The Inflation Rate Disconnect Puzzle: On the International Component of Trend Inflation and the Flattening of the Phillips Curve*

Guido Ascari†
University of Oxford
University of Pavia
RCEA

Luca Fosso‡
University of Pavia
Norges Bank

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Abstract

Since 2000 U.S. inflation has remained both below target and silent to domestic slack and monetary interventions. A trend-cycle VAR decomposition explores the role of globalisation in explaining the puzzling behaviour of inflation. The trend analysis shows that, starting from 90s, despite very well-anchored expectations, slow-moving imported "cost-push" factors induced deflationary pressure keeping trend inflation below target. The cycle block provides evidence in favour of the flattening of Phillips curve, mainly attributable to a weaker wage pass-through. The business cycle behaviour of inflation is determined by a shock originating abroad, which indeed generates the main bulk of volatility in the international prices of intermediate goods and is poorly connected to the domestic slack.

Keywords: Trend-Cycle Decomposition, Trend Inflation, Global Inflation, Phillips Curve, Spectral Analysis
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†Address: Department of Economics, University of Oxford, Manor Road, Oxford OX1 3UQ, United Kingdom. E-mail address: guido.ascari@economics.ox.ac.uk.

‡Address: Department of Economics and Mangement, University of Pavia, Via San Felice 5, 27100 Pavia, Italy. E-mail address: luca.fosso01@universitadipavia.it.

1 Introduction

For decades Central Banks have been working strenuously to secure the health of the entire economic system, by controlling inflation dynamics. After the second oil shock, the Volcker administration in the early '80s put an incredible effort to bring surging inflation expectations to a halt and rebuild the credibility of FED (e.g., Goodfriend and King, 2005). The Phillips curve relationship was strong at that time and the monetary intervention required a high sacrifice ratio in terms of unemployment. After the Volcker disinflation, inflation started stabilising at lower levels and became also more persistent. Recently, the 2009 great financial crisis brought about unprecedented peaks of unemployment rates without triggering deep deflationary pressures, as markets and central bankers expected. Then, following the massive injection of liquidity into the system and the recovery of the economy - the unemployment rate at the end of 2019 was 3.5%, its lowest level in almost half a century - inflation was expected to catch up, but it did not. This puzzling inflation dynamics, led the literature to investigate explanations for both the "missing disinflation" (e.g., Coibion and Gorodnichenko, 2015a) during the financial crisis and the "missing inflation"(e.g., Heise et al., 2020) afterwards. Moreover, the fact that inflation has been stable and persistently below the 2% target in the last two decades calls for the identification of possible deflationary forces.

We contribute to the literature on inflation dynamics in two dimensions. First, we investigate the role of an international supply component of the dynamics of inflation. During the last 30 years the world lived through the fall of the Berlin wall, the rise of emerging markets economies, the entrance of China in the WTO. These events transformed the world we live in, and determined a tremendous rise in globalization and international trade, thanks to reduced transportation costs, trade liberalization, the development in ICT and the integration of emerging economies in international production network through Foreign Direct Investments (FDIs) and Global Value Chains (GVCs). An ever-increasingly integrated world economy has important implications for domestic price dynamics. We can distinguish two main effects: one on the demand and the other on the supply side. On the demand side, a more open economy makes domestic markets more contestable. The harsher competition from abroad reduces the ability of domestic firms to adjust prices and keep profit margins constant (e.g. Heise et al., 2020). However, in this paper we will not focus on the effects of international competition pressures on domestic prices, but on a second effect, namely the international fragmentation of production and the rise in GVCs. As the world economy becomes more integrated, domestic firms find convenient to delocalise and off-shore part of their production, leading to the fragmentation of national value chains and a globally interconnected production network, summarised into the concept of GVCs. As a consequence, firms extensively use imported intermediate goods as input of production. More than half the world's trade in 2019 was accounted for by trade in intermediate products.[1] The main implication of this phenomenon is that firms' costs could become disconnected by domestic conditions, because they depend on imported intermediate goods produced abroad. Our empirical model allows for this implication and asks the data how much this international component of costs is important in shaping the dynamics of inflation in U.S. data.

Second, we propose a unified approach to model inflation, based on a VAR with stochastic trends. In modelling inflation dynamics empirically is important to decompose and to model jointly the trend and the cyclical components. For example, the Phillips is a relation between the cyclical components of unemployment (or output) and inflation, but to determine the cyclical component one needs to take a stand on the trend. Moreover, we want to allow the international supply factors described above to affect both the trend and the cyclical components of inflation. Regarding the former, we decompose trend inflation into three components: a monetary policy; a domestic and an imported cost-push (supply) factors. Regarding the latter, the cyclical block of the empirical model uncovers the cyclical co-movements of inflation with domestic real variables, wage inflation and international import prices.

The trend-cycle analysis is motivated by our main research question, that is, what is the role of international supply factors in determining the dynamics of: (i) trend inflation, hence possibly explaining the recent deflationary pressure on trend inflation; (ii) cyclical inflation, hence possibly explaining its recent puzzling cyclical behaviour. It is worth noting that both issues are of first-order importance from a monetary policy perspective. An inflation level persistently below target threatens the long-run mandate of the central bank. An inflation dynamic that is insensible to the domestic conditions, due to a large portion of marginal costs being imported, becomes harder to control by the central bank.

The main result of our analysis is that the international cost-push factor affects both the trend and cyclical behaviour of inflation. First, the imported international cost-push factor exerts a persistent deflationary pressure on trend inflation over the whole sample period. In particular, despite the switch in the monetary regime successfully anchored long-run expectations around the explicit target of 2%, the international cost-push factor prevented trend inflation to stay on target throughout '90s and over the last decade. Importantly, we did not find any evidence of a change over time of the relative importance of the three components - monetary policy, domestic and imported cost factors - of trend inflation. Second, in the empirical analysis of the cyclical block of the model, we investigate whether the inflation gap has become increasingly exogenous to the domestic block of the model, by means of

[1]The rest is divided between primary, consumer and investment goods, see UNCTAD, 2020, Key statistics and Trends in International Trade, https://unctad.org/system/files/official-document/ditctab2020d4_en.pdf.

Uhlig (2003) identification scheme of the impulse response analysis. The results show a strong flattening of the Phillips curve over time. The relationship between domestic labor market and inflation during the 1960Q1-1984Q4 period is solid, while it disappears in the period 1991Q1-2019Q4. Two facets of the business cycle emerge: (i) a business cycle shock responsible for the main bulk of fluctuations in real variables, as in Angeletos et al. (2020), that push wages upwards but do not affect inflation; (ii) a propagation mechanism that generates a strong co-movement between domestic inflation and international prices, but it is orthogonal to the domestic real variables. Overall, we find a significant decline in the wage pass-through from domestic slack to U.S. inflation, which becomes disconnected from the domestic labor market - the inflation rate disconnect puzzle. Business cycle movements in U.S. inflation are, instead, increasingly characterised by fluctuations originating abroad, through international inputs linkages, leaving little room for domestic slack to move inflation. Third, our results, therefore, find support for the globalization of inflation hypothesis (GIH) - meaning that international factors progressively replace domestic factors as globalization increases - in the cyclical block but not in the trend block of the empirical model, possibly providing a rationale for some conflicting results in the literature.

The paper is organised as follows. Section 2 reviews the related literature. Section 3 presents the data and the methodology to extract the low and the high frequency components of the endogenous variables. Section 4 describes the analysis of trend inflation. 5 contains the main results about the dynamics of inflation at business cycle frequencies and about the flattening of the Phillips Curve. Section 6 concludes.

2 Related Literature

The literature studying the inflation process is extensive. Thus, here we do not aim to survey it comprehensively, but to place our paper into the more relevant recent literature to highlight our contribution.

Our work is mostly related to the literature investigating *global inflation*. While we focus on the U.S., this literature identifies a global common component in inflation dynamics across countries and studies its effects on national inflation. Borio and Filardo (2007) is among the earliest paper proposing a more globally-oriented rather than country-oriented view of inflation by providing supporting evidence in favour of the GIH. They estimate the empirical Phillips curve for a panel of OECD countries and find that including proxies for the global factors - i.e., oil prices, world output gap, China's output gap, etc. - substantially improves the explanatory power. In addition, they find evidence for a considerable increase in the pass-through of international factors into domestic inflation gap since 90s, with a limited role for domestic measures of slack. While Borio and Filardo (2007) focus on the effect of the GIH on the slope of the Phillips curve, Ciccarelli and Mojon (2010) introduce the notion of global inflation, identifying through a factor-augmented model a common global factor that accounts for a strong co-movement among 22 OECD inflation rates both at low and business cycle frequencies. They show that this common global factor has driven the reduction in the level and persistence of national inflation rates over time (see also Mumtaz and Surico, 2012, for similar results in a time-varying VAR with stochastic volatility). Interestingly, Ciccarelli and Mojon (2010) report that inflation has been dominated by the common component since the '60s with no evidence of change over time, which seems to contradict the GIH. However, the results in Borio and Filardo (2007) and Ciccarelli and Mojon (2010) (and likewise other surveyed below) do not necessarily stand in contradiction with each other. The former is about the Phillips Curve that links the inflation gap to measure of domestic (and international) slack, and hence, a cyclical phenomenon, while the latter is about the level and persistence of inflation, hence, more related to the slow-moving component of the inflation. In other words, these results tackle two important, but different, questions. The former question is about whether the sensitivity of the cyclical behaviour of inflation to domestic slack has changed over time due to the increase in globalization, the latter one is about whether there is a common global component driving the level of inflation. Our trend-cycle decomposition nicely lends itself to reconcile these results since we find evidence of a structural change in the relationship between U.S. inflation gap and measure of domestic slack, while we find no evidence of a change in the relationship between the domestic and the international component of trend inflation in U.S. data.

Our approach is close to Eo et al. (2020), Kamber and Wong (2020) and Hasenzagl et al. (2020), who use trend-cycle decomposition to study both the long-run permanent component (trend) and the business cycle component (gap) of inflation dynamics. Kamber and Wong (2020) use a FAVAR model in which they distinguish a foreign block and a domestic block, assume block exogeneity identification restrictions and then perform a Beveridge-Nelson decomposition to distinguish trend and cycle. They find that global factors can have a sizeable influence on the inflation gap, while they play only a marginal role in driving trend inflation. However, in their setup, foreign shocks are mainly due to commodity prices, and, contrary to us they do not use intermediate good prices. Eo et al. (2020) use good and service sectors inflation rates to retrieve the aggregate headline inflation trend. They use service sector as proxy for the non-tradeable component of inflation and show that it is dominant in explaining aggregate trend inflation. They conclude, therefore, that international factors have a limited effect. In the part analysing the cyclical component, Hasenzagl et al. (2020) explore the possibility for inflation gap being synchronised with the proxies of global demand.

We instead focus on the supply side including a measure for imported intermediate inputs inflation in the international block of the model. Moreover, while Hasenzagl et al. (2020) uses a semi-structural approach, we employ a different methodology based on a BVAR with common trends as in Del Negro et al. (2017). Furthermore, in contrast with Hasenzagl et al. (2020), we depart from the standard assumption of trend inflation being the common trend between actual inflation and long-run expectations (e.g., Mertens, 2016) and allow for low frequency supply factors to contribute in shaping trend inflation dynamics. This assumption is motivated by the strand of literature on informational frictions (Coibion and Gorodnichenko (2012), Coibion and Gorodnichenko (2015b), Coibion et al. (2018), Mertens and Nason (2020)). The main takeaway from this literature is that surveys are subject to non-negligible forecast errors, implying that agents' inflation expectations sluggishly incorporate the new incoming information.

Recently, Carriero et al. (2019) extend the analysis in Ciccarelli and Mojon (2010) and Mumtaz and Surico (2012) to a FAVAR that allows commonality in both levels and volatilities, showing that a substantial share of inflation volatility across countries is attributed to the common global factor that drives also trend and persistence. Moreover, they document this common factor to be highly correlated with China's PPI, thus supporting the argument in favour of a China supply shock. The China shock relates to the rapidly increasing participation of China in international trade starting from the '90s, eventually culminated in the entrance of China in WTO in 2001. On the one hand, import competition from low-wage countries could exert downward pressure on U.S. prices. Gamber and Hung (2001) report that some U.S. sectoral prices are sensitive to prices of imports in the same sector. Auer and Fischer (2010) document similar effects both on sectoral prices and on equilibrium inflation. Recently, Heise et al. (2020) test the role of international pressures as potential candidate of the missing inflation puzzle over the last two decades. According to the authors, the slow inflation pick-up is attributable to smaller wage pass-through to inflation, whose decline has been set in motion by increasing import competition. On the other hand, imports from low-wage countries could help maintain low pressure on firms' costs if a large share of imports are intermediate goods. Our analysis aims at capturing this mechanism, as a possible explanation of the missing deflation/inflation puzzle observed in the last decade. Using multi-country industry-level data, Auer et al. (2019) document that international input-output linkages account for half of the global component of producer price inflation (PPI), by creating underlying cost shocks that are propagated internationally through the global input-output network. Auer et al. (2017) extend the analysis in Borio and Filardo (2007) showing that the relative sensitivity of domestic inflation to domestic and to global slack in a Phillips Curve estimation depends on new GVCs proxies. They interpret this as supporting evidence in favour of cross-border trade in intermediate inputs as transmission channel of international slack feeding into domestic inflation.

Forbes (2019) uses three different empirical frameworks - univariate trend-cycle decomposition à la Stock and Watson (2007), Phillips curve estimation and principal components - to investigate the role of globalization for the dynamics in U.S. inflation. The main finding is that global factors - more specifically, commodity and oil prices, exchange rate, world slack, and GVCs - are important to explain the cyclical component of CPI inflation, while less so to explain both the trend component of CPI and the dynamics of core and wage inflation. Moreover, Forbes (2019) document that the role of these global factors in affecting CPI inflation have increased over the last decade providing a possible explanation for the flattening of the Philips Curve.

