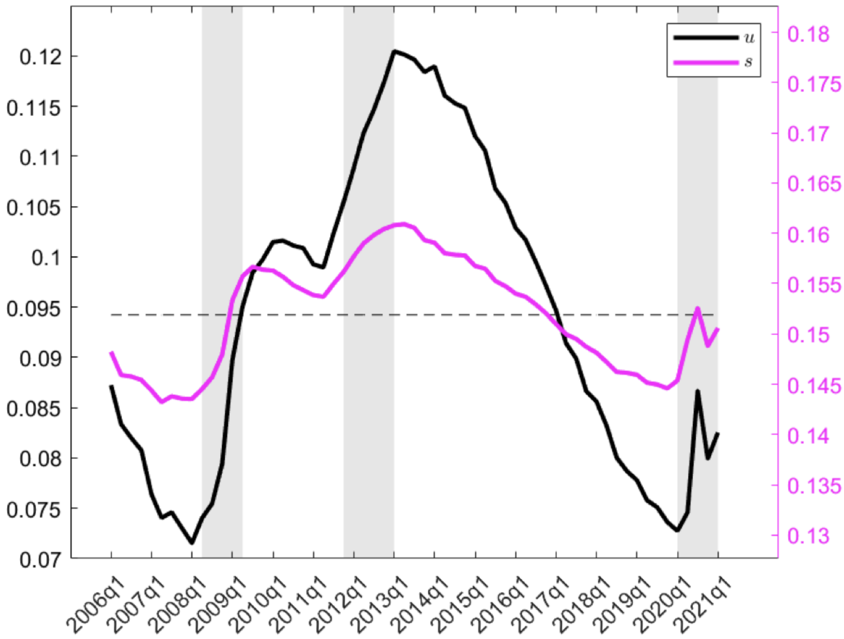


Figure 9: Estimating slackness through search intensities

Note: this figure plots a comparison between the unemployment rate and a more sophisticated measure of labor market slackness built by estimating search intensities for 22 categories of job seekers with heterogeneous characteristics. Source: Trigari, A. (2021). How to measure labor market slack? Worker heterogeneity and monetary policy.

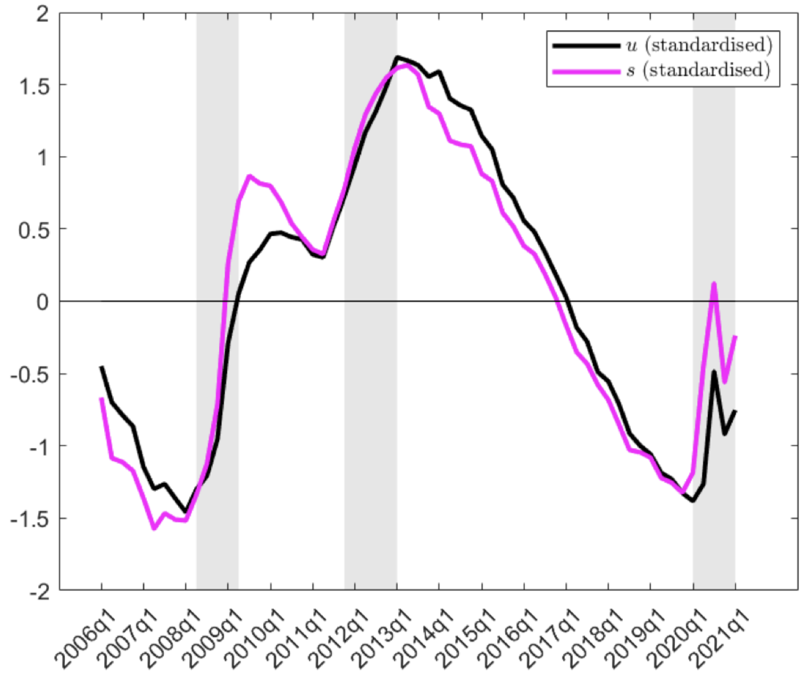


Figure 10: Comparing s and u

Note: the figure plots the standardized values of the unemployment rate and the measure of slackness developed by Trigari, A. (2021). Overall, the developed measure seems to capture relatively more slackness during recessions while raising more promptly during recoveries. Source: Trigari, A. (2021). How to measure labor market slack? Worker heterogeneity and monetary policy.

2.1.3 Issues related to the use of the unemployment gap

Second, using the unemployment gap is problematic because it requires a precise estimation of the natural rate of unemployment. However, the natural rate of unemployment may vary significantly with economic conditions (*Blanchard, 2018*). For example, if long-term unemployment turns into structural unemployment, then the natural unemployment rate will rise during recessions. Evidence in Europe suggests that during the 2008 recession, the rise in long-term unemployment caused an increase of 1.6% in structural unemployment (Figure 11), which is one-third of the total variation in unemployment. The broad point is that Milton Friedman's (*Friedman, 1968*) "natural rate hypothesis" may, instead, be path-dependent as hysteresis may structurally affect the state of the economy (*Blanchard and Summers, 1986*, *Phelps, 1972*, *Cœuré, 2017*). This may be due to the cumulative nature of TFP, increased unemployment protection following recessions (*Blanchard and Wolfers, 2001*, and reduced value of human capital due to long-term loss of morale and skills (*Krueger et al., 2014*, *Yagan et al., 2017*, *Autor et al., 2006*). In this context, central banks are crucial in countering permanent destruction in production capacity by avoiding the output gap and closing 'the wrong way' by unduly delaying the closing of the gap upwards (*Draghi, 2017*)

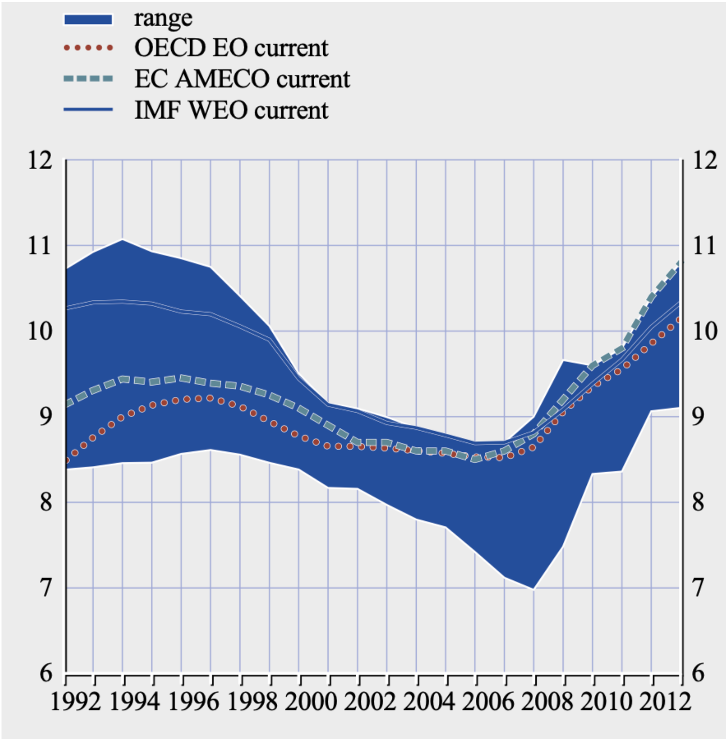


Figure 11: Evolution of structural unemployment in the EU

Note: The figure depicts the structural unemployment rate for the EU. Overall, it is possible to observe the rate has been quite volatile and that it surged markedly during the 2008 crisis. Source: ECB Occasional Paper (2015). Comparisons and contrasts of the impact of the crisis on euro area labour markets

2.1.4 Structural reforms and nominal rigidities

Nominal rigidities play a pivotal role in shaping the dynamics of unemployment and wage growth (*Daly and Hobijn, 2014*) and are often represented as structural parameters in Phillips Curve (PC) models. Structural reforms that target aspects such as firing and hiring costs, employment protection, and workers' bargaining power can significantly impact the constraints that limit economic activity and the functioning of labor markets (*Diego Daruich and Saggio, 2022*). These constraints may weaken the Phillips Curve relationship, for instance, by inhibiting employers from laying off workers during crises or forbidding wage cuts. In this regard, strong labor unions play an essential factor. In fact, strong labor unions may hinder the downward pressure on wages during recessions or negotiate higher wages during upsurges. The literature has widely discussed the theme of the role of labor unions in shaping downward wage rigidity. For example, a recent paper has shown that the relationship between unemployment and inflation is stronger in countries with higher trade union density (*Forslind and Walentin, 2024*). Last, it is interesting to note how, even if reforms free the market from rigidities that are lower than expected, wage growth may persist due to rigidities prevailing in the past. In fact, if downward rigidities have prevented wages from adjusting sufficiently to the amount of slack during the downturn, this will hinder the necessary wage increase of the upturn.

2.1.5 The structure of employment creation

Fourth, the structure of employment creation must be considered when analyzing wage dynamics in Europe. For example, as illustrated in Figure 12, during the post-2008 recovery employment growth in Europe was concentrated primarily in low-wage, low-productivity sectors such as non-market services, agriculture, and construction (*ECB, 2015b*). Meanwhile, sectors with higher productivity levels, like finance and insurance, ICT services, and industries excluding construction, exhibited more modest employment gains. This shift in employment creation towards less productive sectors has essential implications for wage growth. During economic downturns, low-skill workers, who are typically more vulnerable to job losses, exit the labor market, while workers with high salaries tend to remain in their positions. This clearly creates an upward bias in the estimation of wage aggregates during recoveries. Additionally, as these workers re-enter lower-productivity sectors during recoveries, the aggregate wage level will be brought down and the strength of the economic recovery will appear less robust than it really is. As a result, comparisons based solely on aggregate trends, which do not account for these composition effects, may substantially underestimate the degree of wage flexibility. In short, a composition effect may be attenuating the actual wage dynamics. A simple way to control for this composition effect is using individual-level data. Figure 13 provides insights into the elasticity of real wages to unemployment across different datasets and model specifications. When no individual fixed effects are included, the elasticity appears relatively weak, with some estimates even suggesting a slightly positive response. However, once individual fixed effects controlling for composition effects (such as the disproportionate impact of crises on low-skill workers) are included, the wage elasticity becomes significantly more extensive and the coefficient becomes negative. For example, when individual fixed effects are considered, the elasticity of real wages to unemployment is approximately -1, while estimates that consider aggregate data are around zero. This result highlights the importance of considering composition effects when assessing wage flexibility. By using individual-level data and controlling for composition effects, it becomes evident that real wages respond more strongly to changes in unemployment than aggregate data would suggest. This reinforces the idea that labor market dynamics are more flexible than traditional aggregate metrics imply, especially when considering the cyclical exit and re-entry of low-wage workers during periods of economic recovery.

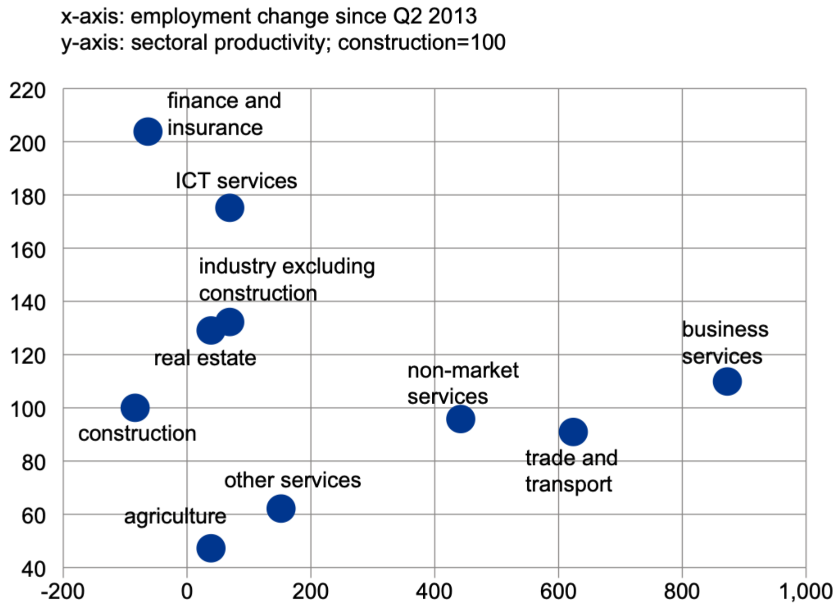
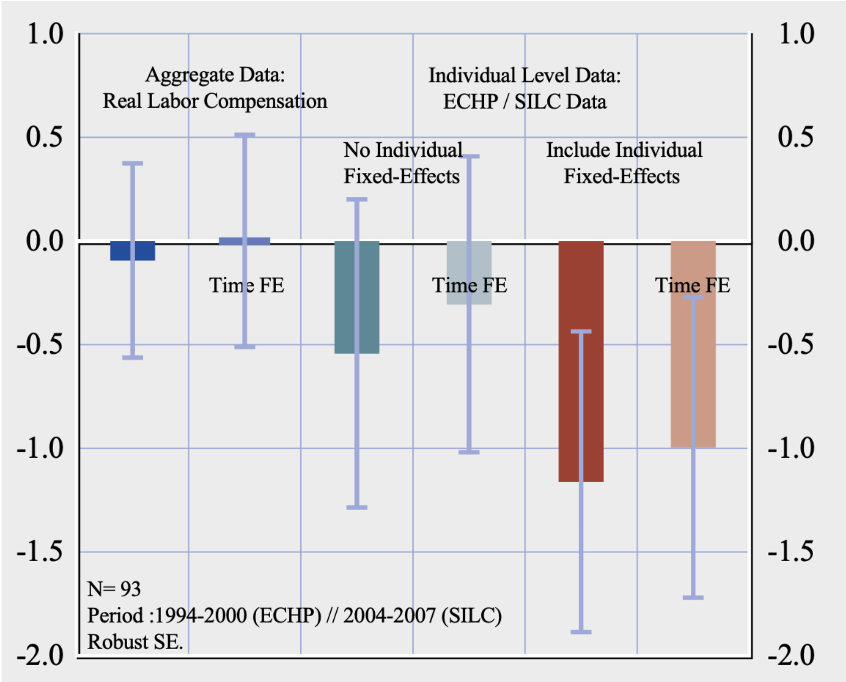


Figure 12: Employment change and sectoral productivity in the EU in the aftermath of the 2008 recession

Note: The figure shows the relationship between employment change and sectoral productivity in the EU during the post-2008 recovery. Employment growth was concentrated primarily in low-wage, low-productivity sectors such as non-market services, agriculture, and construction. In contrast, sectors with higher productivity, such as finance and insurance, ICT services, and industries excluding construction, saw more modest employment gains. Source: ECB Economic Bulletin, 2015. Source: ECB Economic Bulletin (2015). What is behind the recent rebound in euro rea employment?



Sources: Eurostat and ESCB calculations.
Notes: Each bar represent the parameter estimates of the elasticity of real wages to unemployment. OLS estimates with robust standard errors.

Figure 13: Real wage elasticities to unemployment

Note: The figure provides insights into the elasticity of real wages to unemployment across different datasets and model specifications. When no individual fixed effects are included, the elasticity appears weak, with some estimates even suggesting a slightly positive response. However, when individual fixed effects are introduced —accounting for composition effects, such as the disproportionate impact of crises on low-skill workers— the wage elasticity becomes more negative. Estimates based on individual-level data show a significantly stronger response, highlighting the importance of controlling for composition effects when assessing wage flexibility

2.2 External identification issues

2.2.1 Identification of the international common factor

Since 1990, a common pattern has emerged in global inflation dynamics. Consider a sample including 17 advanced economies (Australia, Austria, Belgium, Canada, France, Germany, Greece, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United States) and 24 emerging economies (Bolivia, Chile, Colombia, Côte d'Ivoire, Ecuador, Egypt, El Salvador, Guatemala, Honduras, Indonesia, Israel, Jamaica, South Korea, Malaysia, Mauritius, Mexico, Nigeria, Paraguay, the Philippines, Singapore, South Africa, Taiwan, Tunisia, Turkey). It is possible to analyze the evolution in the range of inflation rates in advanced and emerging economies (*ECB, 2017*). This exercise allows us to appreciate the unfolding of the synchronization of inflation developments in the subgroups of advanced and emerging economies (Figure 14). This increasingly tighter co-movement of inflation has led many authors to think inflation is becoming a more and more global phenomenon. This is the reason why a branch of the literature tested if national inflation rates are increasingly driven by international common factors that affect all the world economies.

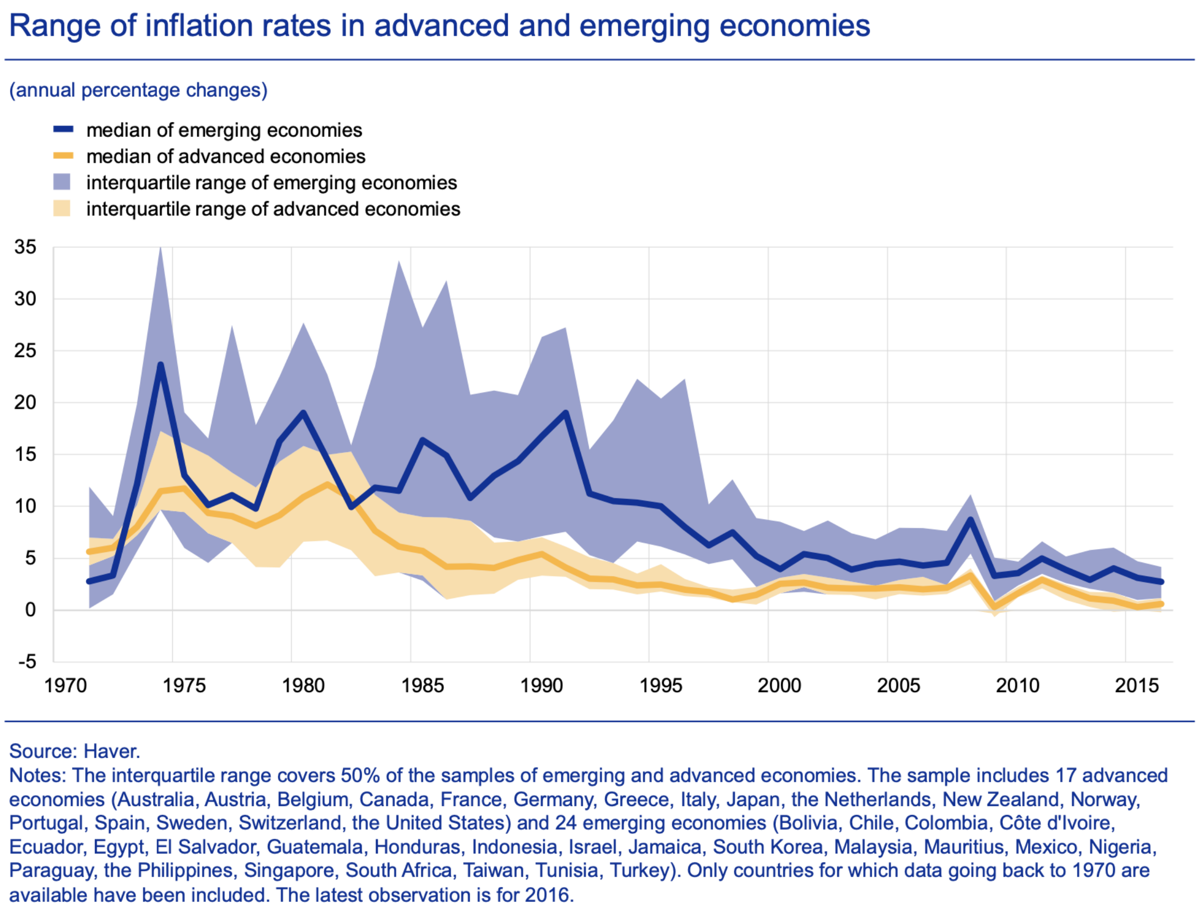


Figure 14: Synchronisation of global inflation patterns

Empirically, *Ciccarelli and Mojon (2005)* observed that 50% of national headline inflation fluctuations were caused by global factors. Figure 15 provides the estimate of the relevance of global common factors as calculated by Ciccarelli and Mojon (red bar), Ferroni and Mojon (*Ferroni and Mojon, 2014*) and ECB staff estimations (blue bars, *ECB, 2017*). The chart shows that, for most periods, common factors account for a significant portion of inflation variability. Now, the issue rests on determining what these common factors are. The identification of these factors is important to control for their role as confounders in the analysis of the impact of national tightness on inflation.

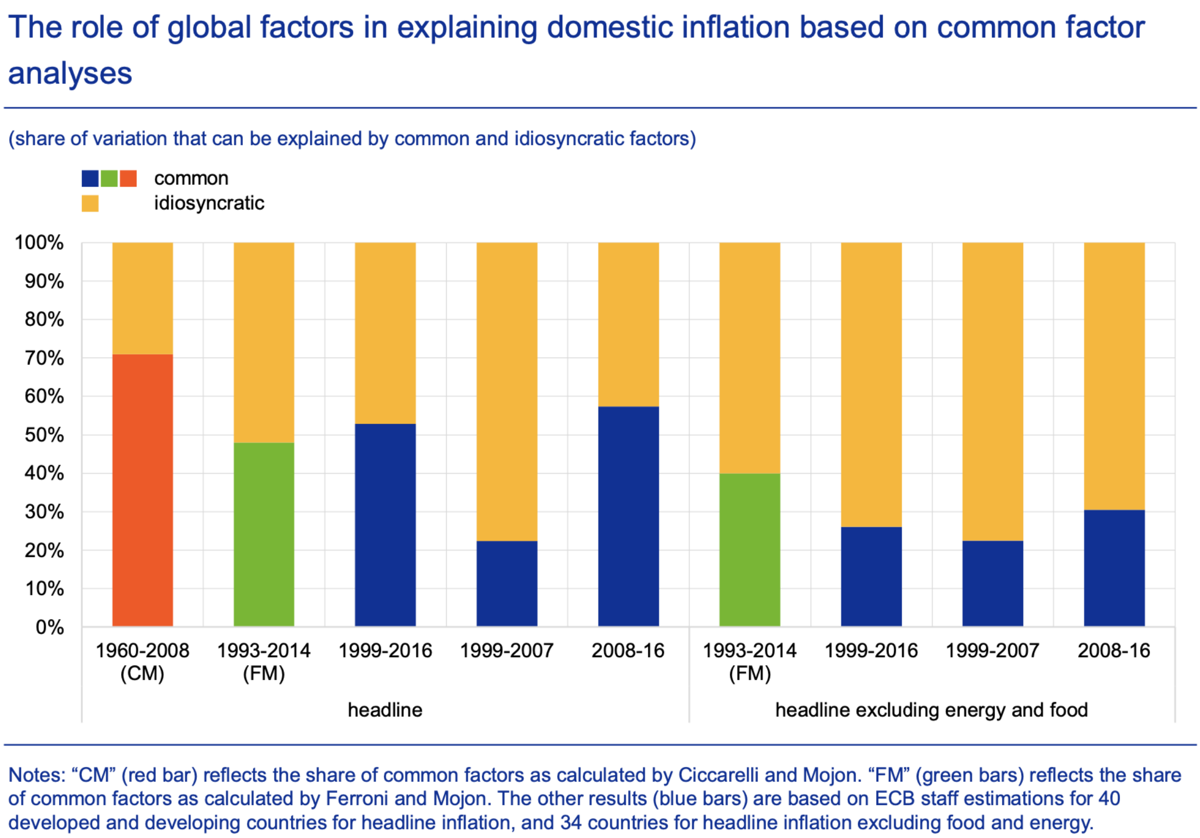


Figure 15: Relevance of the common factor in explaining domestic inflation

2.2.2 Drivers of the common factor

On the external side, inflation is affected mainly by commodity prices and international slackness, with the exchange rate moderating or amplifying the transmission of foreign factors into domestic ones. Concerning international slackness, many authors suggest the influence of this factor has been rising in the last decades due to globalization (*Auer et al., 2017*). Globalization through global markets, GVCs, offshoring, and off-sourcing has intertwined global economies. If we use GVCs as a proxy for the internationalization of production processes, we can clearly visualize the expansion of global market integration across the last fifty years (Figure 16).

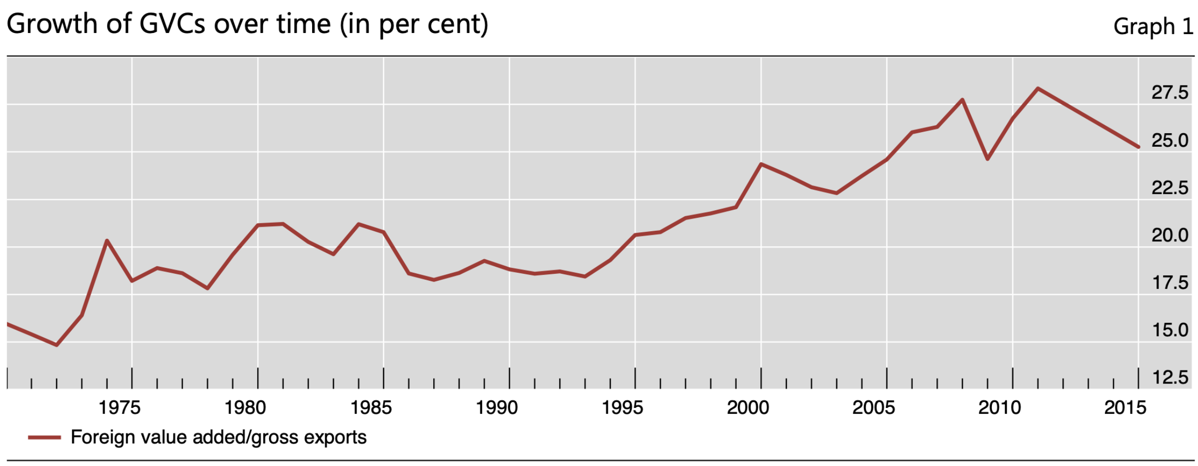
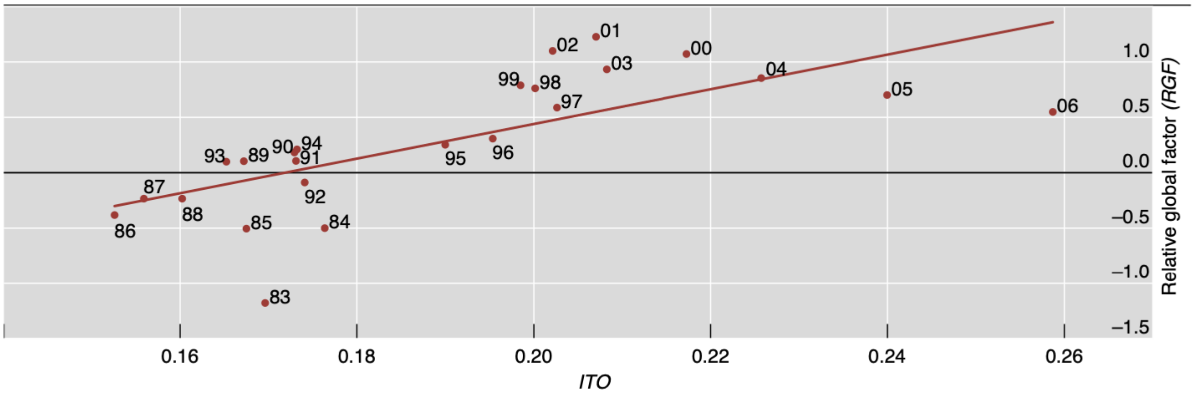


Figure 16: GVCs expansion

Note: The figure illustrates the growth of Global Value Chains (GVCs) over time, measured as the foreign value added in gross exports. The share of foreign value added has increased steadily since the 1970s. This reflects the increasing integration of global production processes over the past decades, with a slight reduction in recent years. Sources: Johnson and Noguera (2016), OECD TIVA and ADB MRIO.