Finally, the debate on the flattening of the Phillips curve and missing deflation/inflation puzzle goes beyond the role of international factors. Coibion and Gorodnichenko (2015a) show the important role played by inflation expectations - see Coibion et al. (2018) for a survey. McLeay and Tenreyro (2020) and Bergholt et al. (2020) argue that the Phillips curve is in good health and inflation is under full control of monetary tools. The reason why it has become hard to estimate its slope empirically should be attributed to an identification problem, induced by optimal monetary policy. Consistent with these results, Hazell et al. (2020) attribute the flatter Phillips curve to the monetary policy regime switch started with Volcker administration. Importantly, our finding about the flattening of the Phillips Curve and the disconnection of inflation dynamics from the domestic business cycle do not suffer of such identification problem because we do not explicitly estimate a Phillips Curve and because our correlations are conditional on a specific business cycle shock.[2]

A more agnostic approach has been, instead, applied by Del Negro et al. (2020). They conduct a horse race between three candidate hypotheses of the poor responsiveness of inflation, namely the mismeasurement of labour market variables, the flattening of the aggregate supply curve and the flattening of the aggregate demand curve, associated with the systematic aggressive response of monetary policy to demand shocks. The three hypotheses are scrutinized through the lens of a VAR and a medium-scale DSGE. Their findings mainly attribute the silent behaviour of inflation to the flattening of the aggregate supply curve and, to a lesser extent, to more aggressive monetary policy.[3]

[2]See Barnichon and Mesters (2020) for an enlightening discussion of the issue and a proposed solution based on the Phillips Curve estimation conditional on monetary policy shocks.

[3]The New Keynesian DSGE literature provides some explanations for the missing deflation/inflation puzzle. Christiano et al. (2015) and Del Negro et al. (2015) show that the inclusion of financial frictions in a standard medium-size DSGE model could help in replicating the small drop in inflation at the darkest hour of the 2009 recession. Gilchrist et al. (2017) show that liquidity constraint firms have an incentive to raise prices in response to adverse financial shocks to avoid the deterioration of their liquidity position, thus mitigating the response of inflation to output fluctuations. Lindé and Trabandt (2019) attributes the

While our results confirm some earlier results in the literature above - importance of global factors for the flattening of the Phillips curve, an alive-and-well wage Phillips Curve, little change in the business cycle dynamics of real variables - our analysis adds the importance of considering intermediate goods to explain both the deflationary forces acting on the trend level of inflation and the changing sensitivity of PCE U.S. inflation to measures of domestic slack. Our trend-cycle decomposition is key to these results and provide complementary evidence to the literature and a rationale for reconciling some existing conflicting evidence.

3 Methodology and Data

We will assume that the vector of endogenous variables χ_t is represented by the following observation equation:

$$\underset{(n\times 1)}{\chi_t} = \underset{(n\times q)}{\Lambda}\,\underset{(q\times 1)}{\bar{\chi}_t} + \underset{(n\times 1)}{\tilde{\chi}_t}, \tag{1}$$

where $\bar{\chi}_t$ and $\tilde{\chi}_t$ are the trend and cyclical components, respectively. Λ is sparse and governs the presence of $q \leq n$ common trends. We leave the discussion about the assumptions on Λ to section 4, as this plays a crucial role for our work. Keep in mind, for the moment, that its elements can be either calibrated, estimated or both. Trends and cycles are assumed to be stochastic and to evolve according to a random walk and an invertible reduced-form VAR, respectively:

$$\bar{\chi}_t = c\mathbf{1}\{i\} + \bar{\chi}_{t-1} + e_t \qquad e_t \sim N(0_q, \Sigma_e) \tag{2}$$

$$\Phi(L)\tilde{\chi}_t = \varepsilon_t \qquad \varepsilon_t \sim N(0_n, \Sigma_\varepsilon), \tag{3}$$

where $\mathbf{1}\{i\}$ is an indicator function accommodating the possibility of a drift in each trend, $\Phi(L) = I - \Phi_1 L - ... - \Phi_p L^p$ and Φ_k, for $k = 1, ..., p$, are $(n \times n)$ the matrices of coefficients. Our model is essentially a multivariate version of the unobserved component model of Stock and Watson (2007)[4]. The state space model in (1) inherits the $((n + q) \times 1)$ vector of innovations from the transition equations in (2) and (3). The innovations are assumed to be i.i.d. and distributed according to a multivariate Normal.

In the same vein of Primiceri (2005), the initial conditions for both trend and cyclical

missing deflation puzzle to the arising non-linearities in price and wage settings when the system is hit by large shocks.

[4]Similar versions to our model have been implemented by Villani (2009) and Del Negro et al. (2017)

components are taken by using pre-sample data, so that :

$$\bar{\chi}_0 \sim \mathcal{N}\Big(\underline{y_0}, V_0\Big) \tag{4}$$

$$\tilde{\chi}_0 \sim \mathcal{N}\Big(0, V(\Phi, \Sigma_\varepsilon)\Big), \tag{5}$$

where $\underline{y_0}$ is the pre-sample mean and V_0 is the (q x q) identity matrix. $V(\Phi, \Sigma_\varepsilon)$ is the unconditional variance of the initial conditions for cyclical components and it is always well defined as we impose stationarity on $\tilde{\chi}_t$. Despite the dimension of the model, it can be efficiently estimated as it is linear in its equations. We use the Kalman Filter to extract the unobserved components in the model and implement simulation smoothing techniques to generate the posterior distribution (see Carter and Kohn, 1994).

Data. The model is estimated using the following variables: unemployment rate; real GDP per capita; real investment per capita; real consumption per capita; PCE inflation; 10-year ahead PCE inflation; wage inflation; imported intermediate inputs price inflation[5]; oil price inflation; TFP growth rate. The sample spans from 1960Q1 to 2019Q4. Data spanning from 1954Q1-1959Q4 is used as pre-sample training for initial conditions and the variance of innovations.

4 The Anatomy of Trend Inflation

We distinguish three distinct components of trend inflation. First, we assume trend inflation to be primarily determined by monetary policy and its ability to anchor inflation expectations. We capture this by modelling a common trend between inflation and 10-years expected inflation, as often assumed in the literature (see, e.g., Mertens and Nason, 2020; Nason and Smith, 2020). Second, we assume that trend inflation can be also influenced by slow-moving "cost-push" factors that are not under full control of monetary policy. These factors are further divided into a domestic and an imported (from abroad) component. The domestic component is given by the dynamics of labour costs, that is by wage inflation adjusted by productivity. The international determinant of the "cost-push" factors is an important focus of this work. We want to allow for the possibility that low frequency movements in international factor prices affect trend inflation, making the latter more difficult to control by monetary policy. Imported intermediate inputs are the most direct proxy of the effect of intensive international input-output linkages, as consequence of globally fragmented production chains. Intensive trade in intermediate inputs should shrink the portion of marginal

[5]We use the series of industrial supplies and materials as proxy for intermediate inputs. In the appendix we summarise the code for all variables.

cost originated domestically and possibly exerts downward pressures to inflation in the long-run. Finally, to control for movements in oil and commodity prices, we explicitly disentangle intermediate inputs from oil prices in the international component. Thus, we propose the following linear decomposition:

$$\bar{\pi}_t^{pce} = \underbrace{(1-\delta)\bar{\pi}_t^e}_{\text{monetary}} + \delta\big[\underbrace{\alpha(\bar{\pi}_t^w - \Delta\bar{a}_t)}_{\text{domestic}} + \underbrace{\beta\bar{\pi}_t^m + \gamma\bar{\pi}_t^o}_{\text{imported}}\big], \tag{6}$$

where we restrict $\alpha + \beta + \gamma = 1$. The coefficient δ captures the pass-through effect of these "cost-push" components on trend inflation that are not directly integrated into long-term inflation expectations. When $\delta = 0$, trend inflation depends only on long-term inflation expectations, that therefore is the only determinant of trend inflation. A large literature convincingly argued that inflation expectations deviate from the full-information benchmark and non-negligible forecast errors could be due to informational frictions (see Coibion et al., 2018, for a survey of this literature). Following the hypothesis that GVCs have shaped inflation dynamics (e.g., Borio and Filardo, 2007; Auer et al., 2017, 2019; Forbes, 2019), we allow for the possibility that globalisation has produced not only short/medium run business cycle effects, but also shifts in the long-run component of inflation, reflecting the slow-moving changes in the functioning of global production networks.

δ determines the difference of inflation expectations from trend inflation. It can be interpreted as a measure of how much agents fail (or sluggishly adjust in a dynamic sense) in integrating these cost-push/supply side components of trend inflation in their long-term inflation expectations. We allow for this de-anchoring between long-term inflation expectations and the statistical measure of trend inflation to depend either on domestic wage pressure or on low frequency movements of international factor prices. The parameters α, β and γ weight the relative importance of these three components. With this specification, we allow the data to tell us whether supply side cost-push factor are important in shaping trend inflation dynamics and whether there is an important international component in it. However, it is important to note that the data could in principle reject that assumption by estimating a negligible role for this components, i.e., a minuscule δ.

Assumptions on Λ in (1). Λ plays a central role for the purpose of decomposing trend inflation into slow-moving factors. In particular, Λ is sparse and the coefficients in (6) are the loadings that impose the long-run relationship between inflation and its three orthogonal components (Appendix A.2 shows the Λ matrix). Each coefficient is estimated using Metropolis-Hastings. We assume δ to be distributed according to a beta distribution centered around 0.2. This prior is tightly in favour of a state of the world in which monetary policy leaves little room to other sources of low frequency fluctuations. Hence, if there will be strong evidence for large slow-moving effects rather than monetary policy, data will eventually speak out for themselves. The priors for β and γ are centered around 0.1 and 0.2, respectively, thereby implying little room for the imported component on the slow-moving fluctuations of domestic inflation[6].

We sample 6000 draws from Gibbs algorithm and retain the last 1000 draws. Following Del Negro et al. (2017), in order to reduce the amount of variation attributed to the trends, the prior variance-covariance matrix Σ_e of the innovations in (2) is diagonal and the non-zero elements are normalized to $\frac{1}{50}$. We assume, instead, a tighter prior for the variance of the real block and unemployment rate trends and normalize to $\frac{1}{250}$. For the stationary VAR(p) describing the cyclical behaviour of the model, we set $p = 4$ and employ a Minnesota prior with the overall tightness hyperparameter set equal to 0.2, as suggested by Giannone et al. (2015). Initial conditions for trends are taken from pre-sample averages, while the prior mean for the cycles is centered around zero.

Figure 1 plots the estimated trend according to (6). Our estimate of trend inflation captures the inertial and lagging trend of long-run expectations relative to trend inflation, both in the upturn in the '70s and in the slowdown during Volcker disinflation. These results are in line with the empirical investigation in Mertens (2016) and consistent with the notion that inflation expectations became unanchored from trend inflation during the '70s and early '80s - δ, in fact, is estimated to be equal to 47%.[7] However, we don't provide here an explanation of why the trend in long-term inflation expectations adjusted only sluggishly and lagged behind in incorporating into expectations the importance of these factors in influencing actual trend inflation dynamics. The empirical results of Coibion and Gorodnichenko (2012, 2015b), Mertens and Nason (2020), and Nason and Smith (2020), which are consistent with models of informational frictions in survey responses, provide a plausible possible explanation for the difference between the trend in inflation expectations and the one in actual inflation. The estimate of trend inflation in Figure 1 falls below 2% from the mid '90s, showing a significant drop until early '2000s and then a steady recovery towards 2% till 2011, followed by a persistent drop thereafter. The trend in inflation expectations, instead, is consistently above the trend in actual inflation and it is extremely well-anchored around the inflation target of 2%, showing the power of the inflation target regime in shaping

[6]Recall that the kernel of the beta distribution is equal to

$$p(\varkappa; a, b) \propto \varkappa^{a-1}(1-\varkappa)^{1-b},$$

where a and b are the shape parameters, which are chosen so to imply the prior means mentioned in the main text.

[7]This would have not been possible in a specification defining trend inflation as the common long-run component between inflation rate and 10-years expectations. In fact, in such specification the estimated trend would have essentially been adherent to observable data on 10-years expectations.

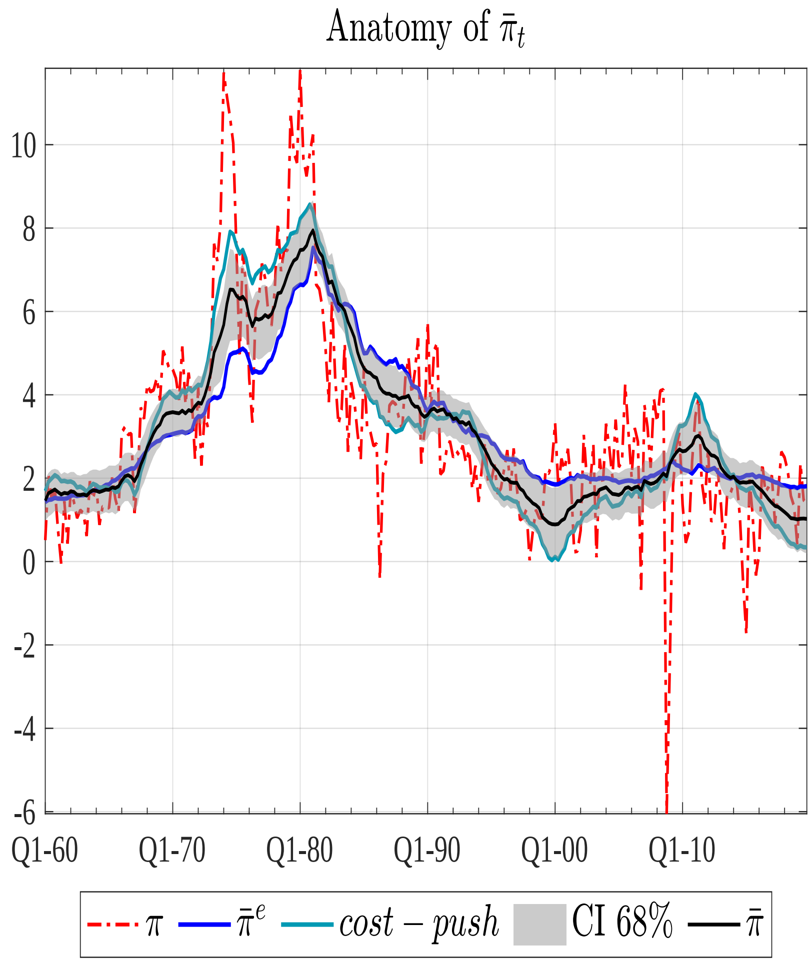

Figure 1: Trend inflation and its monetary and cost-push components.

long-term inflation expectations.[8] Regarding the cost-push factors, Figure 1 shows that their slow moving dynamics drive both the upturn of trend inflation in the pre-Volcker period and the sharp dip afterwards.

Figure 2 focuses on trend inflation dynamics over the last 30 years. Two main facts emerge. First, as said, from mid-'90s the trend in expectations is firmly anchored at the 2% target. Second, the dynamic of trend inflation, however, is different. While it is roughly at the target level in the first decade of the '2000, it is pushed persistently below target by the cost-push trend inflation in the '90s and then again after 2011. Hence, from the '90s the dynamic of trend inflation is dominated by movements in the cost-push component, which exerted a deflationary pressure on trend inflation, unanchoring the dynamics of trend inflation from the target and from the trend in inflation expectations.

[8]Again these patterns are consistent with the results in Mertens (2016).

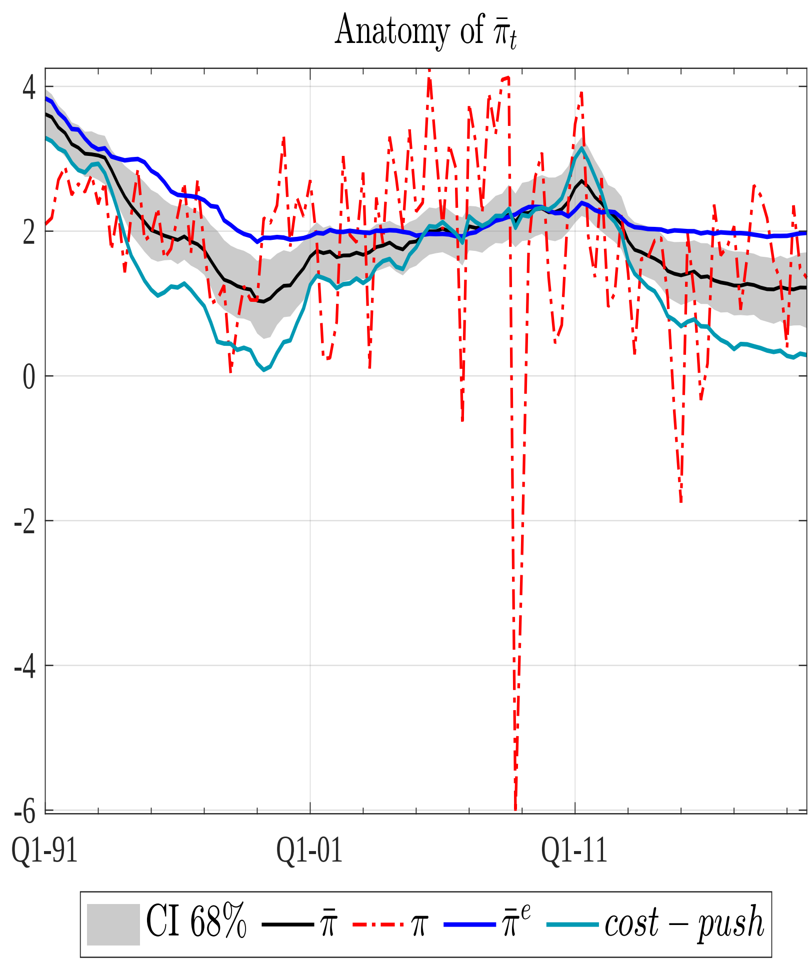

Figure 2: Trend inflation and its monetary and cost-push components, 1991Q1-2019Q4.

Our analysis provides a measurement of the relative importance of these factors: wages, oil and imported intermediate goods. The international component significantly contributes in shaping the slow moving dynamics of the overall cost-push factors, because the estimated relative share of the imported factor is roughly 50%, since $\alpha = 50\%, \beta = 25\%$ and $\gamma = 25\%$. Moreover, we find no evidence of significant time variation in these coefficients when we estimate the model for the pre- and post-Volcker sample. Figure 3 disentangles the respective role of the domestic and imported cost-push factors. The imported trend inflation - blue line - is always below the domestic component - red line throughout the whole sample. Figure 3 provides evidence that the strong deflationary pressure on trend inflation derives entirely from the international component, starting already from mid-'80s and particularly so from the mid-'90s onward. This is roughly the period in which China embraced globalization becoming an increasingly important hub in international trade - the China shock. Branstetter

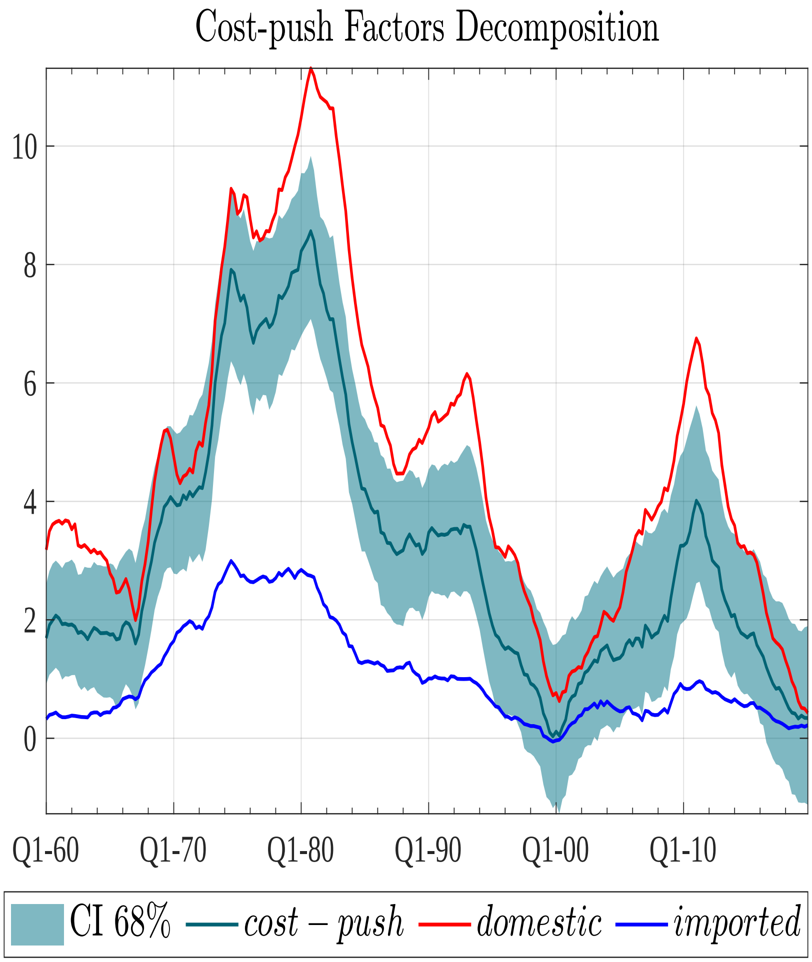

Figure 3: The cost-push component of trend inflation and its domestic and imported components.

and Lardy (2008) document the rapid growth of Chinese exports in the decade prior to WTO accession and the dramatic acceleration of liberalization of trade and foreign direct investment (FDI) in the mid-'90s. Coase and Wang (2012) argue that important reforms at the beginning of the '90s enabled the emergence of a common national market, imposing the discipline of competition to economic agents and state-owned enterprises, and thus paving the way for the transformation of the China economy.[9]

Overall the results show that the decline of U.S. trend inflation from the '80s has been driven both by substantial improvements in monetary policy, leading to more anchored

[9] After the famous "southern tour" of Dei Xiaoping in 1992, China implemented price reform in 1992, tax reform in 1994, and began to privatize state enterprises in the mid-1990s. See also, e.g., Storesletten and Zilibotti (2014) and Autor et al. (2016).

	$\tilde{u}$	$\tilde{y}$	$\tilde{i}$	$\tilde{c}$
$\tilde{u}$	-	-0.988	-0.988	-0.941
$\tilde{y}$		-	0.993	0.95
$\tilde{i}$			-	0.95

Table 1: Correlations between unemployment gap, output gap and investment gap.

inflation expectations, and by a dominant deflationary role of the international price of intermediate goods.

5 Inflation Dynamics and the Business Cycle

This section focuses on the stationary block of the model and analyses the business cycle behaviour of inflation, filtered by the potential noise arising from lower frequencies. In the remainder of this section we present the results on: (i) the cyclical measures of real economic activity; (ii) the flattening of the slope of the Phillips curve; (iii) the disconnection of inflation dynamics from real activity; (iv) the (non flattening) slope of the wage Phillips curve; (v) the spectral density analysis.

5.1 A Common Business Cycle Index

A key feature of our trend-cycle decomposition is that we do not impose any structural assumptions on the relations between cyclical components. For instance, we do not relate output gap to unemployment gap by means of a semi-structural Okun's law as often done in the literature. We leave the cycles unconstrained and let the data speak out for themselves. Notwithstanding, Figure 4 shows that the estimated cyclical components of real variables - unemployment, output, investments and consumption - clearly share a common pattern, suggesting that business cycle fluctuations are originated from a common propagation mechanism. All four cyclical estimates share very similar patterns, and are basically the mirror images of unemployment gap. The estimation retrieves an interchangeable measure of business cycle slack without imposing any structure to the model. This is confirmed, indeed, by table 1, which shows as the gaps in the real variables are perfectly correlated.

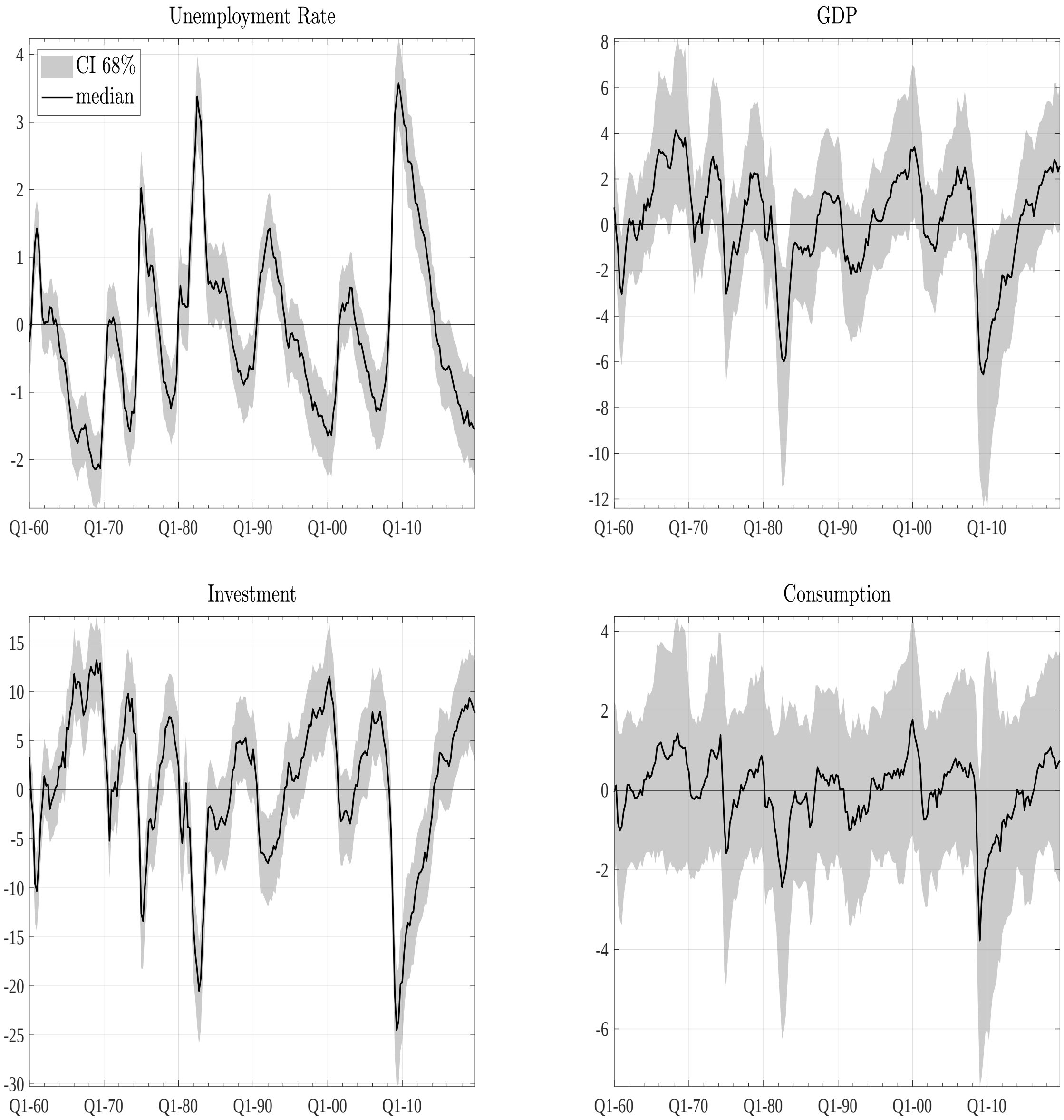

Figure 4: The cyclical components of unemployment, output, investment and consumption.