These developments represent a challenge to the classical assumptions behind the traditional country-centric view of trade and inflation determination. This adds some bias to the PC estimation: firstly, the relationship between internal slackness and inflation can be hindered as, for example, national demand shocks are expected to spill over into higher imports rather than into higher prices, thus lowering the sensitivity of wages to domestic demand pressures (and this effect should be more visible in the tradeable goods sector). Moreover, global competition could constrain wage bargaining in national economies as producers may now threaten the option of offshoring. Unsurprisingly, as the global importance of international trade grew in the last decades, the explanatory power of Phillips curves also augmented with global output gaps. Figure 17 depicts how the coefficient on the relative global factor rose sharply in the period spanning from 1986 to 2006.

GVCs and the explanatory power of global output gaps over time [1] Graph 3



[1] The relationship between *ITO* = (exports + imports of intermediate goods and services)/GDP and the relative global factor (*RGF*) for the years from 1983 to 2006. Each observation shows the cross-country average of *ITO* and *RGF* in a given year for 18 countries. The red fitted line has a slope of 15.6 (significant at the 1% level).

Source: authors' calculations.

Figure 17: Evolution of the explanatory power of global output gaps

Secondly, import prices will have a disinflationary/inflationary impact. For example, many authors suggest that China's entrance into globalized markets had a significant role in the early 2000s disinflation (*Amiti et al., 2017*). When the Chinese economy opened up to international markets, and tariffs and quotas were gradually removed, it was as if the global workforce had increased by hundreds of millions of workers. Relative differences in production costs and relative abundance of labor led to a striking reduction in the prices of those manufactured products where Chinese industries had a competitive advantage. Even if very specific, a vastly famous case is the EU footwear case. In the footwear with leather uppers industry, the volume of Chinese imports sextupled from 30,662 pairs in 2004 to 183,568 pairs in 2005 (when the EU quota was eliminated), while China's market share in EU countries rose from 4.4% of total imports in 2004 to 22.9% in 2005. Overall, the EC reported an average Chinese sales price of €7.5 compared to €19.8 in 2004 for a sample of EU footwear producers (*Dunoff and Moore, 2014*). This clearly represents an extreme scenario but nevertheless exemplifies the downward price pressure generated by the Chinese economy's integration into the world markets. One last interesting factor is that *Amiti et al. (2017)* also found a parallel, substantial reduction in the export prices of other countries selling to the US.

Last, and crucially, commodity prices have a crucial effect on national inflationary levels. To cite the paper I referenced to introduce the discussion on global effects, *Ciccarelli and Mojon (2005)* found that around 50% of variation in the common factor in global inflation can be explained by movements in oil and food commodity prices. In this respect, oil prices represent the most important driver of global inflationary pressures (Figure 18).

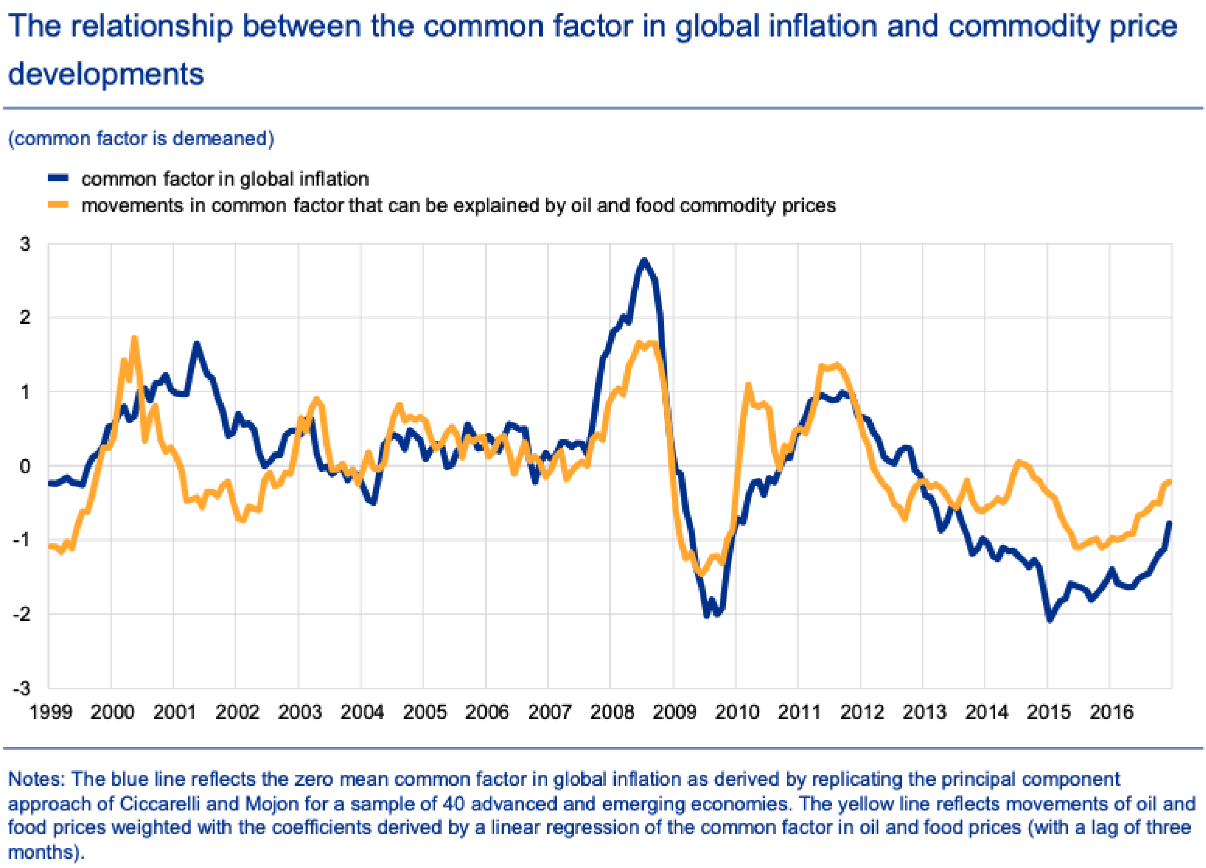


Figure 18: Evolution of the explanatory power of global output gaps

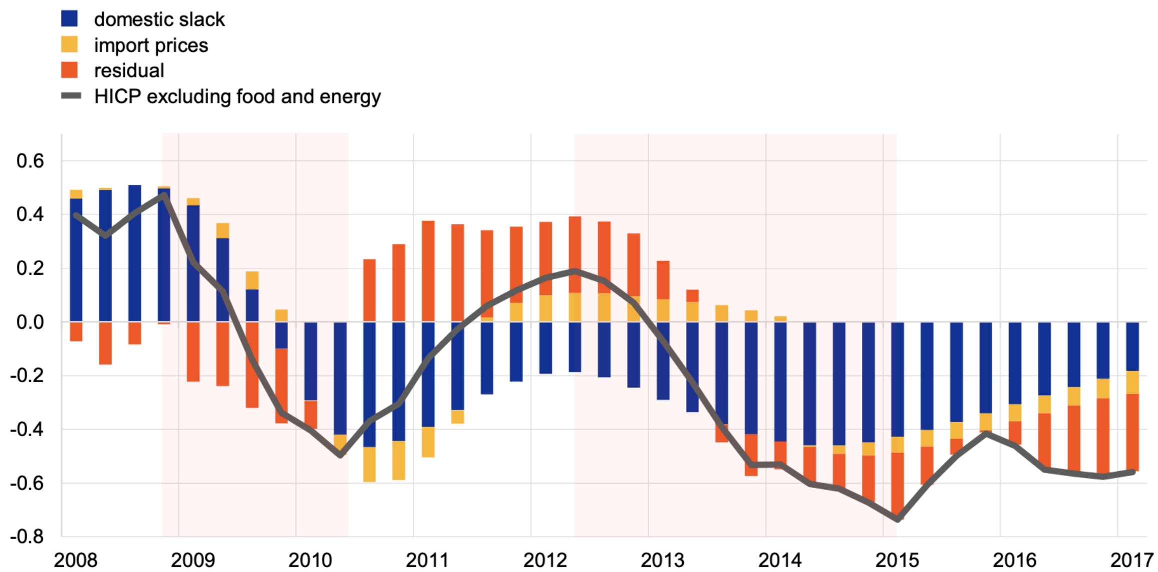
One important consequence of this finding is that global factors are connected to commodity price cycles. When commodity prices surge, the calculated common factor rises. In this regard, the variability in the estimates presented in Figure 15 can be largely due to the time period analyzed. Ciccarelli and Mojon (2005) are the only ones that include the 1960 to 1980 period. Hence, the inclusion of the oil crisis may probably be the reason why the author's estimates are the largest ones observed. Overall, while global factors are extremely relevant, the analysis of their contribution to aggregate inflation is significantly time-sensitive-

3 Identifying bias through Inflation Decomposition

We have seen how relevant external factors can be in generating inflation in the national economy. We want to find the marginal effect of domestic factors while controlling for external ones. Disentangling domestic and external factors is challenging as they are deeply interrelated through multiple channels. That's why inflation decomposition techniques are used to quantify the relative importance of domestic and foreign factors in driving inflation and explore how it has evolved over time. It is crucial to understand how relevant internal slackness is in driving inflation and whether its effect oscillates within business cycles.

3.1 Phillips Curve Inflation Decomposition

Hence, practically, first, the effect of the domestic component needs to be extracted from the overall inflation rate. This can be performed in many ways, for example, through a traditional PC approach exploiting the output gap as a measure of slack, past inflation to capture inertia, and import price inflation to capture global slackness (*ECB, 2015a*). Figure 19 presents the decomposition of inflation in the euro area, explicitly focusing on HICP inflation excluding food and energy. The black line traces deviations of inflation from its model-implied mean. It is possible to see how, from 2008 to 2017, inflation dynamics were primarily shaped by a combination of domestic slack, import prices, and residual factors. The blue bars represent the contribution of domestic slack to inflation. In the aftermath of the 2008 recession, domestic slack played a significant role in driving disinflation, as evidenced by the negative blue bars from 2009 to 2011. The peak disinflationary impact occurred around 2010 and 2014, reaching approximately -0.4. As the economy began to recover after 2011, the influence of domestic slack on inflation lessened, though it remained negative until around 2017, reflecting persistent slack in both the labor market and the output gap. The orange bars represent the effect of import prices, providing insight into global factors' role in driving inflationary trends. Import price inflation played a counter-cyclical role, especially in 2010 and 2011, as rising global commodity prices, particularly in oil and energy, helped offset the deflationary impact of domestic slack. However, from 2013 onwards, the contribution of import prices turned negative and added disinflationary pressure to an already disinflationary environment. Residual factors, depicted in yellow, capture inflation dynamics that the model does not fully explain. Their contribution fluctuates but generally remains small. It is interesting to see how deflationary pressures started to mount during the recessionary periods (illustrated through the two red-shaded areas). Overall, this graph underscores the importance of domestic slack in driving inflation outcomes in the post-2008 period. The persistent negative contribution of domestic factors highlights the long-lasting deflationary effects of the economic downturn on the euro area economy.



Sources: Eurostat and ECB calculations.
Notes: The black line shows deviations of HICP excluding energy and food inflation from its model-implied mean. Contributions (including residuals) are also shown as deviations from their model-implied mean. Contributions are calculated based on an equation in which HICP excluding energy and food inflation (the annualised quarterly growth rate of the seasonally adjusted series) is regressed against its own lag, the lagged output gap of the European Commission, the third lag of import price inflation and a constant. The shaded areas indicate two disinflation periods.

Figure 19: Inflation Decomposition through a PC model

3.2 BVAR Inflation Decomposition

3.2.1 Plotting inflation decomposition

However, more sophisticated approaches can be identified. One example is the one proposed by *Bobeica and Jarociński (2017)*, where inflation decomposition is performed on quarterly data based on a BVAR model with seven variables and a matrix of structural shocks. This paper examines the puzzling nature of inflation dynamics during and after the Great Recession, focusing on two fundamental phenomena: the "missing disinflation" and "missing inflation" episodes. Using conditional forecasts and inflation decomposition techniques within a Bayesian Vector Auto-regression (VAR) framework, this analysis provides insights into the domestic and global drivers of inflation in the Euro area and the United States. The variables employed in the inflation decomposition analysis are the price of oil, rest-of-the-world real GDP (or the share of domestic real GDP in the world real GDP), real GDP, consumer prices, short-term interest rate, 10-year bond spread, and nominal effective exchange rate. The hyperparameters used in the model are the same as the ones of *Sims and Zha (1998).* First, structural shocks are defined, and restrictions are applied to the BVAR model. Three kind of restrictions are experimented: Cholenski, CLD and CDL+BB (Figure 20).