5.2 The Flattening of the Phillips Curve

Figure 5 displays two panels one for the period spanning from 1960Q1 to 1984Q4 and from 1991Q1 to 2019Q4, respectively.[10] Each panel plots the estimated unemployment and inflation gaps one on top of the other for the two sample periods under consideration. Inflation and unemployment closely track each others in the first sample, while less so in the second one.

[10] The second sample starts in 1991, because we use the the 1985Q1-1990Q4 time window as pre-sample training for the estimation.

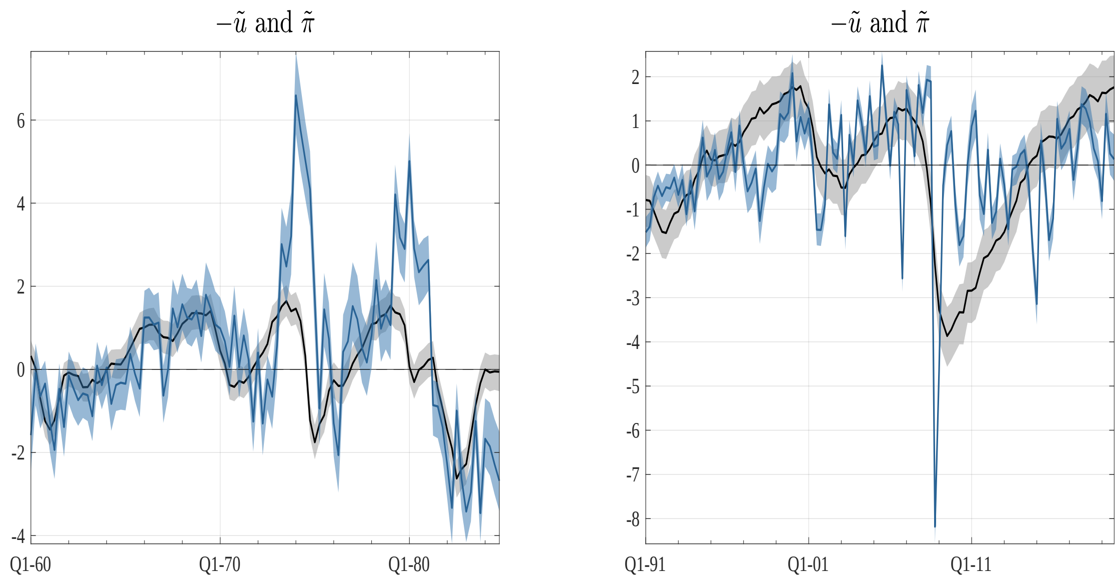

Figure 5: The cyclical components of unemployment (solid black line) and inflation (solid blue line). Shaded areas refer to 68% credibility bands. Left panel: 1960Q1-1984Q4 ; right panel: 1991Q1-2019Q4.

The scatter plot in the left-hand panel in Figure 6 visualizes a steep relationship between the inflation gap and the unemployment gap in the pre-Great Moderation period. While we do not perform a structural estimation of a Phillips curve, the graph provides evidence of a Phillips curve type of relationship. Note that as our approach has already filtered out the low frequencies, the cyclical components estimated with Kalman filter naturally lend themselves to get an estimate of a reduced-form of Phillips curve relationship that should concern the cyclical components.[11] The scatter plot in the right-hand panel of Figure 6 shows a much flatter relationship between the inflation gap and the unemployment gap in the Great Moderation period, in accordance with the evidence in the literature about the flattening of the Phillips Curve. While the results clearly shows evidence of a flattening of the Phillips curve, the next Section takes a step further to analyze its causes.

5.3 The Inflation Rate Disconnect Puzzle

To shed further lights on the Phillips Curve relationship between inflation and unemployment, we employ a methodology based on the analysis of impulse response functions presented in Uhlig (2003) (see also Giannone et al., 2019). This methodology extracts the linear combination of reduced-form shocks which maximizes the forecast error variance de-

[11]Think about the standard NK Phillips Curve, in which variables are usually expressed in log-deviation from trend.

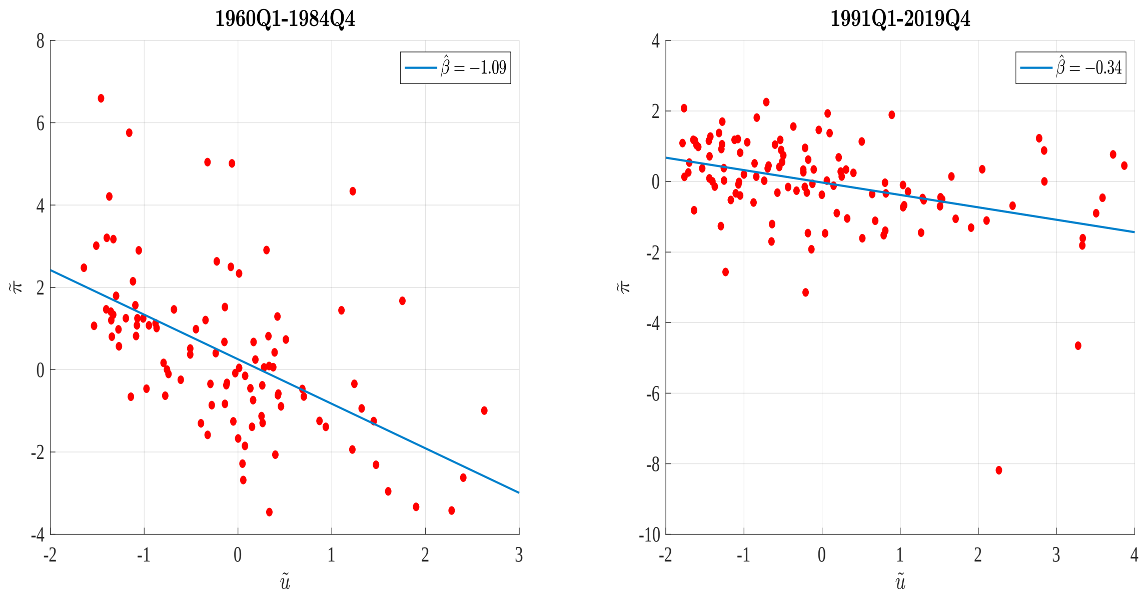

Figure 6: Scatter plot of the cyclical components of unemployment. Left panel: 1960Q1-1984Q4 ; right panel: 1991Q1-2019Q4.

composition (FEVD) of one specific variable over some interval horizon. In a recent work, Angeletos et al. (2020) revisit Uhlig's (2003) methodology to identify what they label the "main business cycle shock" (MBC shock), which drives most of the FEVD of all the main real variables - output, consumption, investment and hours - at business cycle frequencies.[12] This MBC shock determines a common propagation mechanism, because the estimated IRFs of the main real variables are highly interchangeable and share the same pattern, no matter which real variable's FEVD is targeted. The high correlations displayed in Figure 4 between the cyclical measures of real variables suggest we might be able to find similar results, so that this methodology naturally applies to our identified cyclical components.[13] In contrast with Angeletos et al. (2020), however, our main purpose is to use this methodology to investigate the relationship between inflation dynamics and the business cycle in the domestic real variables.

Consider the 1960Q1-1984Q4 subsample first. Figure 7 plots the impulse response functions (IRFs) of a shock targeting the FEVD of the unemployment gap over the 6Q-32Q horizon. This shock produces a mild positive response of output and consumption, but the probability bands are large and contain zero. Hence, for this subsample the procedure finds it difficult to identify a common propagation mechanism as in Angeletos et al. (2020). However, here the focus is on the dynamics of inflation and on to what extent this shock reflects a sound Phillips curve relationship, rather than on the identification of a main force driving

[12] They estimate the model in the frequency domain and focus on business cycle bands 6Q-32Q.

[13] Angeletos et al. (2020) do not distinguish trend and cyclical components.

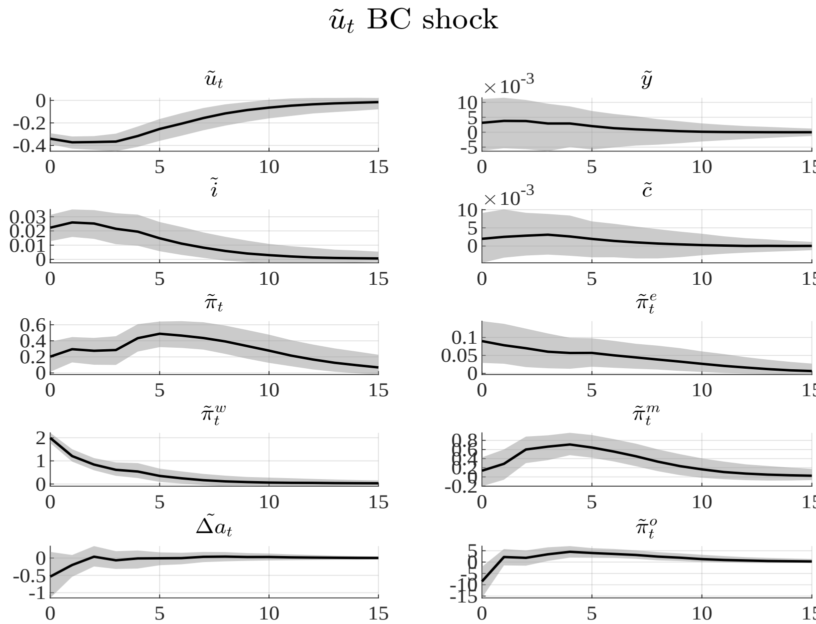

Figure 7: IRFs maximising the FEVD of $\tilde{u}$. Sample 1960Q1-1984Q4; median response and 68% uncertainty band.

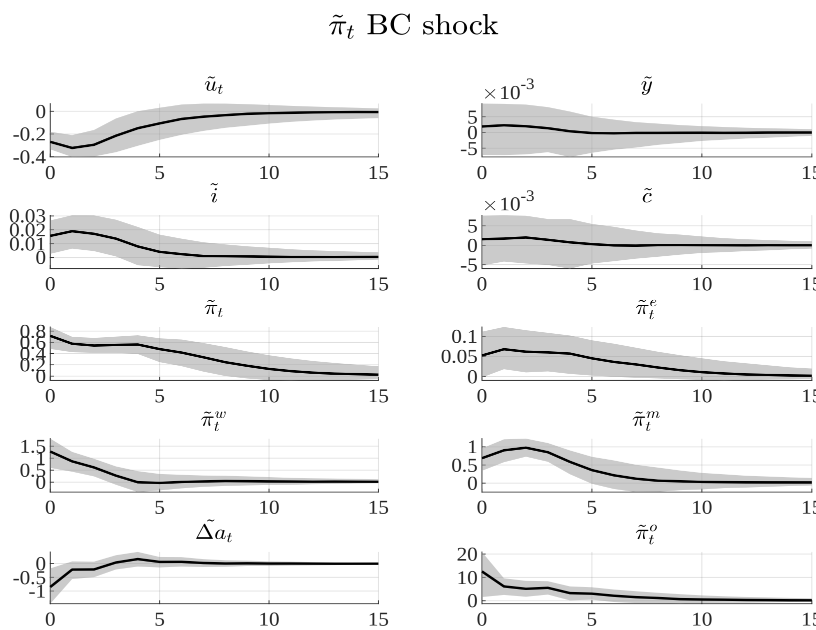

Figure 8: IRFs maximising the FEVD of $\tilde{\pi}$. Sample 1960Q1-1984Q4; median response and 68% uncertainty band.

real business cycle fluctuations. The response of inflation gap is, indeed, positive and dies out around quarter 15. Moreover, Table 2 shows that the shock explains 45% of the total cyclical variance of inflation and 70% of wages variance. Thus, this “unemployment shock”, that maximizes the FEVD of the unemployment gap, singles out a shock that generates inflationary pressures. Moreover, the bands for output and consumption, even if they contain zero, have more mass on the positive side and the response of investment is significantly positive. Hence, one might argue that the “unemployment shock” looks like an investment shock, as the MBC in Angeletos et al. (2020).

We now apply the same reasoning to extract the shock that maximises the FEVD of inflation gap. The IRFs are reported in Figure 8, and they show a similar pattern to the previous Figure 7. The exception is the opposite behaviour of the oil and imported intermediate goods inflation for the two different shocks identified in Figure 7 and 8. It is likely that a mix of supply and demand shocks drove inflation dynamics in this period. In any case, Table 2 shows again a strong link between labour market and inflation gap, because this “inflation shock” explains 47% and 35% of the FEVD of the unemployment gap and wage gap, respectively. Hence, though the procedure does not identify distinctly a unique common force generating business cycle fluctuations for this sub-period, the procedure points to well-functioning wage and price Phillips curves, tying the dynamics of wages and prices to the local labour market.

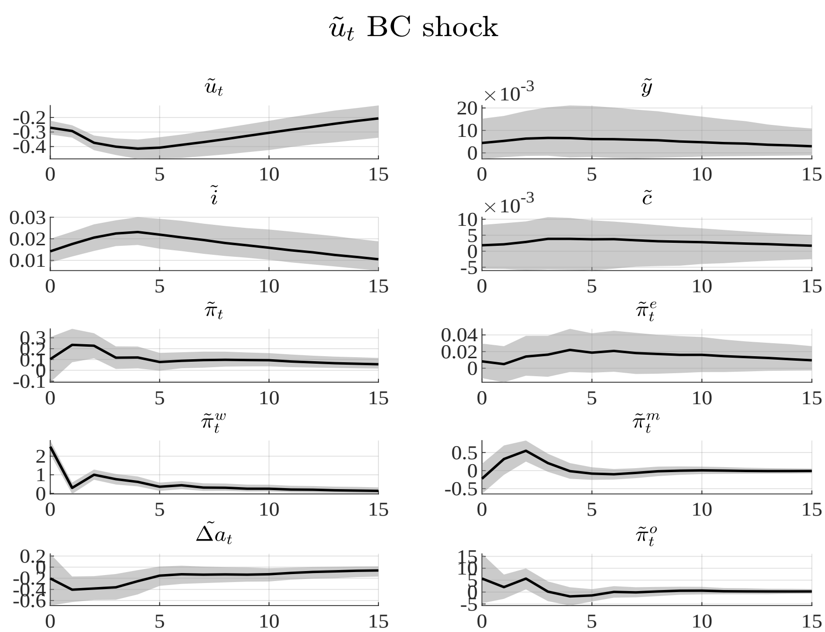

Figure 9: IRFs maximising the FEVD of $\tilde{u}$. Sample 1991Q1-2019Q4; median response and 68% uncertainty band.