Variable \ shock	Global	Global	Domestic	Domestic	Monetary policy	Spread	Exchange rate
I. Choleski							
Price of oil	+	0	0	0	0	0	0
Rest-of-the-world real GDP	•	+	0	0	0	0	0
Real GDP	•	•	+	0	0	0	0
Consumer prices	•	•	•	+	0	0	0
Short-term interest rate	•	•	•	•	+	0	0
Spread	•	•	•	•	•	+	0
Exchange rate	•	•	•	•	•	•	+

	Oil supply	Global demand	Domestic demand	Domestic supply	Monetary policy	Spread	Exchange rate
II. Corsetti et al. (2014) (CDL)							
Price of oil	+	+	•	• (≈0)	0	0	0
Share of world real GDP	•	−	+	+	0	0	0
Real GDP	−	+	+	+	0	0	0
Consumer prices	+	+	+	−	0	0	0
Short-term interest rate	0	•	•	•	+	0	0
Spread	•	•	•	•	•	+	0
Exchange rate	+ (•)	•	•	+	•	•	+
III. Corsetti et al. (2014) and Baumeister and Benati (2013) (CDL+BB)							
Price of oil	+	+	•	• (≈0)	•	•	0
Share of world real GDP	•	−	+	+	−	•	0
Real GDP	−	+	+	+	−	−	0
Consumer prices	+	+	+	−	−	−	0
Short-term interest rate	0	•	+	•	+	0	0
Spread	•	•	•	•	−	+	0
Exchange rate	+ (•)	•	•	+	+	+	+

Notes: • = unconstrained, + = positive sign, − = negative sign, 0 = zero restriction, ≈0 = magnitude restriction that centers the error band of the responses at zero. All restrictions are imposed on impact. The exchange rate is defined so that a + means an appreciation. In parentheses we show the restrictions used for the US VAR whenever they differ from the euro area VAR.

Figure 20: Summary of Sign Restrictions

Source: Missing disinflation and missing inflation: the puzzles that aren't (2017), Elena Bobeica, Marek Jarociński

Cholenski is a timing restriction: global shocks affect all variables immediately, while domestic shocks affect global variables only with a delay. CDL is derived following the work of *Corsetti et al. (2014)* and *Conti et al. (2015)*. This strategy relies on distinguishing domestic demand shocks from global demand ones. The last distinction, CDL+BB is the CDL one plus further restrictions that identify monetary policy shocks as proposed by *Baumeister and Benati (2013)*. In this specification, contractionary monetary policy has an immediate negative effect on output and prices, a negative effect on the bond spread and a positive effect on the exchange. Once restrictions are set, the VAR is identified and relative contributions are defined. Figure 21 plots the decomposition of the driving forces to the euro area inflation. The graphs depict inflation decomposition for both the Euro area (HICP - Harmonized Index of Consumer Prices) and the United States (CPI - Consumer Price Index). We focus on the Euro area (left panels). While both internal and foreign dynamics have had a crucial role in the period analyzed, the plot allows us to appreciate how the relative importance of these shocks has changed substantially over time. In Europe, domestic non-monetary factors show significant negative contributions in the 2008 to 2010 period and after 2013, while positive contributions were exhibited from 2010 to 2013. Global factors exhibit significant volatility and have accounted for about 60% of Europe's deviation. However, during energy shocks, global factors account for the quasi-totality of the variation.

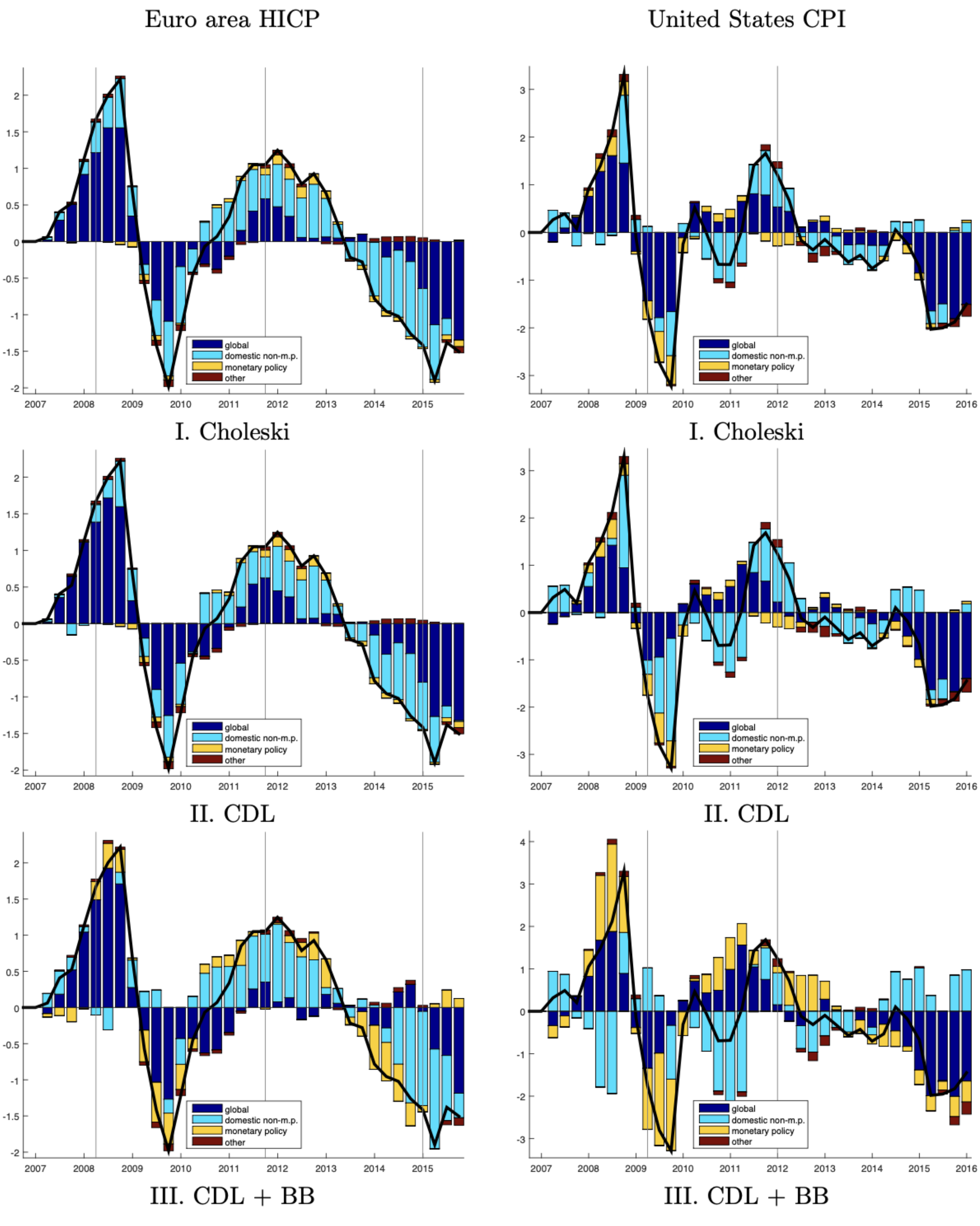


Figure 21: Inflation Decomposition

Note: The black line is the deviation of year-on-year inflation from the unconditional forecast as of 2006Q4, the bars show the contributions of different types of shocks to this deviation. Source: Missing disinflation and missing inflation: the puzzles that aren't (2017), Elena Bobeica, Marek Jarociński

3.2.2 Conditional forecasts on the actual path of domestic real activity

As the literature has questioned VAR models for their inability to forecast inflation, the authors employ a conditional forecast to understand whether their model's results align with the missing inflation and missing disinflation narrative. Results show that in the EU and in the US, there is no under-prediction of inflation during 'missing disinflation' periods once conditional forecasts on the actual path of domestic real activity are employed. At the same time, analogous estimations do not over-predict inflation during the euro area missing inflation. Overall, conditional forecasts match inflation efficiently. What's extremely interesting is understanding why conditioning works, or, better, what are the essential factors to condition on in order to get efficient estimates. The answer is not straightforward. Consider Figure 22: if we refer to the 'first recession' (defined in the paper as the period 2008 to 2012), conditioning on real activity and financial variables does not lead to accurate estimates. In fact, still missing disinflation is observed (subplot 1 and subplot 4). Instead, if external variables are used for conditioning, the predicted inflation rate matches almost perfectly the observed one. This finding underscores the importance of global inflationary pressures during the Great Recession (subplot 10). However, let's consider the 'second recession' (defined as the period 2012-2014). We observe that conditioning on real activity gives very precise estimates (subplot 2 and 5), while conditioning on external variables leads to a substantial improvement with respect to the unconditional forecast scenario (subplot 11) but is less effective. To conclude, the relevance of global shocks is very high, however, the relative importance of global and domestic factors has varied strongly over time.

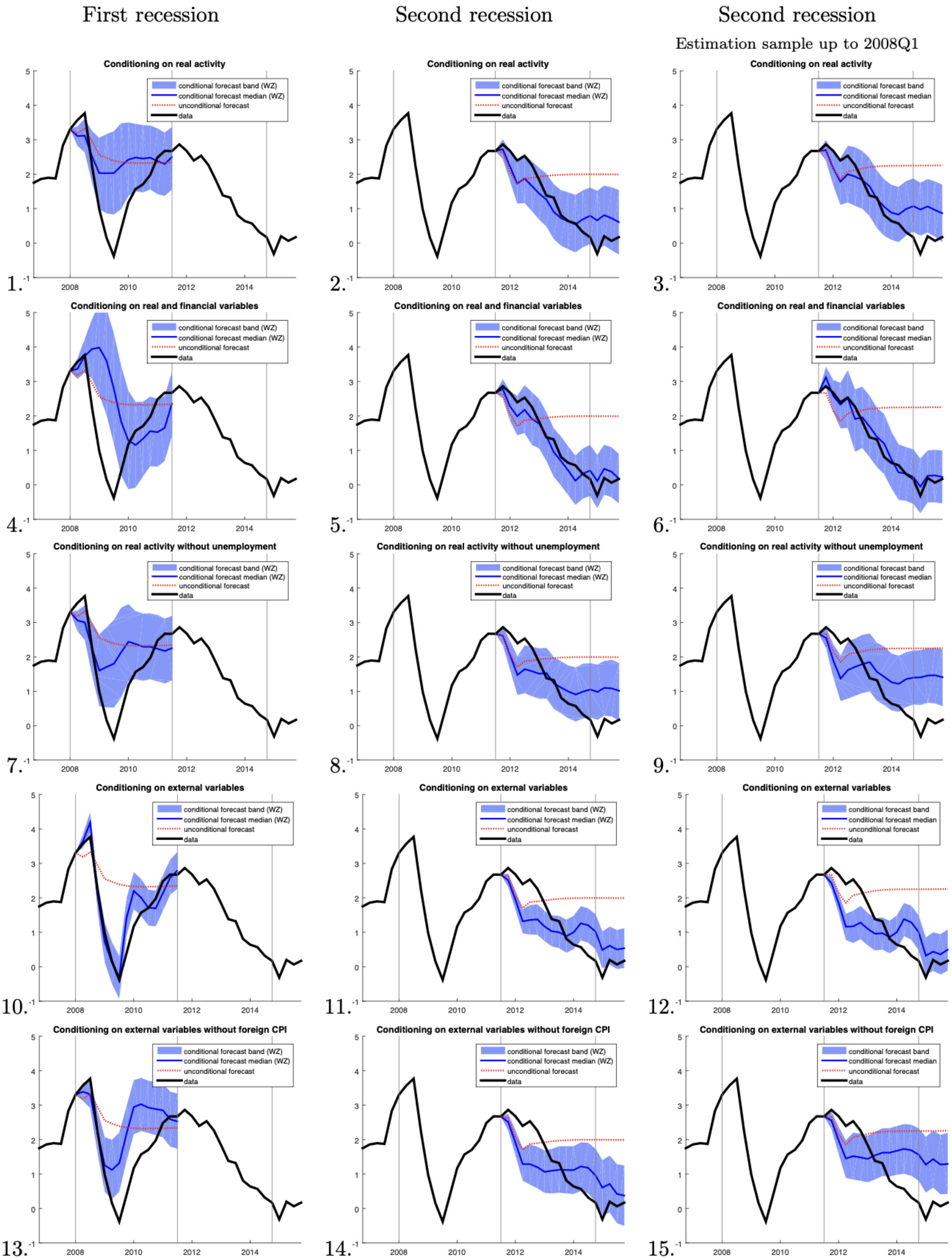


Figure 22: Conditional Forecast of Inflation

Note: The subplots illustrate how conditioning on internal and external variables enhances the reliability of inflation forecasts during both the first and second recessions. Source: Missing disinflation and missing inflation: the puzzles that aren't (2017), Elena Bobeica, Marek Jarociński

4 Inflation Expectations and Simultaneity of Demand and Supply

4.1 Enhancing the model with inflationary expectations

Inflationary expectations play a role of paramount importance in the PC equation. If we solve equation (1) forward and assume unemployment follows an AR(1) process, we can write:

$$\pi_t = -\psi \tilde{u}_t + E_t \pi_{t+\infty} + \omega_t, \tag{3}$$

Where $\tilde{u}_t$ denotes the deviation of unemployment from its long-run expected value, $E_t \pi_{t+\infty}$ represents long-term inflation expectations, and the parameter ψ is proportional to κ in equation (1).