Let us now move to the second subsample spanning from 1991Q1 to 2019Q4. Figure 9 exhibits the IRFs to the shock maximising the FEVD of unemployment gap over busi-

Table 2: Forecast error variance decomposition. 68% uncertainty band in squared brackets.

1960Q1-1984Q4				
		$\tilde{u}_t$ **shock**		
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{c}_t$	$\tilde{\pi}_t$
0.8502	0.2253	0.5408	0.1837	0.4504
[0.8152,0.8799]	[0.1404,0.3518]	[0.4418,0.6310]	[0.1145,0.2777]	[0.3631,0.5287]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{a}_t$	$\tilde{\pi}_t^o$
0.4254	0.6976	0.3491	0.0705	0.1502
[0.3109,0.5292]	[0.6537,0.7405]	[0.2841,0.4210]	[0.0487,0.0975]	[0.1125,0.1998]
		$\tilde{\pi}_t$ **shock**		
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{c}_t$	$\tilde{\pi}_t$
0.4723	0.1710	0.2911	0.1601	0.6871
[0.3305,0.6158]	[0.1059,0.2650]	[0.1962,0.4045]	[0.1041,0.2283]	[0.6358,0.7357]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{a}_t$	$\tilde{\pi}_t^o$
0.3077	0.3481	0.4897	0.1040	0.2323
[0.2010,0.4239]	[0.2357,0.4608]	[0.4284,0.5542]	[0.0717,0.1485]	[0.1795,0.3010]

1991Q1-2019Q4				
		$\tilde{u}_t$ **shock**		
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{c}_t$	$\tilde{\pi}_t$
0.9368	0.3632	0.8153	0.2885	0.1699
[0.9212,0.9512]	[0.1978,0.6345]	[0.7631,0.8504]	[0.1761,0.4418]	[0.1226,0.2259]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\Delta\tilde{a}_t$	$\tilde{\pi}_t^o$
0.3275	0.6131	0.0970	0.1428	0.0668
[0.2064,0.4976]	[0.5548,0.6688]	[0.0746,0.1259]	[0.1042,0.1884]	[0.0492,0.0900]
		$\tilde{\pi}_t$ **shock**		
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{c}_t$	$\tilde{\pi}_t$
0.0604	0.0798	0.0901	0.0981	0.7166
[0.0365,0.1052]	[0.0561,0.1154]	[0.0590,0.1390]	[0.0685,0.1369]	[0.6758,0.7533]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\Delta\tilde{a}_t$	$\tilde{\pi}_t^o$
0.0919	0.1045	0.4703	0.1063	0.6218
[0.0637,0.1272]	[0.0803,0.1343]	[0.4289,0.5164]	[0.0854,0.1282]	[0.5858,0.6515]

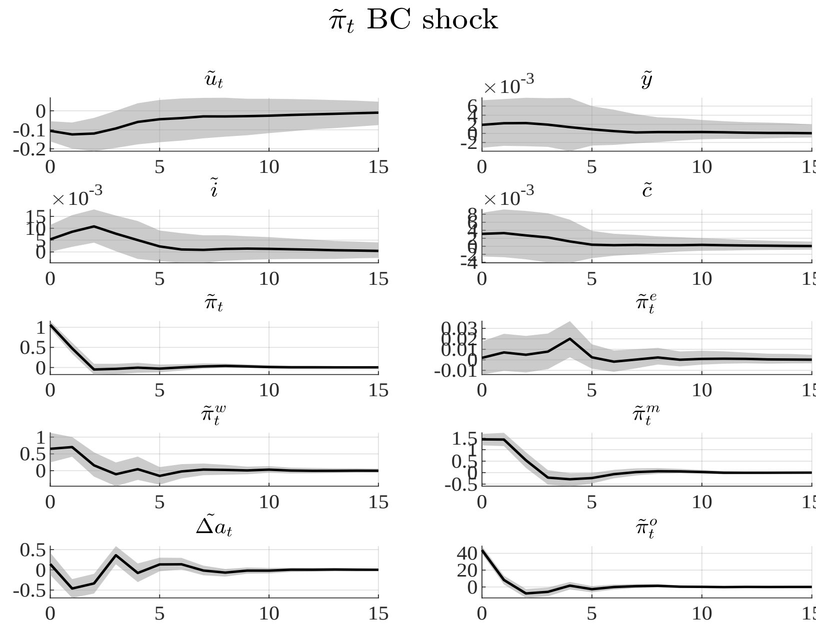

Figure 10: IRFs maximising the FEVD of $\tilde{\pi}$. Sample 1991Q1-2019Q4; median response and 68% uncertainty band.

ness cycle frequencies. The procedure identifies what could be interpreted as an investment shock, as it moves all the real variables (despite the bands are very large for output and consumption and include zero), wage and price inflation in the opposite direction with respect to unemployment. Table 2 confirms that the real block shows a strong co-movement. The shock, in fact, characterises approximately 94% of the total volatility of the unemployment gap, 82% of the investment gap, 36% of output gap and 30% of consumption gap. Moreover, if we change the target variable from the unemployment gap to output or investment gaps we recover the same results, meaning that the procedure is able to identify a common propagation mechanism - i.e., the MBC in the words of Angeletos et al. (2020) - generating the main bulk of business cycle fluctuations in real variables. Furthermore, the IRFs for the wage inflation gap suggests that this shock generates a labour demand shift that translates into a strong positive response of wages. Table 2 shows that this "unemployment shock" generates about 60% of wages total fluctuations, suggesting that the labour market is still a good barometer for business cycle. However, in contrast with the previous subsample, wages do not produce inflationary pressure. The response of the inflation gap to this shock is more muted and the portion of variance of the inflation gap explained by the shock has declined by approximately two thirds. In the lights of these results, we can exclude that the poor response of inflation is due to a structural change in the labour market that would make it an unreliable indicator of economic slack. While wages do respond to unemployment fluctuations, the wage pass-through to inflation has sensibly declined over time. Other studies report a similar results, see Coibion and Gorodnichenko (2015a), Galí and Gambetti (2019), Forbes (2019), Del Negro et al. (2020) and Heise et al. (2020).[14] We will investigated further this result in Section 5.4. Note that the muted response of inflation can not be due to an aggressive or improved monetary policy reaction, as suggested by McLeay and Tenreyro (2020) among others. As a matter of fact, our analysis features conditional correlations and therefore, the unemployment gap should have also remained closed conditional to the "unemployment shock", if an improved monetary policy was the reason behind the inflation muted response.

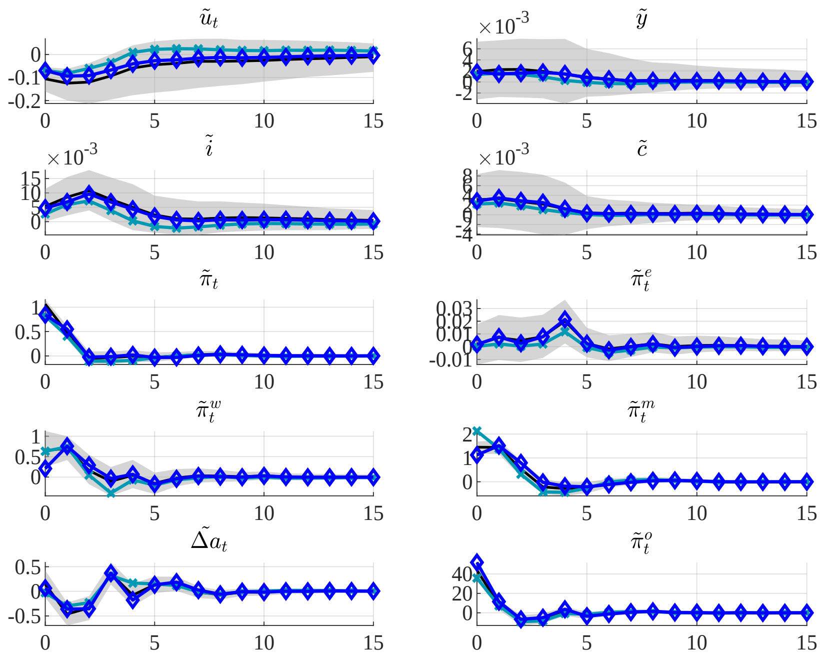

Figure 11: IRFs maximising the FEVD of $\tilde{\pi}$ (black –), $\tilde{\pi}^m$ (green -×-) and $\tilde{\pi}^o$ (blue -◇-). Sample 1991Q1-2019Q4; median response and 68% uncertainty band.

Inflation, therefore, seems to have become increasingly exogenous to the business cycle behaviour of measure of economic slack, suggesting a disconnection with the local labour market. And yet it moves: how? To understand the drivers of inflation at business cycle frequencies, Figure 10 plots the impulse responses to the shock that maximises the variance of inflation gap over the business cycle. The responses to this shock - which explains approximately 70% of domestic inflation gap total variance - reveal a disconnection between

[14]Similar results have been found on Euro area inflation by Conti et al. (2019), who claim that inflation has become inelastic to the wage pass-trough stemming from an aggregate demand shock.

the real side and the price side over the business cycle. First, this shock is essentially orthogonal to the real side of the economy because the output and consumption reactions are not significant, investment only marginally so, and the unemployment one is mildly negative with a large significance band. Second, this shock generates a strong positive - and precisely estimated - co-movement between domestic inflation, imported intermediate inputs inflation and oil inflation. The results in Table 2 are even more striking: the "inflation shock" explains a negligible part of domestic fluctuations and of wage inflation - 8-13% -, while it explains a large part of the international measures of prices inflation, i.e., 47% of the variance of imported intermediate goods- $\tilde{\pi}_t^m$ - and 62% of the one of oil prices - $\tilde{\pi}_t^o$. Hence, in the second subsample, our procedure distinguishes two different propagation mechanisms of the business cycle. First, a MBC shock - as in Angeletos et al. (2020) - responsible for the main bulk of volatility in real variables and the labour market, including wage inflation, but with a very limited wage pass-through effect to price inflation. Second, an "inflation shock" that characterises the cyclical behaviour of domestic inflation and that originates from imported international prices. Heise et al. (2020) attribute the decrease of the wage pass-through to U.S. inflation to the increased imported competition that reduces domestic firms ability to change prices of final goods in response to fluctuations in the domestic labour market, thus, focusing more on the demand side. By looking, instead, at prices of intermediate goods and of oil, we provide evidence that there is also an important supply side part to the explanation, as international cost-push factors affect firms costs and thus domestic inflation. Our results should be seen as complementary to the ones in Heise et al. (2020) and not alternative. To further corroborate this evidence, we look at the impulse responses generated from a shock maximising the cyclical variance of either imported intermediate inputs inflation or oil inflation. If the strong co-movement between domestic inflation and international prices originates by a common international shock, then these impulse responses should be interchangeable to the one in Figure 10 and explain approximately the same amount of business cycle volatility of these three variables. Figure 11 shows that all three set of responses are almost perfectly correlated. The results, thus, validate this hypothesis of a common international mechanism characterising the cyclical behaviour of all the three measures of prices. Both identifications generate at least 45% of total fluctuations in domestic inflation and less than 10% of the real block of the model (see Appendix A.6.3).

Finally, the IRFs demonstrate the success in anchoring long-term inflation expectations accomplished by the switch in the Fed's monetary policy regime across the two subsample. In the first subsample the inflation expectations gap, i.e., $\tilde{\pi}_t^e$, reacts in a very similar way to the inflation gap to both shocks identified in Figure 7 and 8. In contrast, in the second subsample the inflation expectations gap barely moves at all (in terms of the median response) and not significantly so. The inflation expectations gap in the second subsample seems also disconnected from the two identified shocks in Table 2 (while in the first subsample the "unemployment shock" explains roughly 42% of its variability). Besides, the unconditional standard deviation of $\tilde{\pi}^e_t$ is 0.23 in the first subsample and 0.075 in the second subsample, showing a dramatic decrease of its volatility around its trend - which as we saw in Section 4 was stabilized in the Great Moderation sample too.

Overall, the takeaways from the impulse response analysis can be summarised as follows. First, in the 1960Q1-1984Q4 sample, the link between inflation and domestic economic slack was strong. Second, in the 1991Q1-2019Q4 sample, the procedure identifies a MBC shock - as in Angeletos et al. (2020) - that looks like an investment shock and that generates most of the volatility in the real block and in the labour market variables. Third, in this subsample, the propagation mechanism of the MBC does not translate into inflationary pressures. Fourth, wage dynamics do not transmit to inflation in the second subsample. Therefore, the lower responsiveness of inflation is not due to changes in the labour markets, as wage inflation is still tightly linked to the other measures of economic slack, as we show in the next Section. Fifth, while disconnected from the dynamics of domestic real and labour market variables, the cyclical behaviour of inflation is subject to the same international forces driving changes in international prices of intermediate inputs and oil prices. These results suggest that the share of inflation dynamics explained by domestic variables has decreased substantially, while it grew in importance the cost-push component generated internationally that affects domestic inflation dynamics via international linkages. Finally, there is evidence of a strong anchoring of inflation expectations in the second subsample.

5.4 The Wage Phillips Curve is Alive and Well

This Section shows that the labour market conditions are still a reliable barometer of business cycle temperature that materializes in wage pressure also in the post-'90s sample. As a result, the flatness of the price Phillips Curve is not due to a flat wage Phillips Curve.

Recently, there has been a growing interest in exploring the hypothesis of a flatter wage Phillips curve relationship. Galí and Gambetti (2019), for instance, test this hypothesis by estimating a VAR with time-varying parameters, and provide evidence against the flattening of the wage Phillips curve. We estimate the shock that maximises the cyclical variance of wages over business cycle frequencies. Had the relationship between wages and unemployment stayed strong also in the second subsample, that is, had the slope of the wage Phillips Curve remained constant and steep, we should observe wage dynamics to share the same main sources of fluctuations of the unemployment gap in both subsamples. Figure 12 and 13 plot the responses to the shock that maximises the FEVD of $\tilde{\pi}^w_t$ for the 1960Q1-1984Q4 and the 1991Q1-2019Q4 periods, respectively. On top of these responses, we also plot the impulse response functions to the shock that maximises the FEVD of the unemployment gap, $\tilde{u}_t$, - from Figures 7 and 9, respectively. The plots visualize the presence of an unique common underlying propagation mechanism, suggesting a strong link between $\tilde{\pi}_t^w$ and $\tilde{u}_t$ in both subsamples. Hence, the flattening of the wage Phillips curve is rejected in the data, providing additional evidence against the hypothesis of a change in the functioning of the labour market as being responsible for a flattening of the Phillips curve.

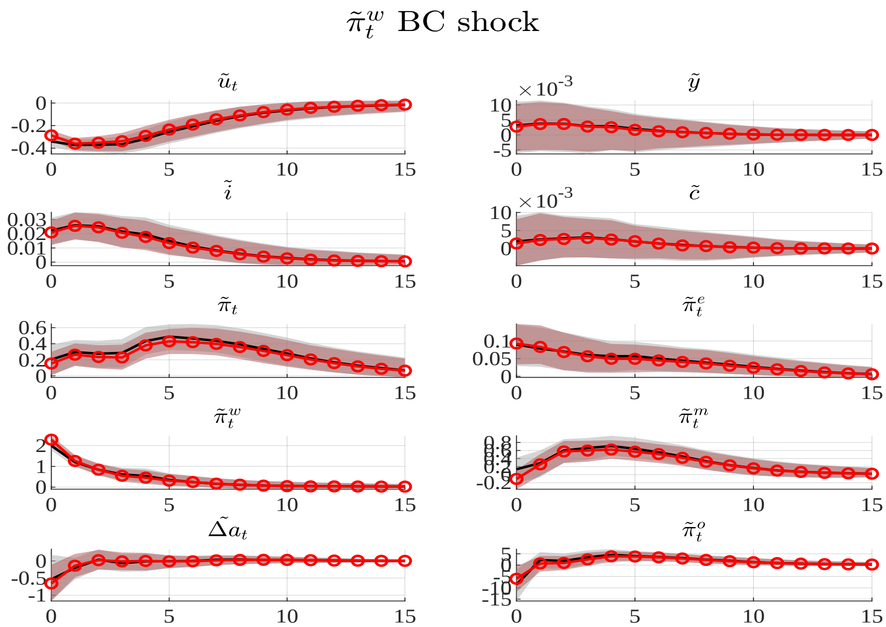

Figure 12: IRFs maximising the FEVD of $\tilde{\pi}^w$ (red -○-) and $\tilde{u}$ (black −). Sample 1960Q1-1984Q4; median response and 68% uncertainty band.

5.5 Further Evidence From Spectral Analysis

Cycles are by construction zero-mean covariance stationary processes, thus they are suitable candidates for spectral analysis. Spectral analysis is an alternative way of representing the autocovariance structure of an economic time series, mapping it from the time domain into the frequency domain, by means of the Fourier transform. The estimation of the theoretical spectrum is not a trivial task, as the periodogram is an unbiased but inconsistent estimator. For this reason is necessary the appropriate application of a window function which smooths the estimate. For sake of synthesis the discussion on windowing and spectral estimation is left to the online appendix. We perform the spectral analysis to corroborate further the above results. First, the analysis provides an additional robustness check of the loosening of

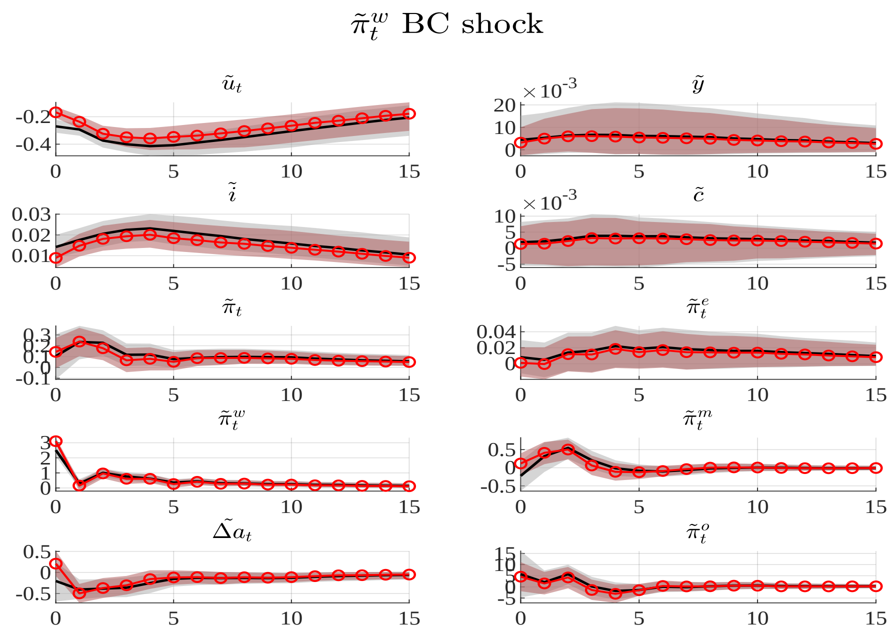

Figure 13: IRFs maximising the FEVD of $\tilde{\pi}^w$ (red -○-) and $\tilde{u}$ (black −). Sample 1991Q1-2019Q4; median response and 68% uncertainty band.

the relationship between the unemployment gap and the inflation gap since the '90s. Second, if the cyclical behaviour of inflation is originated by a shared propagation mechanism with international prices, then the volatility peak should be tuned on the approximately the same frequencies. The same intuition applies for real variables, so our prior is that they are all tuned on the same frequencies, as well.

Figure 14 plots the spectral densities for unemployment and inflation gap over the two samples. The first column compares the spectral densities over the 1960Q1-1984Q4 sample. Unemployment and inflation gap are approximately synchronized on the same frequencies and the peak for both variables occurs at Q25. In contrast, when analysing the 1991Q1-2019Q4 sample (second column of Figure 14), the variance peak of unemployment gap occurs around Q40, suggesting a more persistent behaviour of unemployment in the Great Moderation era. This result is consistent with a recent work of Beaudry et al. (2020), who run a spectral analysis on labour market variables, finding that the variance peak of unemployment realizes after roughly 40Q. Moving to inflation gap, it seems hard to clearly detect a global peak. However, it seems that most of the fluctuations materializes at much higher frequencies compared with unemployment gap.

Figure 15 visualizes the spectral density of imported intermediate inputs inflation for the two subsamples. Comparing them to the densities of domestic inflation clearly emerges that the two variables are synchronized on the same frequencies. For sake of brevity, the spectral

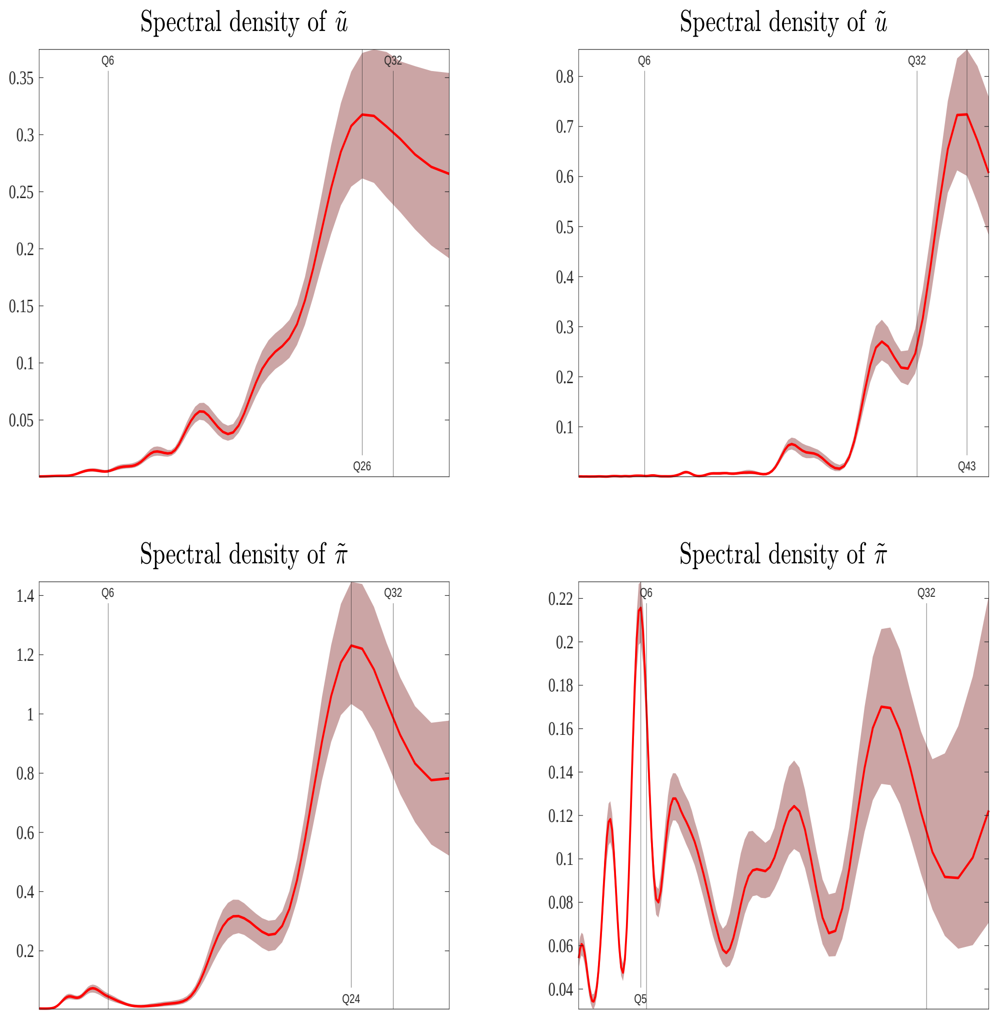

Figure 14: Spectral densities of $\tilde{u}$ and $\tilde{\pi}$. First column: sample 1960Q1-1984Q4; the second column: sample 1991Q1-2019Q4.

density of oil price is relegated to Appendix A.6.2.

Finally, Figure 16 also plots the spectral densities of real variables for the second subsample, that corroborates once more the hypothesis of a common propagation mechanism.[15] Despite the large uncertainty bands, Figure 16 shows that all the gaps in the real variables exhibit the same timing of the realization of the variance peak as the unemployment gap, thus supporting the existence of the MBC as Angeletos et al. (2020). Wage inflation exhibits a peak after 32Q, providing additional evidence in support of an alive-and-well wage Phillips Curve.

To sum up, the main takeaways from the spectral analysis can be summarised as follows. Firstly, the unemployment gap and the inflation gap shared the frequency peak, when

[15] The results hold also for the first subsample, see Appendix A.6.2.

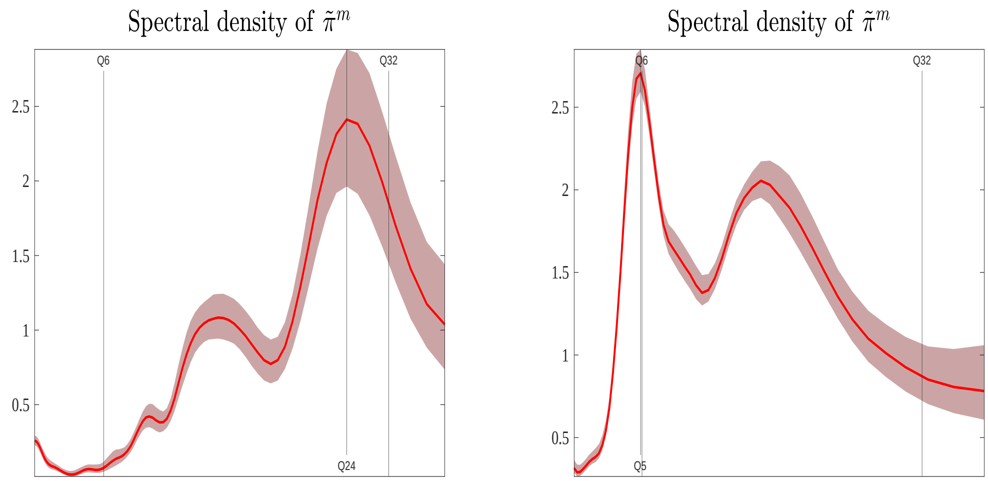

Figure 15: Spectral density of $\tilde{\pi}^m$. Left panel: sample 1960Q1-1984Q4; right panel: sample 1991Q1-2019Q4.

considering the pre-Great Moderation era. In contrast, since 1990s, their fluctuations peak at very distant frequencies, implying a disconnection between the two variables. Secondly, domestic inflation and imported inflation spectrum peaks are steadily synchronised throughout the two samples. Last but not least, all the gaps in real variables, and to some extent in wage inflation, exhibit their variance peak at the same frequencies of unemployment gap, supporting labour market variables as good barometers of business cycle temperature.

6 Concluding Remarks

This paper proposes a novel approach to study the role of international factors contributing both to the decline of trend inflation and to the flatness of the slope of the Phillips curve. We implement a multivariate unobserved component analysis, which enables to explicitly isolate the frequencies of interest and then analyse the trend and the cycle independently.