This formulation links inflation and expected inflation in a one-to-one relationship. Therefore, the gross relationship between unemployment and inflation will be largely uninformative if we do not control for expected inflation. In fact, if as expected $E_t \pi_{t+\infty}$ co-moves negatively with u, the estimation of the coefficient on unemployment would be positively biased. Hence, the unemployment coefficient would appear larger than it is, and we would overestimate the impact job market slackness has on the inflation rate. Overall, *Sargent (1982)* had already noted that hyperinflations tend to end very quickly, too quickly to be explained by a large k, and apparent shifts in monetary regimes drive them. Sargent argues that the sudden end of hyperinflations is driven by shifts in fiscal policy that restore the government's credibility and commitment to balanced budgets. In his view, stabilizing the budgetary situation—often through radical reforms such as tax increases and expenditure cuts—was vital in bringing inflation back under control. Practically, it is possible to argue that the most relevant piece of evidence on the Phillips curve, the Volker disinflation, was likely deeply biased by a shift in expectations. During the Volker era, the surge in unemployment was associated with a reduction in the inflation rate (*Volker,* *1990*). However, at the same time, Volker's tight stance profoundly changed inflationary expectations, directly affecting the current inflation rate.

Regardless of the specifics of the Volcker disinflation, a broader understanding of the evolution of inflationary expectations is essential to grasp the significance of this theme. Observing how long-term inflation expectations, as reported by the Survey of Professional Forecasters, have changed over the past few decades provides valuable insights into the potential biases they introduce (Figure 23). These expectations dropped sharply during the Volcker disinflation and became remarkably stable from 1995 onward. This stability highlights the lasting impact of credible monetary policy in anchoring inflation expectations, which, in turn, plays a crucial role in shaping actual inflation dynamics. At the same time, low and stable inflationary expectations reduce the upward bias on the unemployment coefficient.

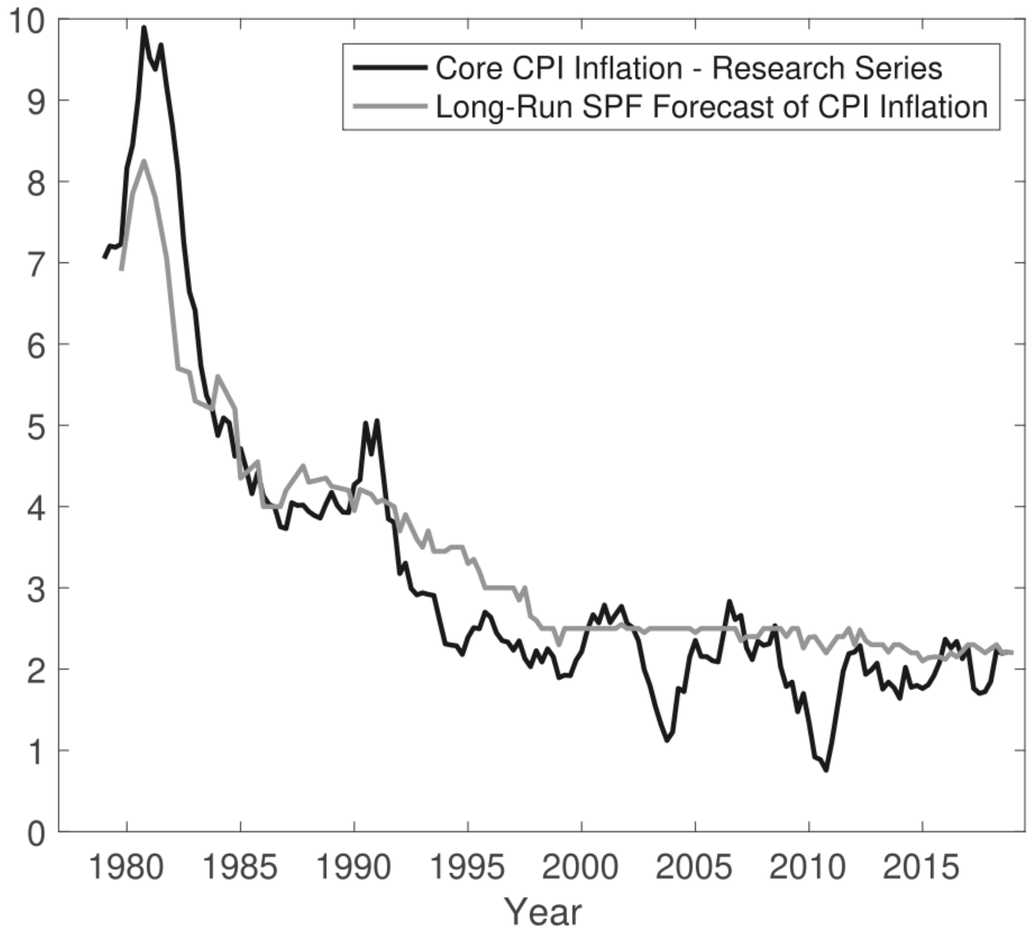


Figure 23: Long Term Inflation Expectations and CPI Inflation

Note: The gray line plots 10-year-ahead inflation expectations for the Consumer Price Index (CPI). From 1990 onward, these come from the Survey of Professional Forecasters. For the 1980s, these come from Blue Chip and are available on the Research and Data site of the Federal Reserve Bank of Philadelphia. The black line plots 12-month core CPI inflation using the Bureau of Labor Statistics' research series. This research series uses current methods to calculate inflation back in time. Source: The slope of the Phillips curve: Evidence from US states (2022), J. Hazell, J. Herreno, E. Nakamura, J. Steinsson.

4.2 Controlling for inflationary expectations

At this point, it is clear that controlling for the effect of expectations is necessary to obtain a reasonable estimation of the unemployment coefficient, as they represent a crucial identification challenge. However, controlling for inflationary expectations has led to unreliable results as estimates are quite sensitive to specification details. *Mavroeidis et al. (2014)* show that reasonable variation in the choice of data series, the specification, and the time period used yields a wide range of estimates for k roughly centered on a value of zero. The issue seems to be a weak-instruments problem as there isn't enough variation in the aggregate data to identify unemployment separately and expected inflation coefficients. As we will see, exploiting regional data is an alternative and more effective solution to the problem.

4.3 Discussion on rational expectations

It is important to note that while assuming rational expectations provide a simplification to the provided models, this assumption may be largely incorrect. Rational expectations have been a cornerstone in modern monetary policy since the mid-20th century. First introduced by John Muth (*Muth, 1961*) and later popularized by Robert Lucas (*Lucas, 1972*), rational expectations theory posits that individuals and firms use all available information, including knowledge of government policies, to form expectations about future economic conditions. This assumption implies that economic agents are forward-looking and do not consistently make systematic errors in forecasting future inflation or other macroeconomic variables. This has profound practical implications. If policies are predictable, agents will anticipate their effects and neutralize their impact.

However, while rational expectations offer a robust framework, empirical studies have raised questions about its realism. These studies show that actual expectations often deviate from rationality, with agents frequently relying on adaptive or backward-looking methods, leading to systematic forecast errors. *Coibion and Gorodnichenko (2015)* find that agents' actual expectations are characterized by information rigidity, which refers to the slow adjustment of agents' expectations in response to new information, and suggest using sticky-information models in which only a fraction of agents update their expectations each period. It is important to note that while professional forecasters' inflation expectations are generally consistent with actual inflation dynamics, survey evidence suggests that consumers' inflation expectations are biased upward and that a good predictor of respondents' expectations is their perception of the current value of the analyzed variable. It is also interesting to note inflation expectations are not anchored according to the five criteria proposed by Kumar (*Olivier et al., 2018*), and that agents have a supply-side understanding of inflation. Informing respondents about inflation (recent values, Fed's inflation target, or forecast) immediately after the treatment reduces inflation expectations (*Coibion et al., 2023*). Intuitively, inflation expectations should be insensitive to the provided information because people should know this publicly available information. Moreover, *Candia et al., 2022b* find that perceptions about past inflation predict perceptions of the Fed's inflation target and uncertainty about future inflation, and *Candia et al., 2022a* find that households' knowledge about market interest rates is limited, with information about mortgage rates having a potent effect on interest rate perception. *Gorodnichenko and Weber (2019)* find that providing households with simple statistics about inflation, such as the most recent rate of inflation, the Fed's inflation target, or the FOMC's inflation forecast, has statistically and economically significant effects on inflation expectations: this type of information reduces households' average forecast of inflation by 1.0-1.2 percentage points. But in 6 months, expectations converge again toward the pretreatment values, and underlying CB needs repeated communication.

4.4 Simultaneity of Demand and Supply

The last issue analyzed in this chapter is related to the simultaneity problem of distinguishing demand shocks from supply shocks. There are two issues in this sense: first, supply shocks create a positive co-movement between inflation and unemployment, while demand shocks, the ones on which the PC idea builds up, make a negative co-movement. I will refer to the work *Madeira et al. (2023)* to define the problem of simultaneity of Demand and Supply. A simple three-equation New Keynesian (NK) model is already capable of framing the issue. The equations are: i) the IS relationship with a demand shock, ii) the Phillips curve with a supply shock, and iii) the Taylor rule. Figure 24 presents the results. Hence, supply shocks are associated with both high inflation and low economic activity, generating a clear trade-off for central bankers. As a side note, it is interesting to note that, as expected, supply shocks also generate higher disagreement in FOMC meetings.

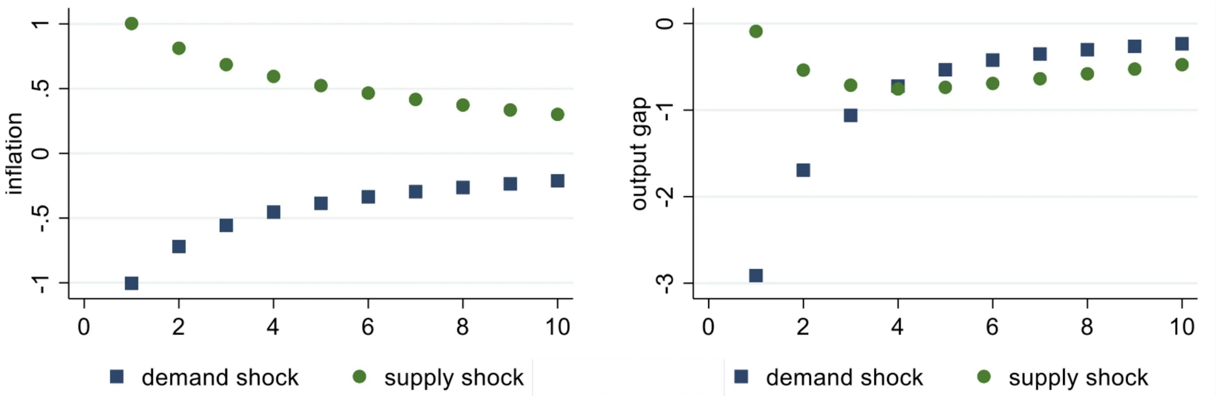


Figure 24: Demand and supply shocks in a standard three-equations NK model

Note: The panels show IRFs for inflation and the output gap in response to demand and supply shocks that move inflation away from the target by 1 percentage point. Each unit in the horizontal axis corresponds to one calendar quarter. Source: The origins of monetary policy disagreement - the role of supply and demand shocks (2023), Madeira, C., Madeira, J., and Monteiro.

The authors also use a medium-scale DSGE model developed by *Smets and Wouters (2007)* that includes sticky prices and wages, habit formation in consumption, and adjustment costs. The model's exogenous disturbances include productivity, price markup, wage markup, exogenous spending, monetary policy, risk premium, and investment shocks. The variables used are the log difference of the GDP deflator, real GDP, real consumption, real investment, real wage, the log of hours worked, and the federal funds rate. The estimation period is 1950:1 – 2018:1. The shocks classified as supply are wage markup, price markup, and productivity shocks. The demand shocks are the exogenous spending, risk premium, and investment shocks, and there is a single monetary policy shock, defined through a shock to the interest rate policy rule. Supply shocks are considered to be causing an increase in inflation and a reduction in output, while demand shocks assume a positive co-movement between the two variables. Again, inflation decomposition allows us to visualize how these two families of shocks affected inflation developments in the last decades (Figure 25). For example, demand shocks created large deflationary pressures in the aftermath of the 2008 recession, while supply shocks had a very relevant role during the 70s.