In the analysis of the slow-moving drivers of inflation, we allow for the presence of common stochastic trends and propose an anatomy of trend inflation, dissecting trend inflation into different low-frequency components. Our anatomy distinguishes between domestic and international - imported intermediate goods - determinants of trend inflation. The results attribute the decline in trend inflation observed from the mid-'80s to the monetary policy regime switch toward explicit targeting and to the dynamics of international prices of imported intermediate goods.

From the analysis on the stationary block of the model several facts emerge. First, the Phillips Curve relationship between the unemployment gap and the inflation gap shows a

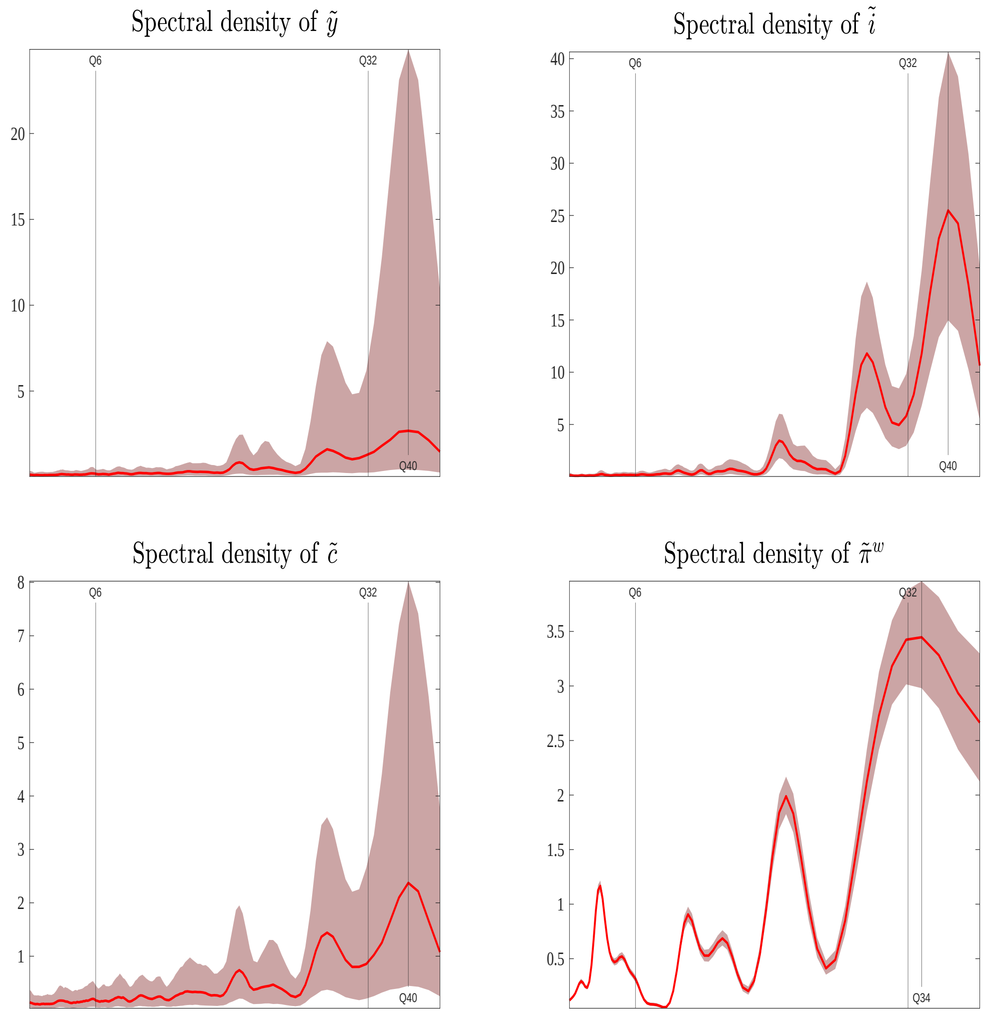

Figure 16: Spectral densities of the main real variables and of $\tilde{\pi}^w$. Sample 1991Q1-2019Q4.

strong flattening over time. Second, the impulse response analysis in the 1991Q1-2019Q4 sample uncovers two main components of business cycle. First, in accordance to the results in Angeletos et al. (2020), there is a common propagation mechanism among the cyclical components of the main real variables, i.e., a MBC shock that looks like an investment shock. However, this shock is non-inflationary. This is mainly attributable to the fact that the transmission channel from wage to inflation dynamics has broken down in this subsample - while was active in the 1960Q1-1984Q4 sample. The labour market has remained relatively stable over time and, thus, a reliable barometer of business cycle temperatures. The muted response of inflation is neither due to an aggressive monetary policy reaction, nor to a structural change in the local labour market dynamics. As a matter of fact, our analysis features conditional correlations and, therefore, the unemployment gap should have also remained closed had it been monetary policy the reason behind the inflation muted response.

Second, the business cycle behaviour of inflation in the 1991Q1-2019Q4 sample is mainly characterised by a shock originating abroad, which generates the main bulk of volatility in international prices of intermediate goods and is orthogonal to the domestic slack. Therefore, we conclude that, in the sample 1991Q1-2019Q4, domestic inflation disconnected from the local labour market and increasingly co-moved with the prices of imported intermediate inputs and oil, through international linkages. Overall, the international component of inflation should not only be considered as a business cycle phenomenon, but should rather be deemed to leave long-run scars on the level of inflation.

To conclude, our empirical exercise calls into question the room for effective monetary policy interventions. If inflation is no longer tied to domestic the labour market, to what extent central banks can steer inflation to the target? We leave this question to future research.

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A Appendix

A.1 Data

All data is available in FRED website with the exception of total factor productivity and long-run inflation expectations. The growth rate of TFP is downloaded from Fernald dataset and the series is the utilization-adjusted TFP. The long-run PCE inflation expectations are obtained from the Survey of Professional Forecasters from 2007 onward, while for the period from 1970 to 2006, we use the survey-based long-run (5- to 10-years ahead) PCE inflation expectations series of the Federal Reserve Board's FRB/U.S. econometric model.[16] All nominal

Table 3

DATA	CODE
Unemployment Rate	UNRATE
Real Gross Domestic Product per capita	A939RX0Q048SBEA
Gross Domestic Product	GDP
Gross Private Domestic Investment	GPDI
Personal Consumption Expenditures: Durable Goods	PCDG
Real personal consumption expenditures per capita: Nondurable goods	A796RX0Q048SBEA
Real personal consumption expenditures per capita: Services	A797RX0Q048SBEA
Personal consumption expenditures (implicit price deflator)	DPCERD3Q086SBEA
10-year ahead PCE expected inflation rate	
Compensation of Employees: Wages and Salary Accruals	WASCUR
Imports of goods: Industrial supplies and materials, except petroleum (chain-type price index)	B649RG3Q086SBEA
Spot Crude Oil Price: West Texas Intermediate (WTI)	WTISPLC
Total Factor Productivity (Growth rate)	DTFPu

variables, namely PCE inflation, long-run expected inflation rate, wage inflation, imported intermediate input inflation, oil inflation are expressed in annualized rates. Real investment per capita is the sum gross private domestic investment and durable goods multiplied by real GDP per capita and divided by nominal GDP. Real consumption per capita is the sum of real consumption of non-durable and services per capita. Finally, all variables but unemployment rate are in logs.

[16] The log-run inflation expectations series is the same used by Del Negro et al. (2017) and is available at https://github.com/FRBNY-DSGE/rstarBrookings2017.

A.2 Definition of Λ.

$$\begin{bmatrix} u_t \\ y_t \\ i_t \\ c_t \\ \pi_t \\ \pi_t^e \\ \pi_t^w \\ \pi_t^m \\ \pi_t^o \\ \Delta a_t \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & (1-\delta) & \delta\alpha & \delta\beta & \delta\gamma & -\delta\alpha \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}}_{\Lambda} \begin{bmatrix} \bar{u}_t \\ \bar{y}_t \\ \bar{i}_t \\ \bar{c}_t \\ \bar{\pi}_t^e \\ \bar{\pi}_t^w \\ \bar{\pi}_t^m \\ \bar{\pi}_t^o \\ \Delta\bar{a}_t \end{bmatrix} + \Phi(L) \begin{bmatrix} \tilde{u}_t \\ \tilde{y}_t \\ \tilde{i}_t \\ \tilde{c}_t \\ \tilde{\pi}_t \\ \tilde{\pi}_t^e \\ \tilde{\pi}_t^w \\ \tilde{\pi}_t^m \\ \tilde{\pi}_t^o \\ \Delta\tilde{a}_t \end{bmatrix} \quad \text{(A1)}$$

A.3 Gibbs Sampler For The Estimation of The VAR

The model is estimated employing a Gibbs sampler, which is structured into two steps:

1. The algorithm draws from the joint distribution $\bar{y}_{0:T}, \tilde{y}_{-p+1:T}, \lambda | c, \phi, \Sigma_e, \Sigma_\varepsilon, y_{1:T}$, which is given by the product of the marginal posterior of λ conditional on the other parameters $\lambda | c, \phi, \Sigma_e, \Sigma_\varepsilon, y_{1:T}$:

$$p(\lambda | c, \phi, \Sigma_e, \Sigma_\varepsilon, y_{1:T}) \propto L(y_{1:T} | \lambda, c, \phi, \Sigma_e, \Sigma_\varepsilon) p(\lambda)$$

   Since the conditional posterior of λ does not have an analytical form, we implement a Metropolis Hastings step. The posterior of the states $\bar{y}_{0:T}, \tilde{y}_{-p+1:T}$ conditional on λ and the other parameters is estimated using Durbin and Koopman (2002)'s simulation smoother to draw the latent states.

2. The second step involves the estimation of the two VARs. The constant drift for the real variables is assumed to have independent prior $c \sim \mathcal{N}(0, 10^3)$. The posterior distribution of c and Σ_e are given by:

$$\Sigma_e | \bar{y}_{0:T} \sim \mathcal{IW}(\underline{\Sigma}_e + \hat{S}_e, \kappa_e + T),$$

   where $\hat{S}_e$ is the sum of squared errors of the latent trends. The posterior distributions of the coefficients of the stationary VAR are given by:

$$\Sigma_\varepsilon | \tilde{y}_{0:T} \sim \mathcal{IW}(\underline{\Sigma}_\varepsilon + \hat{S}_\varepsilon, \kappa_\varepsilon + T)$$
$$p(\phi | \Sigma_\varepsilon, \tilde{y}_{0:T}) \sim \mathcal{N}(vec(\hat{\Phi}), \Sigma_\varepsilon(\tilde{X}\tilde{X}' + \underline{\Omega}^{-1})^{-1}),$$

   where $XX' = \sum_{t=1}^{T} \tilde{x}_t \tilde{x}_t'$, $\hat{S}_\varepsilon = (\tilde{X}\tilde{X}' + \underline{\Omega}^{-1})^{-1}(\tilde{X}\tilde{\boldsymbol{y}} + \underline{\Omega}^{-1}\underline{\Phi})$, $\hat{S}_\varepsilon = \boldsymbol{\varepsilon}\boldsymbol{\varepsilon}' + (\Phi \hat{-} \underline{\Phi})'\underline{\Omega}^{-1}(\Phi \hat{-} \underline{\Phi})$ and $\boldsymbol{\varepsilon} = \tilde{\boldsymbol{y}} - \hat{\Phi}'\tilde{X}$.

A.4 Identification Scheme

As we navigate in the time domain universe, the identification of structural shocks follows Uhlig (2003). The reduced-form VAR of cyclical components is given by:

$$\tilde{\chi}_t = C(L)\varepsilon_t \qquad \varepsilon_t \sim N(0_n, \Sigma_\varepsilon) \tag{A2}$$

where $C(L) = \Phi(L)^{-1}$ and $\varepsilon_t = A\upsilon_t$ composite innovations. Let A be the impulse matrix obtained from some decomposition of the Σ_ε:

$$E[\varepsilon_t\varepsilon_t'] = \Sigma_\varepsilon = AE[\upsilon_t\upsilon_t']A' = AA'$$

Now, assume $\hat{A}$ being an alternative decomposition of Σ_ε. For sake of simplicity let $\hat{A}$ be the Cholesky triangular factor, such that:

$$\Sigma_\varepsilon = \hat{A}\hat{A}'$$

Then, there must exist an orthonormal matrix Q that enables to reconcile $\hat{A}$ with A:

$$A = \hat{A}Q \tag{A3}$$

Now, the k-th step ahead forecast error is given by:

$$\epsilon_{t+k} = \sum_{i=0}^{k} \hat{B}_i Q \upsilon_{t+k-i} \tag{A4}$$

where $\hat{B}(L) = C(L)\hat{A}$. The variance covariance matrix of the k-th step ahead forecast error is given by $\Sigma_\varepsilon(k) = \sum_{i=0}^{k} \hat{B}_i\hat{B}_i'$. It is possible to further decompose the variance so to get the contribution of the j-th shock:

$$\Sigma_\varepsilon(k,j) = \sum_{i=0}^{k} (\hat{B}_i q_j)(\hat{B}_i q_j)' \tag{A5}$$

The goal is to find the impulse vector that maximizes the forecast error variance of the selected variable over a specific frequency band, say $[\underline{k}, \overline{k}]$, as follows:

$$\begin{aligned} \sigma_\varepsilon^2(\underline{k}, \overline{k}; q_1) &= q_1' \left(\sum_{k=\underline{k}}^{\overline{k}} \sum_{i=0}^{k} \hat{B}_i'\hat{B}_i \right) q_1 \\ \sigma_\varepsilon^2(\underline{k}, \overline{k}; q_1) &= q_1' \mathcal{S} q_1 \end{aligned} \tag{A6}$$

Recall that q_1 is a column of the orthonormal matrix Q, so it must be orthonormal itself. Finally, if we write the program in its Lagrangian form:

$$\mathcal{L}(q_1) = q_1'\mathcal{S}q_1 - \lambda[q_1'q_1 - 1]$$
$$\text{F.O.C.:}$$
$$\mathcal{S}q_1 = \lambda q_1.$$

The problem eventually boils down to an eigenvector-eigenvalue problem. Hence, the orthonormal vector q_1 is the eigenvector associated with the largest eigenvalue of the forecast error variance over a specific frequency interval.