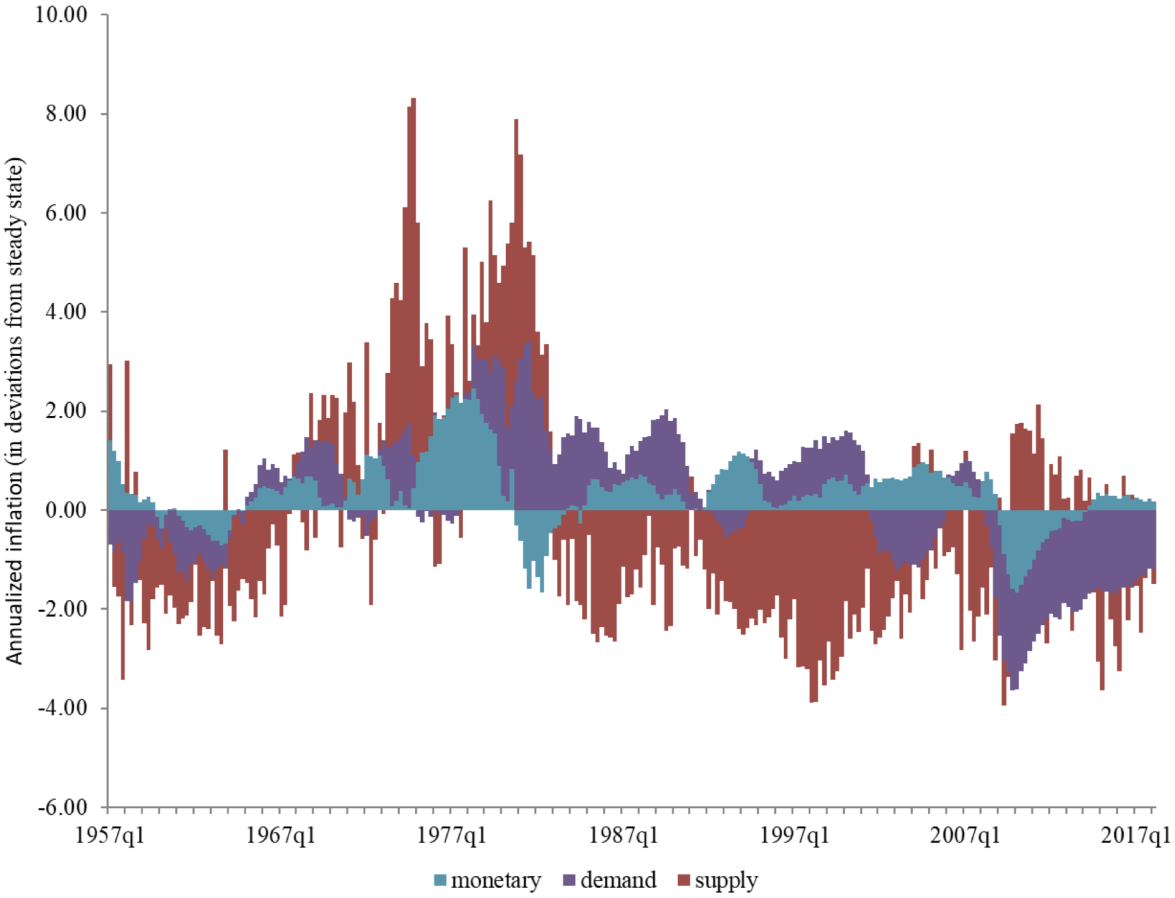


Figure 25: Supply, Demand shocks, and Inflation Variability

Note: Values were annualized by multiplying by 4. The data sample is from 1957:1 to 2018:1. Source: The origins of monetary policy disagreement - the role of supply and demand shocks (2023), Madeira, C., Madeira, J., and Monteiro.

4.5 The effects of Endogenous MP on the Phillips Curve

Central banks set their policies in order to minimize losses, this means that policy makers perform expansionary monetary policy as a reaction to demand shocks, increasing inflation when output is below potential. This targeting rule will successfully offset the relationship between slackness and inflation, blurring the identification potentially leading. In fact, if central banks are successful in offsetting aggregate demand shocks, only the effect of supply shocks in the data, leading potentially to a positive coefficient. This point is related to a more general issue, referred to as the Goodhart law, that states that 'any observed statistical relationship will tend to collapse once pressure is placed upon it for control purposes' (*Goodhart, 1984*). This means that under optimal control policy, the correlation between the policy target and the policy instrument should be 0 (*Goodhart, 1989*, *Peston, 1972*, *Worswick, 1969*). Hence, if an indicator does not seem to have explanatory power. A corollary to this reasoning is that a flat Phillips curve is also a necessary consequence of successful monetary policy. *McLeay and Tenreyro (2018)* frames the issue in a simple way: the authors use the standard NK model (*Galí (2008)*), with the usual IS and. By construction, the Phillips curve will be positively sloped (note we are using here ouptut gaps and not unemployment). However, once the model is augmented with a description of optimal monetary policy, things change. Consider the CB is minimising losses following $L_t = \pi_t^2 + \lambda x_t^2$, then the resulting optimal targeting rule is of the form $\pi_t = -\frac{\lambda}{\kappa} x_t$. Cost-push shocks lead the policy maker to balance the inflation-output tarde-off creating a negative output gap to reduce inflation. The Phillips relation apparently fades away in the data. If we substitute the optimal targeting rule into the quadratic loss function we get that $\pi_t = \frac{\lambda}{\kappa^2+\lambda(1-\beta\rho)} u_t$. This specification clarifies that under the described conditions inflation deviations are proportional to the exogenous cost-push shock, hence behave themselves as variables following an exogenous process. The most interesting feature of this model is that it is built under the assumption that the PC is working, however it clarifies the fact even if the PC relation exists it may not be observable empirically. The authors simulate the described model using parameters $\kappa = 0.1275$, $\lambda = 0.0213$, $\beta = 0.99$ and $\rho = 0.5$. The slope of the Phillips curve computed with output gaps is negative (Figure 26).

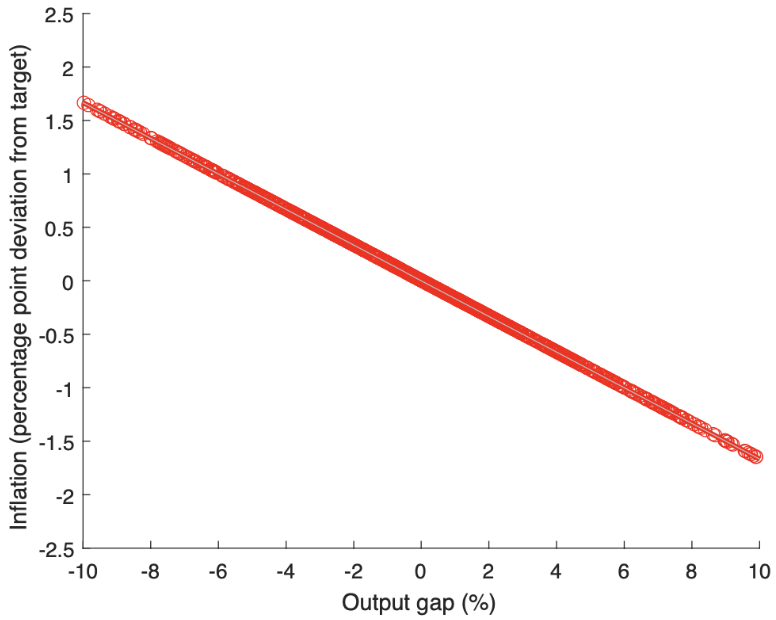


Figure 26: Observed Phillips relationship under endogenous monetary policy

Notes: 1000 periods of data are simulated from the model described by (1) and (2). We draw each et from a standard normal distribution. Source: McLeay, M. and Tenreyro, S. (2018). Optimal Inflation and the Identification of the Phillips Curve.

This, as previously discussed at length, is the result of optimal discretionary policy response to cost-push shocks. Figure 27 shows how cost-push shocks shift the PC without altering its slope. While the PC remains positive, the observed equilibrium, with monetary policy set optimally, will always lie on the negatively sloped optimal targeting rule.

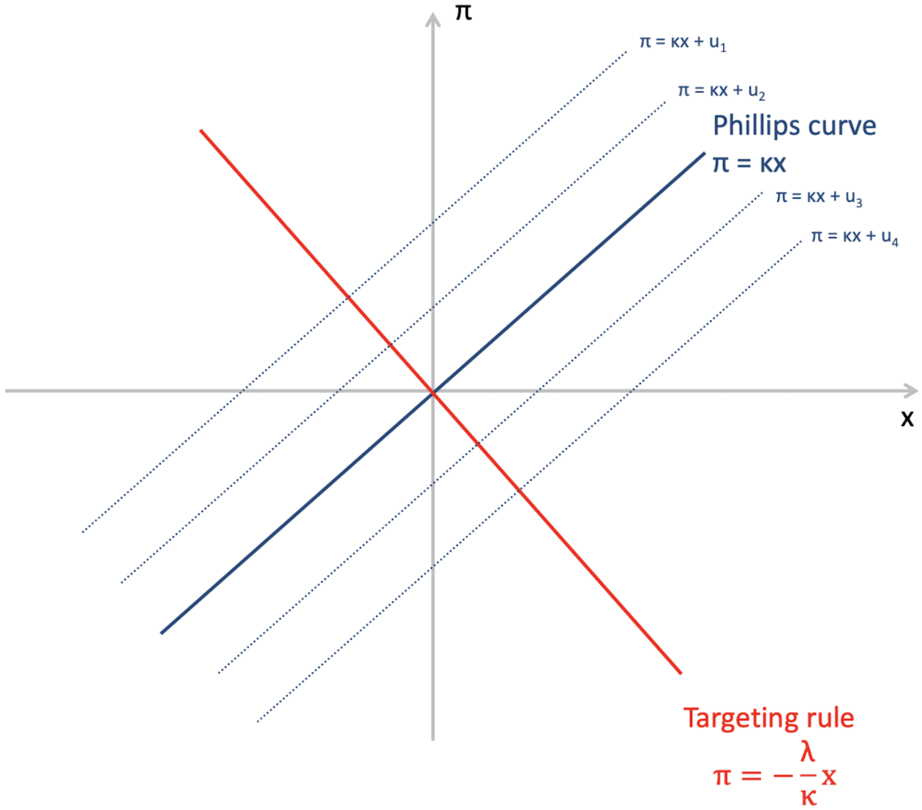


Figure 27: Observed Phillips relationship under endogenous monetary policy

Note: the figure plots how the targeting rule generates an apparently flat relationship between the output gap and inflation as the Phillips curve is shifted by cost-push shocks. Source: McLeay, M. and Tenreyro, S. (2018). Optimal Inflation and the Identification of the Phillips Curve.

4.6 Controlling for Supply shocks

To control for supply supply shock there are several options: First, it is possible to control for cost-push and other trade-off inducing shocks to aggregate supply, in line with the approach proposed by *Gordon (1981)*. The problem here is that controlling for every supply shock affecting the economy is not trivial. The effectiveness of this methodology rests on the type of shock considered. Some shocks are cyclical, while some are not; some are more easily identifiable than others and make it possible to understand the timing of the shock. In this sense, this methodology was easier to use in the 70s, when supply shocks were mainly related to energy crises. It is interesting to see how

Second, it is possible to build Instrumental Variables (IV) capable of capturing demand fluctuations while not being affected by supply shocks. Many instruments are available: one possibility is to identify monetary shocks and use them as a set of external instruments (*Romer and Romer, 2004*,*Kuttner, 2001*,*Gürkaynak et al., 2005*). The issue here is that if the variance in monetary shocks is low and few truly exogenous shocks are identified, or the marginal effect of the shocks has reduced (*Boivin and Giannoni, 2006*), the instrument may be too weak to be explanatory. Another, completely different, option (related to the use of regional data) is to build shift-share instruments that proxy productivity shocks in the tradeable intermediate-input industries (*Bartik, 1991*). Such an instrument works as follow: consider a productivity shock for a tradeable intermediate input, say in the manufacturing sector. Then, manufacturing intensive cities will experiment tighter labor markets. So, productivity shocks affect local demand for labor differently, and, specifically, affect more areas specialized in the industry that experienced the productivity shock. Being the local demand market common across sectors of the same local entity (MSA), higher demand for labor from intermediate goods industry will lead to higher wages, and consequentially higher marginal costs for local final-goods firms. This will translate into higher prices. Note that productivity shocks have a direct impact on intermediate input prices paid by local final goods firms. However, this is not a concern as intermediate input data is available and can be controlled for. One last solution encompasses the use of regional data. As we will see, this is the most effective option, especially if coupled with an IV approach.

5 How Regional Data can lead to efficient estimates of the Phillips curve

All the sources of bias presented in this paper should be addressed to estimate the structural coefficient relating unemployment to inflation. While this is clearly too optimistic to be possible, new estimations strategies may provide a very effective solution. If we consider cases of open economies composed by multiple regions, in the framework of NK models, it is possible to estimate regional and national Phillips curves though regional data. While some adjustments are required, the key idea is exploiting regional variation in unemployment rate to estimate its effects on regional prices. This idea of using regional variation is relatively new in the literature, with a series of papers as *Kiley (2015b)*, *Babb and Detmeister (2017)*, *Hooper et al. (2020)*, *Fitzgerald et al. (2020)*, *Beraja et al. (2019)*. This section will focus on the model developed by *Hazell et al. (2020)*.

5.1 Regional variation, Non-tradeable goods and Time dummies

First, enough variation in regional unemployment rates is required. Figure 28 presents the historical unemployment rate movement, Texas, and Pennsylvania.