A.5 Refresh on Spectral Density Estimation

Take zero-mean covariance stationary random variable y_t and compute its sample autocovariance function:

$$\hat{\gamma}_y(j) = \frac{1}{T}\sum_{t=j+1}^{T}(y_t - \bar{y})(y_{t-j} - \bar{y}),$$

where $\bar{y} = \frac{1}{T}\sum_{t=1}^{T} y_t$ is the sample mean. The sample autocovariance is the object we will plug into the Fourier transform to express the atucovariance structure of y_t as function of waves. In other words, we will make use of the Fourier transform to map the autocovariance structure from the time domain to the frequency domain. Let us first discuss the estimation of univariate spectra and then move to the bivariate case. The theoretical spectrum is retrieved by means of the discrete Fourier transform:

$$f_y(\omega) = \frac{1}{2\pi}\sum_{j=-\infty}^{+\infty}\gamma_y(j)e^{-i\omega j}$$

$\omega = \frac{2\pi k}{T}$ is the frequency (i.e.: how quickly the process oscillates). The theoretical spectral density of y_t is given by:

$$f_y(\omega) = \frac{1}{2\pi}\sum_{j=-\infty}^{+\infty}\gamma_y(j)\cos(\omega j)$$
$$f_y(k) = \frac{1}{2\pi}\sum_{j=-\infty}^{+\infty}\gamma_y(j)\cos\left(\frac{2\pi k}{T}j\right)$$

In practice, the estimation is far from being a trivial task. This is because data are finite. This implies that the empirical counterpart of the theoretical spectrum is a truncated version called periodogram:

$$\hat{f}_y(k) = \frac{1}{2\pi}\sum_{j=-(T-1)}^{(T-1)}\hat{\gamma}_y(j)\cos\left(\frac{2\pi k}{T}j\right)$$

Tough unbiased, the periodogram is an inconsistent estimator of the theoretical spectrum. To cope with the large variance associated with inconsistency, an auxiliary function is convoluted with the autocovariance so to smooth the variance. The auxiliary function is called window. Window functions are basically weighting functions and there are of different families. For the estimation of cycles' spectra in our paper we use Hamming window smoothing[17]. Once the window smoothing is applied to the periodogram, the estimator looks like:

$$\hat{f}_y(k) = \frac{1}{2\pi} \sum_{j=-(T-1)}^{(T-1)} w_k(j)\hat{\gamma}_y(j) \cos\left(\frac{2\pi k}{T} j\right)$$

[17]As robustness check, we also apply Bartlett triangular smoothing and the results do not change.

A.6 Additional Figures

A.6.1 Other Trends

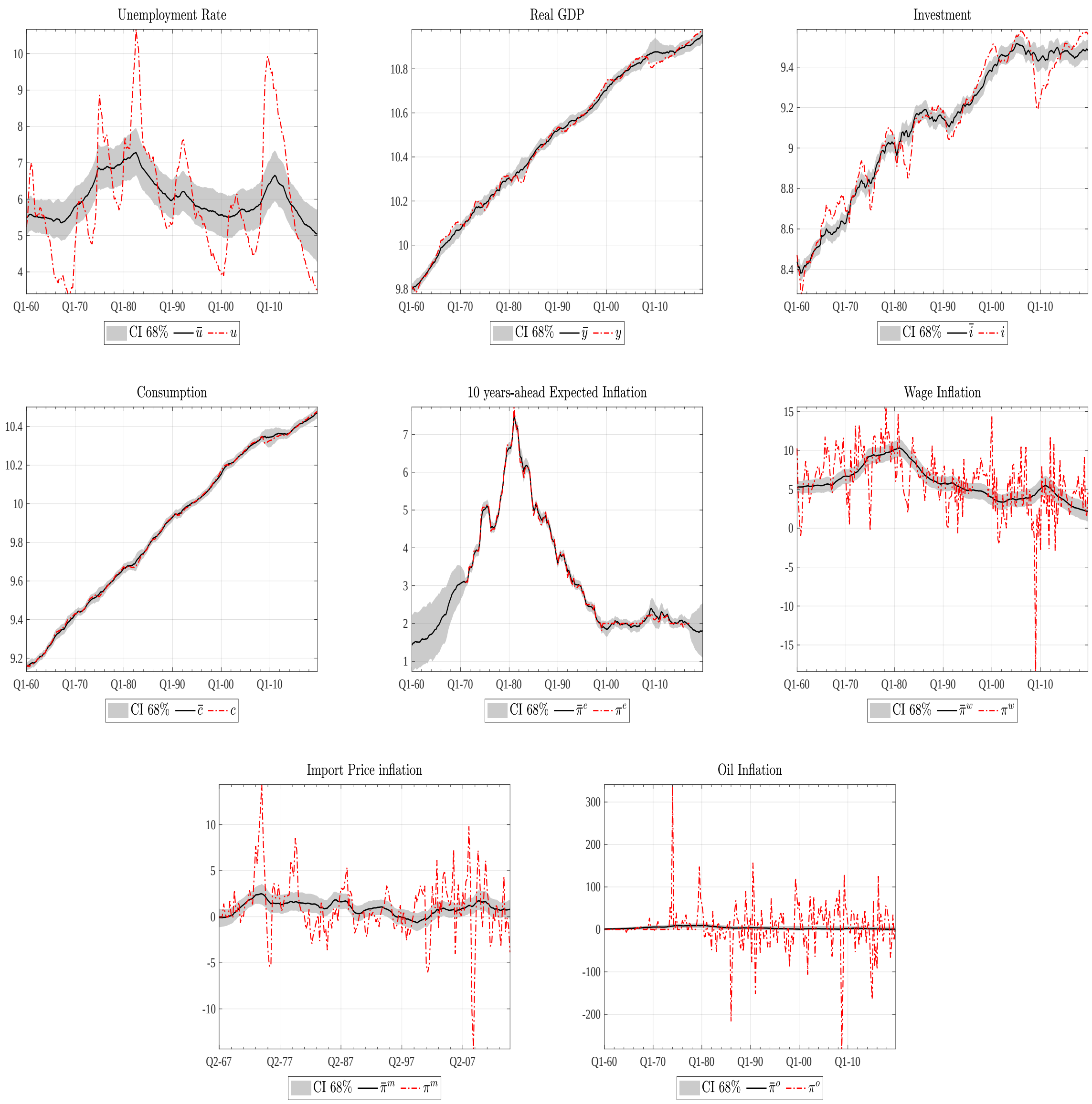

Figure 17: Estimated trends of the variables.

A.6.2 Spectral Densities

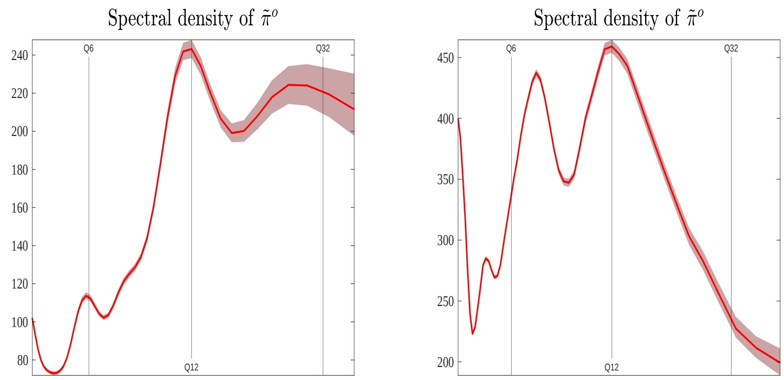

Figure 18: Spectral density of $\tilde{\pi}^o$. Left panel: sample 1960Q1-1984Q4; right panel: sample 1991Q1-2019Q4.

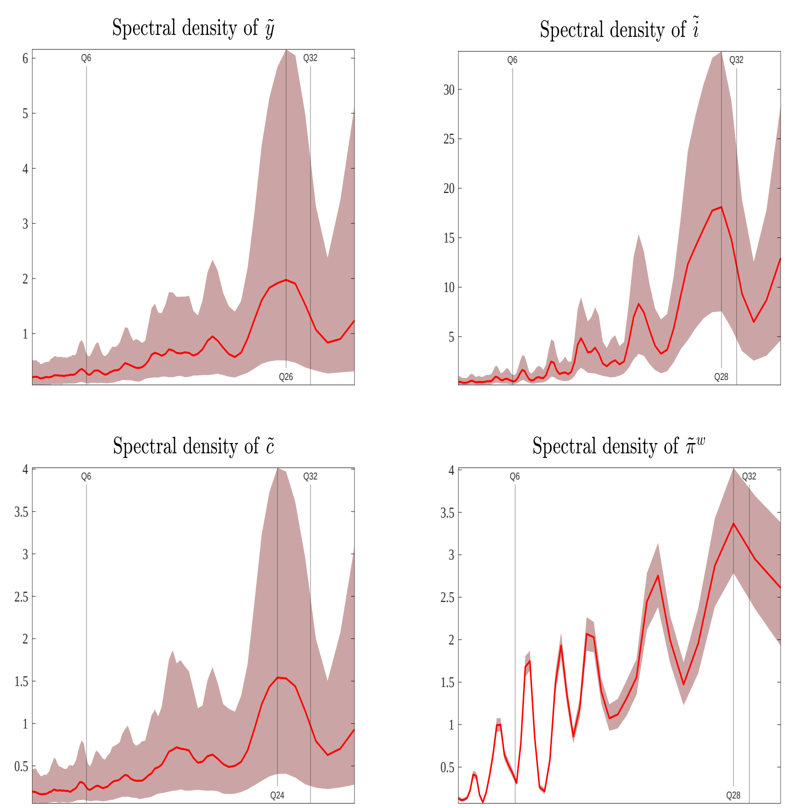

Figure 19: Spectral densities of the main real variables and of $\tilde{\pi}^w$. Sample 1960Q1-1984Q4.

A.6.3 Additional Tables

Table 4: Forecast error variance decomposition. 68% uncertainty band in squared brackets.

91Q1-19Q4				
$\tilde{\pi}_t^m$ **shock**				
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{c}_t$	$\tilde{\pi}_t$
0.0416	0.0714	0.0669	0.0814	0.4692
[0.0254,0.0701]	[0.0506,0.0996]	[0.0437,0.0980]	[0.0578,0.1121]	[0.4109,0.5217]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{a}_t$	$\tilde{\pi}_t^o$
0.0717	0.1106	0.6985	0.0813	0.4505
[0.0518,0.0990]	[0.0897,0.1362]	[0.6607,0.7353]	[0.0649,0.0979]	[0.3855,0.5180]
$\tilde{\pi}_t^o$ **shock**				
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{c}_t$	$\tilde{\pi}_t$
0.0407	0.0845	0.0755	0.1051	0.5335
[0.0235,0.0654]	[0.0578,0.1165]	[0.0513,0.1117]	[0.0751,0.1435]	[0.4976,0.5721]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{a}_t$	$\tilde{\pi}_t^o$
0.0940	0.0845	0.4373	0.1007	0.8523
[0.0705,0.1281]	[0.0672,0.1076]	[0.3963,0.4816]	[0.0807,0.1215]	[0.8272,0.8716]
$\tilde{\pi}_t^w$ **shock**				
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{c}_t$	$\tilde{\pi}_t$
0.7104	0.2803	0.6105	0.2257	0.1366
[0.6409,0.7727]	[0.1640,0.4600]	[0.5301,0.6816]	[0.1505,0.3290]	[0.0959,0.1805]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{a}_t$	$\tilde{\pi}_t^o$
0.2453	0.7914	0.0837	0.1270	0.0537
[0.1660,0.3641]	[0.7629,0.8176]	[0.0592,0.1088]	[0.1000,0.1581]	[0.0402,0.0700]

Table 5: Forecast error variance decomposition. 68% uncertainty band in squared brackets.

91Q1-19Q4				
		$\tilde{y}_t$ **shock**		
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{c}_t$	$\tilde{\pi}_t$
0.2482	0.6946	0.2028	0.0710	0.0732
[0.0430,0.8564]	[0.6370,0.7641]	[0.0420,0.7112]	[0.0300,0.1777]	[0.0342,0.1417]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{a}_t$	$\tilde{\pi}_t^o$
0.0596	0.1549	0.0590	0.0640	0.0474
[0.0306,0.1470]	[0.0406,0.5088]	[0.0326,0.0909]	[0.0334,0.1107]	[0.0282,0.0773]
		$\tilde{i}_t$ **shock**		
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{c}_t$	$\tilde{\pi}_t$
0.9198	0.3477	0.8266	0.2901	0.1867
[0.8965,0.9389]	[0.1935,0.6086]	[0.7808,0.8607]	[0.1778,0.4420]	[0.1370,0.2418]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{a}_t$	$\tilde{\pi}_t^o$
0.3257	0.6030	0.1075	0.1431	0.0774
[0.1986,0.4905]	[0.5420,0.6631]	[0.0801,0.1401]	[0.1057,0.1853]	[0.0544,0.1108]
		$\tilde{c}_t$ **shock**		
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{c}_t$	$\tilde{\pi}_t$
0.1305	0.0566	0.1171	0.6395	0.0759
[0.0305,0.5558]	[0.0241,0.1459]	[0.0328,0.4753]	[0.5950,0.6916]	[0.0352,0.1383]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{a}_t$	$\tilde{\pi}_t^o$
0.0488	0.0920	0.0561	0.0501	0.0531
[0.0263,0.1176]	[0.0338,0.3118]	[0.0312,0.0930]	[0.0272,0.0926]	[0.0279,0.0932]