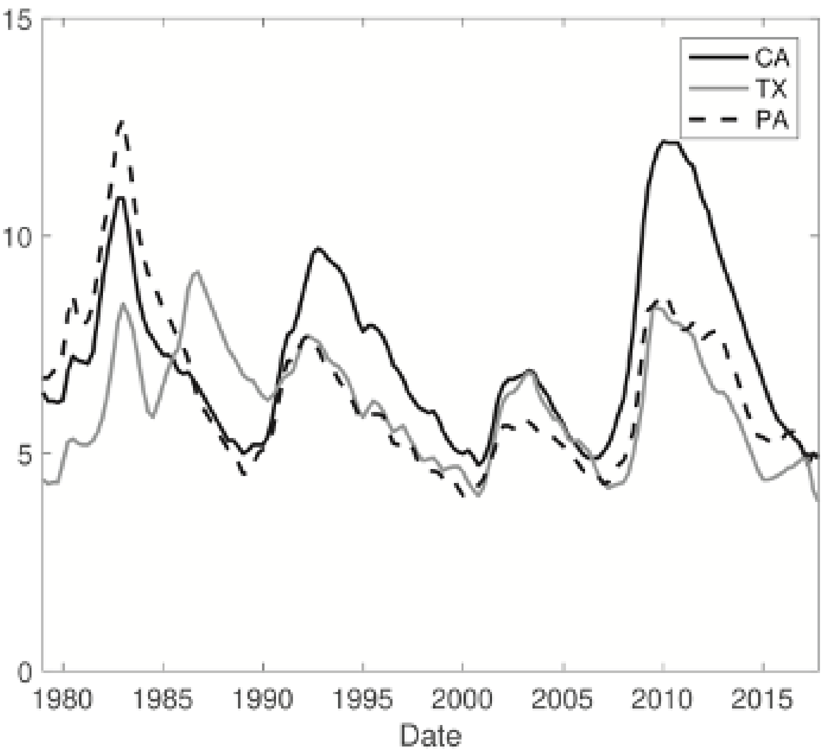


Figure 28: Regional Variation in unemployment rates

Note: This figure plots the regional variation in unemployment rates for California, Pennsylvania, and Texas. Overall, we can see there is significant heterogeneity in the data. Source: The slope of the Phillips curve: Evidence from US states (2022), J. Hazell, J. Herreno, E. Nakamura, J. Steinsson.

While there is some co-movenent, there is also significant variability. For example, California was hit by the 1991 and 2007–2009 recessions much more than Texas and Pennsylvania or Texas experienced a recessions in the mid-1980 due to the reduction of oil prices, while most of the other US states did not.

Second, with regional data it is important to use non-tradeable prices and not tradeable ones. In fact, tradeable goods prices are set at the national or international level and hence have nothing to do with regional employment dynamics, leading to a Phillips Curve whose slope is 0 (these prices are not sensitive to local employment dynamics). Mathematically the slope of the regional Phillips Curve for overall consumer price inflation, including both tradeable and non-tradeable inflation, is smaller by a factor equal to the expenditure share on non-tradeable goods.

Third, regional data is crucial as it allows to control national monetary policy, for inflation expectations and national demand and supply shocks. Controlling for these factors is not difficult as dummies can be used. If we recall the problems analyzed in the previous sections of this work, we now have that shits in monetary policy regimes (and inflationary expectations) can now be controlled by time dummies, being these shocks common to all regions. Moreover, also national demand and supply shocks can now be controlled in the same way. Additionally, while endogenous monetary policy counters national demand shocks biasing to zero our estimation of the PC, central banks cannot offset regional demand shocks as they are using a single national interest rate, hence the regional demand effect will not be compensated as before by monetary policy. Lastly, country dummies control for different intrinsic regional characteristics.

5.2 The estimating equation

The model by *Hazell et al. (2020)* is very informative, as it allows us to understand how regional data works, how controls are implemented and why the literature has found contrasting results when using regional data.

Firstly, the authors derive the equation for the regional Phillips curve through a traditional model set up encompassing Household, firms and Government policy optimization:

$$\pi^N_{H,t} = \beta E_t \pi^N_{H,t+1} - \kappa \hat{u}_{H,t} - \lambda \hat{p}^N_{H,t} + \nu^N_{H,t} \tag{4}$$

In this equation: $\pi^N_{H,t} = p^N_{H,t} - p^N_{H,t-1}$ is home nontradeable inflation, $\hat{p}^N_{H,t} = \frac{P^N_{H,t}}{P^N_{H,t-1}} - 1$ is the percentage deviation of the home relative price of nontradeables from its steady-state value of one, $\nu^N_{H,t}$ is a nontradeable home supply shock, ν_t is a corresponding aggregate supply shock, and the parameter $\kappa = \lambda\varphi^{-1}$, where $\lambda = \frac{(1-\alpha)(1-\alpha\beta)}{\alpha}$. Now the coefficient κ on this regional PC is the same as the coefficient κ of the aggregate Phillips curve, and this is due to the fact only non-tradable goods prices are being used. In fact, the national

PC reads as follows:

$$\pi_t = \beta E_t \pi_{t+1} - \kappa \hat{u}_t + \nu_t, \tag{5}$$

Now, by solving the regional Phillips curve equation (4) forward, we get:

$$\pi_{i,t}^N = -E_t \sum_{j=0}^{\infty} \beta^j (\kappa \tilde{u}_{i,t+j} + \lambda \hat{p}_{i,t+j}^N) + E_t \pi_{t+\infty}^N + \omega_{i,t}^N \tag{6}$$

where $\tilde{u}_{H,t} = u_{H,t} - E_t u_{H,t,t+\infty}$ and $\omega_{H,t}^N = E_t \sum_{j=0}^{\infty} \beta^j \nu_{H,t+j}^N$. Now, the crucial point here is that $E_t \pi_{t+\infty}^N$ is constant across regions, hence empirically, as said before, we will substitute it with time and regional controls. The empirical estimation of the regional PC will then be:

$$\pi_{it}^N = -E_t \sum_{i=0}^{\infty} \beta^j (\kappa u_{i,t+j} + \lambda \hat{p}_{i,t+j}^N) + \alpha_i + \gamma_t + \tilde{\omega}_{it}^N \tag{7}$$

However, an essential issue must be discussed. The empirical specifications used in many other research papers assumes that both $u_{H,t}$ and $\hat{p}_{H,t}^N$ follow AR(1) processes with autocorrelation coefficients equal to ρ_u and $\rho_p N$. But then, the equation estimates will no longer be equation 7, but rather:

$$\pi_{it}^N = -\psi u_{it} - \delta \hat{p}_{it}^N + \alpha_i + \gamma_t + \tilde{\omega}_{it}^N \tag{8}$$

But clearly now $\psi = \frac{\kappa}{1-\beta\rho_u}$ and $\delta = \frac{\lambda}{1-\beta\rho_{p_N}}$, and being unemployment quite persistent, we will necessarily have ψ larger than κ. Hence this formulation of the regional PC will lead regional Phillips curves to appear steeper than they really are.

5.3 Results

The analysis finds very low coefficient for κ of 0.0062 (Figure 29) in line with the results of *Rotemberg (1982)*, *Galí (2008)*, *Nakamura and Steinsson (2014)*.

	κ
Rotemberg and Woodford (1997)	0.019
Galí (2008)	0.085
Nakamura and Steinsson (2014)	0.0077
Our full sample IV estimate	0.0062

Figure 29: Comparison with prior studies in the literature

Note: Estimates from Rotemberg and Woodford (1997), Galì (2008), and Nakamura and Steinsson (2014) are adjusted by the elasticity of output with respect to employment in the model in these papers. For Nakamura and Steinsson (2014), calibration with GHH preferences is used. Source: The slope of the Phillips curve: Evidence from US states (2022), J. Hazell, J. Herreno, E. Nakamura, J. Steinsson.

Empirical estimates of the Phillips curve based on aggregate data show that the curve was 100 times steeper in the period before 1990 compared to the period after 1990 (see the subsection on empirical evidence in section one for reference). However, the model by Nakamura find only a modest flattening of the PC coefficient with an estimate for the pre-1990 sample that is just two times bigger than the one for the post-1990 one (Figure 30).

HAS THE PHILLIPS CURVE FLATTENED?

	Lagged unempl. IV without time fixed effect		Lagged unempl. IV with time fixed effect		Tradeable-demand IV with time fixed effect	
	Pre-1990 (1)	Post-1990 (2)	Pre-1990 (3)	Post-1990 (4)	Pre-1990 (5)	Post-1990 (6)
Panel A: Estimates of κ from equation (17)						
κ	0.0278	0.0002	0.0107	0.0050	0.0109	0.0055
	(0.0025)	(0.0017)	(0.0080)	(0.0040)	(0.0062)	(0.0028)
Panel B: Estimates of ψ from equation (19)						
ψ	0.449	0.009	0.198	0.090	0.422	0.332
	(0.063)	(0.025)	(0.113)	(0.057)	(0.232)	(0.157)

Figure 30: Results for the two sub-samples

Notes. The table presents estimates of κ and ψ, before and after 1990. Columns (1), (3), and (5) present results for the sample period 1978–1990; and columns (2), (4), and (6) for the sample period 1991–2018. All specifications include state fixed effects. Specifications in columns (3)–(6) include time fixed effects. The instruments in columns (1)–(4) are the fourth lag of the tradeable-demand instrument and the relative price of nontradeables (i.e., OLS in Panel B). In columns (5) and (6), the instruments are the fourth lag of the tradeable-demand instrument and the relative price of nontradeables. In all columns, we estimate κ by two- sample 2SLS and apply the correction to our standard errors from Chodorow-Reich and Wieland (2019). Standard errors are reported in parentheses, clustered by state. All regressions are unweighted. Source: The slope of the Phillips curve: Evidence from US states (2022), J. Hazell, J. Herreno, E. Nakamura, J. Steinsson.

The analysis presented finds that the slope of the PC is small and was small also in the past. This can be interpreted as a clear evidence that the 1980s shift in monetary policy regime confounds estimates on the Phillips curve based on time series variation in the pre-1990 sample. The Phillips cure looks flatter because the coefficient on unemployment is no longer affected by the upward bias generated by the reduction in inflationary expectations. While fluctuations in expected inflation rates were substantial in the period with only a modest fraction of the large changes in inflation in the early 1980s can be accounted for by the direct effect of increasing unemployment. Hence, the Volker disinflation worked due to the fact agents perceived a shift in monetary regime and adjusted their inflationary expectations, rather than through a weak labor market (in fact, in the 1981 to 1986 period inflationary expectations declined by 4%, representing two thirds of the total decline in inflation).

6 Labor Market Strains and Non-Linearities in the PC

Nominal rigidities have been largely identified in data (*Akerlof et al., 1996*, *Lebow et al., 2003*, *Kahn, 1997*, *Dickens et al., 2007*). As nominal rigidities impede the wage adjustmetn process, it is fundamental to understand if and how they affect the slope of the Phillips Curve. In the introduction I had stressed that workers' reluctance to accepts wages below the prevailing wage rate could counter deflationary pressures, giving rise to a non linear Phillips relationship. This idea is not new, in fact, it traces back to the original 1958 paper of A. W. Phillips. In his words: "*...it appears that workers are reluctant to offer their services at less than the prevailing rates when the demand for labour is low and unemployment is high so that wage rates fall only very slowly. The relation between unemployment and the rate of change of wage rates is therefore likely to be highly non-linear*". Therefore, originally, the PC was plotted by Phillips as a non-linear relationship. Considering the empirical evidence, many authors have found non-linearities in the data: *Daly and Hobijn (2014)*: show that both the slope and curvature of the Phillips curve depend on the level of inflation and the extent of downward nominal wage rigidities. Similar results are found by *Hooper et al. (2020)*, *Babb and Detmeister (2017)*, and *Kiley (2015a)*. Moreover, *Crust et al. (2023)* find a steeper Phillips curve when unemployment-to-vacancy ratio is below 1.

6.1 Low inflation and Non-linearities

Non-linearities, being generated by rigidities, are foreseen to appear under some special circumstances. Imagine an economy is hit by a recession. When inflation is high, if firms need to adjust real marginal cost, they let wages stagnate as prices rise. When inflation is low, if firms need to reduce costs, they have to to negotiate wage cuts. However, workers and unions will oppose wage reductions. As a consequence, wages will not decline as much as the actual level of slackness would imply. So, to sum up, low inflation economies running into recessions are expected to experience a flatter PC while high inflation economies should not be impacted by this dynamic. *Forbes et al. (2021)* tested this theory in the data. Following the estimation strategy of *Forbes et al. (2017)* they develop a low inflation bend model within a cross-country data set. The authors regress inflation on a measure of domestic slackness intersected with a dummy (more infra) while controlling for inflationary expectations, world slack, real exchange rate, oil prices and other proxies of globalization. It is interesting to note that they do not use the unemployment rate as a proxy for slackness. They employ a principal component of labor market slack that includes for example hours worked, the share of involuntary part-time workers, and the share of temporary workers (for the reasons discussed in chapter 2).

Results are presented in table 1. Column (2) tests a "shifting linear" model that assumes the PC is flatter when inflation is low. In this scenario, slack is intersected with a dummy equal to 1 when lagged four-quarter core inflation is less than 3%. The interaction is significant at 5% and steepens the curve when inflation is high to -0.30 (almost two times of the constant linear model) while flattens it when inflation is low (-0.09). Column (4) tests the "low inflation bend" model that conceptualises the idea that price rigidities enter into effect only when slack is high and inflation is low. In this framework, slack is intersected with a dummy equal to 1 when inflation is smaller than 3% and domestic slack is greater than 0. The coefficient on the interaction term is significant at 1% and the R^2 is the highest of the four columns. The slope is -0.30 but flattens markedly to 0.02 when slack is positive and inflation is low. "The first four columns do not include global slackness controls, while the remaining four do. However, the results remain robust.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	*Constant linear*	*Shifting linear*	*Constant nonlinear*	*Low inflation bend*	*Constant linear*	*Shifting linear*	*Constant nonlinear*	*Low inflation bend*
Domestic slack	-0.17*** (0.03)	-0.30*** (0.07)	-0.35*** (0.08)	-0.30*** (0.05)	-0.15*** (0.03)	-0.32*** (0.06)	-0.35*** (0.08)	-0.31*** (0.05)
Inflation < 3		0.21** (0.09)				0.27*** (0.08)		
Domestic slack > 0			0.35** (0.14)				0.38** (0.14)	
Domestic slack > 0 and inflation < 3				0.32*** (0.10)				0.38*** (0.10)

Table 1: Results for a PC with domestic slackness intersected with three possible dummies

Note: CPI = consumer price index. Robust standard errors in parentheses. * p ¡ 0.10, ** p ¡ 0.05, *** p ¡ 0.01. Source: Forbes, K., Gagnon, J., and Collins, C. G. (2021). Low Inflation Bends the Phillips Curve around the World.

If we now plot the PC derived for the high inflation sample versus the one of the low inflation sample, we observe that low inflation economies experience a flatter PC during recessions while high inflation economies are not affected by such dynamic. In fact, we can see how in the left plot, the one presenting the no inflation scenario, the PC is flatter when slackness is greater than 0, while in the right plot no kink is observed. This result is in line with the theoretical reasoning presented at the beginning of this chapter.

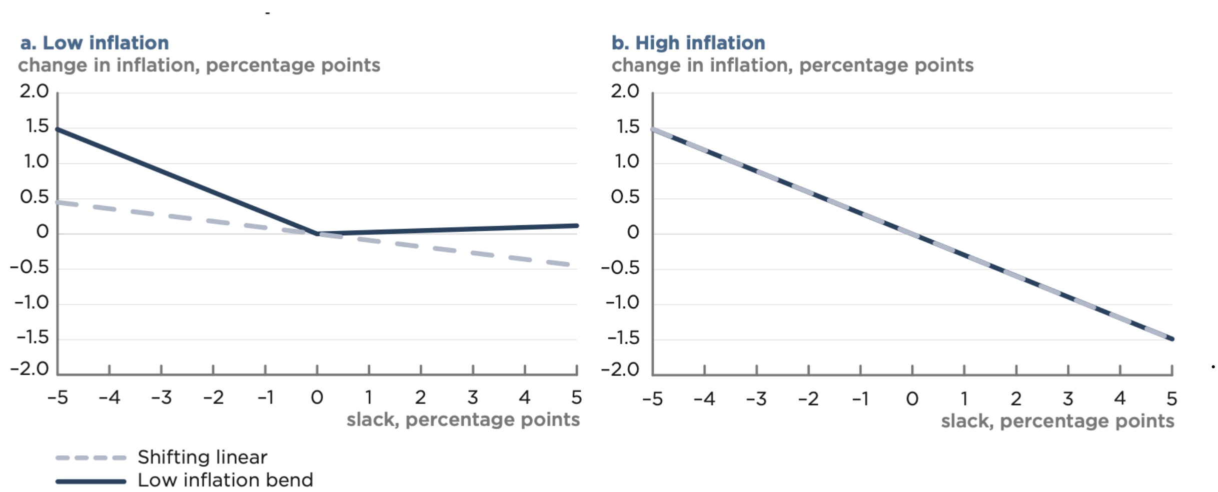


Figure 31: Phillips curves for low inflation and high inflation economies

Note: The figure plots the results of Table 1. The left panel represents the low inflation bend result for the low inflation scenario, while the right panel presents the high inflation scenario. Source: Forbes, K., Gagnon, J., and Collins, C. G. (2021). Low Inflation Bends the Phillips Curve around the World.

6.2 Inflationary expectations and biased estimates

However, a concern related to this analysis may require some attention. As described in the previous chapters, one of the crucial aspects to consider when performing Phillips Curve estimations is controlling for the effect of inflationary expectations, and using proxies is often regarded as an unreliable strategy. If inflationary expectations are not adequately controlled for they generate a particularly critical issue in this specific low-inflation versus high-inflation framework. In fact, the behavior of inflationary expectations differs largely between the two scenarios: when inflation is high inflationary expectations are less anchored and more volatile, plus, they have more space for adjustment. For example, if we consider the high inflationary US economy of the 70s, inflationary expectations were high and progressively started to decrease. However, the greater the adjustment of inflationary expectations, the more biased the estimates of the PC. Hence, considering that a reduction in inflationary expectations generate a positive bias in the estimation of the Phillips Curve, one would expect estimates in high-inflation economies to be biased upwards. Unfortunately, the lack of high-quality data probably precludes the possibility of replicating the regional analysis described in the previous chapter on a larger scale.

6.3 Non-linear Phillips curve in regional data

To conclude, I will discuss a model developed by *Gitti (2024)*, as it adds a significant contribution to the literature on the Phillips curve while encompassing many crucial aspects analyzed in the previous chapters.

First the author addresses the flaws of the unemployment rate by using labor market tightness as a measure of economic slackness. This measure, also called vacancy-to-unemployment ratio, is considered by many authors a more efficient measure of real economic slackness (*Benigno and Eggertsson (2023)*, *Barnichon and Shapiro (2022)*).

Second, the work also makes use of regional data, with 21 US Metropolitan Statistical Areas (MSAs) as units of observation. This is done for two main reasons: firstly, time series observations of labor market tightness are limited (before 2018, the US labor market was inefficiently tight only during World War II, the Korean War, and the Vietnam War). Regional data provide a markedly larger degree of variation in both core inflation and labor market tightness. Secondly, regional data allow us to control for expectations, national supply shocks, and other confounders through time and fixed effects (as previously discussed).

Third, a shift-share instrument of the type presented in a previous section (Bartik) is used to control for regional supply shocks, thereby controlling for the simultaneity bias between demand and supply.

Additionally, the author develops an expanded New Keynesian (NK) model to provide the foundation for the empirical strategy employed. The model encompasses two regions in a monetary union to match the choice of panel regional data and includes a vertically linked production structure consistent with the type of instrumental variable (IV) chosen. Then, search and matching frictions are incorporated in the spirit of the Diamond-Mortensen-Pissarides (DMP) framework to establish a relationship between inflation and tightness and to formally introduce the concept of unemployment into the model. Lastly, wage rigidities are introduced to generate a kink in the Phillips Curve (PC) relationship. They are added to the model through the inclusion of employment agencies that oversee the search-and-matching process while optimizing their profits. The market is defined as tight or slack with respect to a threshold θ_{it}, which is equal to the average level of labor market tightness in the MSA. The flexible wage rate is defined as the free market equilibrium wage rate.

When the market is tight, the equilibrium (flexible) wage rate rises, and workers accept salary increases. However, when the market is slack and the flexible wage rate decreases, workers are reluctant to accept a reduction in their nominal wages. In this setting, the wage will be equal to the prevailing wage rate ($(\bar{w}_i)^\lambda \left(w_{it}^{\text{flex}}\right)^{1-\lambda}$, more infra) and firms will hire fewer workers than under flexible wages (a corollary of this reasoning is that with nominal rigidities, the sacrifice ratio will be higher during recessions, as it will take time for slack labor markets to affect prices). To sum up, the wage rate in region i at time t is equal to:

$$w_{it} = \begin{cases} w_{it}^{\text{flex}} & \theta_{it} > \theta_{it}^* \\ (\bar{w}_i)^\lambda \left(w_{it}^{\text{flex}}\right)^{1-\lambda} & \theta_{it} \leq \theta_{it}^* \end{cases}$$

The prevailing wage rate is affected by the degree of rigidity (λ) such that, if wages are fully rigid ($\lambda = 1$), the prevailing wage rate equals the steady-state level. To conclude, if the current level of tightness θ_{it} is higher than θ_{it}^*, wages will be flexible (and increasing). Conversely, wages will slowly decrease towards the flexible level if θ_{it} is smaller than θ_{it}^*. Overall, if λ is smaller than one, the coefficient κ_θ on the Phillips Curve (PC) will be smaller than the coefficient $\kappa_\theta^{\text{tight}}$ such that $\kappa_\theta \equiv \kappa_\theta^{\text{tight}}(1-\lambda)$. This is reasonable because, during slack labor markets, the wage rate adjusts towards the flexible rate at a pace defined by the coefficient λ. This means that when the market is slack, deflationary pressures are reduced. The paper then solves the equation forward, assuming AR(1) processes and, for the reasons described in *Hazell et al., 2020*) estimates the parameter ψ_θ, deriving $\psi_\theta^{\text{slack}} = \psi_\theta^1, \quad \text{while} \quad \psi_\theta^{\text{tight}} = \psi_\theta^1 + \psi_\theta^2$.

Empirically, a dummy variable equal to 1 is used whenever θ is greater than the MSA average. Time and fixed effects are used to control for monetary policy regime changes, inflationary expectations, and national supply and demand shocks. The instrumental variable (IV) is used to control for regional supply shocks. Once the estimation is run, a piece-wise log-linear regional Phillips Curve is found (Figure 32). The curve is three times steeper when tightness is above the derived threshold θ_{it}: the PC has a slope of

8.4% when $\theta_{it} > \theta^*_{it}$, while it is significantly flatter, with a value of 3%, when $\theta_{it} \leq \theta^*_{it}$.

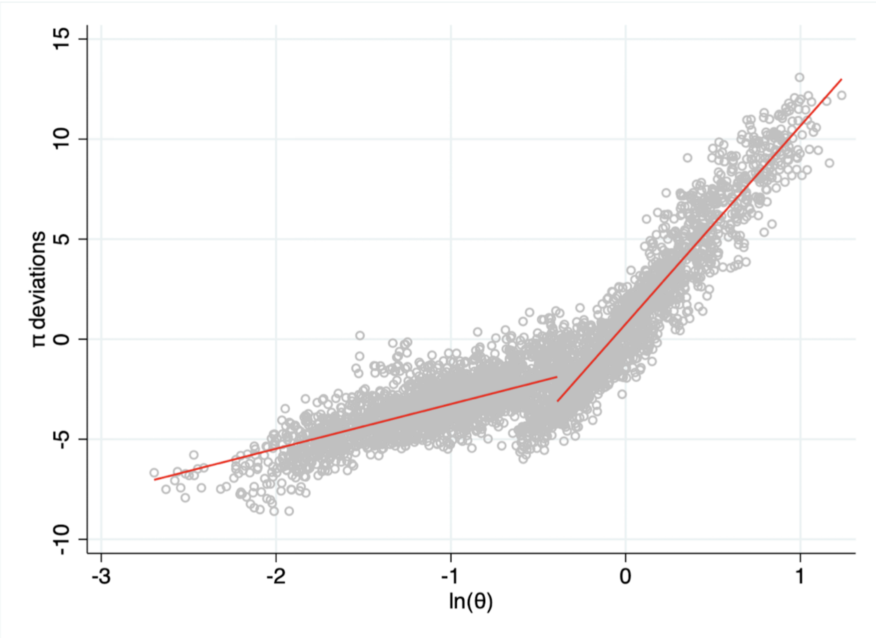


Figure 32: Results for a PC where domestic slackness is intersected with three possible dummies

Note: The figure shows the scatter plot of core inflation deviations and the log of labor market tightness across 21 U.S. metropolitan areas. Inflation deviations are defined as the difference between the 12-month core inflation rate and the estimated controls and fixed effects in column (4) of Table 1. The red lines plot the Phillips curve estimated in column (4) of Table 1. Source: Gitti, G. (2024). Nonlinearities in the regional Phillips curve with labor market tightness

7 Conclusion: Consequences for Monetary Policy

When dealing with inflation, a comprehensive approach must be used. Each crisis is different, and understanding the heterogeneous and multifaceted sets of elements that generate inflation (or disinflation) is crucial. For each different source of inflation, a distinct policy decision may be required. In identifying which factor is more relevant in generating inflation, we observed that domestic slackness is less relevant than what was traditionally thought. This leads to the conclusion that strong labor markets should not be perceived as alarming as they once were. This is the reason why the Fed recently updated its monetary policy framework (*Brainard, 2021*): the Fed recognizes "that price inflation is much less sensitive to labor market tightness than historically, that is, a flat Phillips curve." This has a clear consequence for monetary policy: the Fed's focus will no longer be on minimizing "deviations from maximum employment in either direction," but rather on eliminating "shortfalls from maximum employment." Moreover, another crucial point that emerges from the analysis carried out in the previous chapters is the importance of forward guidance and the credibility of central banks. Expectations matter enormously, and central bankers, through coherent, clear, and impactful communication, can have a strong effect on the economy. For example, although the Outright Monetary Transactions (OMT) program in the Euro Area has never been formally implemented, its mere announcement in the summer of 2012 strongly reassured markets that the recession was over. However, one last consideration emerges from the prospect of a non-linear Phillips curve. If central banks rely on a linear Phillips curve model, they would likely underestimate the sensitivity of prices to tight labor markets. On the one hand, this implies that with a strong labor market, it is possible to disinflate without hurting the labor market much, as a small reduction in economic activity would lead to a marked fall in inflation. The reverse side of the coin is that if central banks expect a linear Phillips curve, they will underestimate the inflationary pressures originating from tight labor markets. This may lead them to pursue accommodative monetary policy that would result in unexpected surges in inflation. Overall, the optimal policy path set by the central bank would be wrong, as the trade-off between inflation and unemployment would be assessed for expected values of inflation that are mistakenly below their true level.

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