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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

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Guido Ascari†
De Nederlandsche Bank
University of Pavia
RCEA

Luca Fosso‡
University of Pavia

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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 BVAR decomposition explores the role of imported intermediate goods in explaining the puzzling behaviour of inflation. The trend analysis shows that, starting from the '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 a flattening of the 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

JEL Codes: C11, C32, E3, E31, E52

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†De Nederlandsche Bank, Spaklerweg 4, 1096 BA Amsterdam, Netherlands. E-mail address: guido.ascari@dnb.nl.

‡Address: Department of Economics and Management, 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 incredible effort to bring surging inflation expectations to a halt and rebuild the credibility of the 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 networks 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 of final goods, 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 curve 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 two distinct components: a domestic one due to inflation targeting anchoring long-term inflation expectations and a foreign one due to imported cost-push (supply) factor. Regarding the latter, the cyclical block of the empirical model relates the cyclical co-movements of inflation to 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 international component 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

[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.

domestic block of the model, by means of 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 substantially weakens in the period 1985Q1-2019Q4. From the results on the second subsample, two facets of the business cycle emerge: (i) a main 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 intermediate goods prices, but it is orthogonal to the domestic real variables. Overall, we find evidence of an "inflation rate disconnect puzzle", whereby inflation becomes disconnected from the domestic labor market due to a significant decline in the wage pass-through from domestic slack to U.S. inflation. 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 have progressively over time replaced 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 the global determinants of 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 rates. 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 the '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 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 measures 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-tradable 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 a low frequency supply factor 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) tested 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 has 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

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

Assume χ_t the vector of observables to be the sum of two unobserved states:

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

$\bar{\chi}_t$ describes the slow-moving (trend) dynamics due to permanent shocks. $\tilde{\chi}_t$, instead, defines the transitory (cyclical) fluctuations in the data. Λ is sparse and accommodates the presence of $q \leq n$ common trends. We leave the discussion about the assumptions on Λ to section 4, as it plays a crucial role for our work. Keep in mind, for the moment, that its elements can be either calibrated, estimated or both. Similarly to Del Negro et al. (2017) and Hasenzagl et al. (2020), trends and cycles are assumed to be stochastic and evolve according to a random walk and an reduced-form invertible VAR, respectively:

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

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

where c_t is meant to capture a common growth rate in the trends of real output and investment and is assumed to follow a random walk without drift. $\Phi(L) = I - \Phi_1 L - ... - \Phi_p L^p$ and Φ_k, for $k = 1, ..., p$, are the lag coefficients matrices of dimension $(n \times n)$. Our model is equivalent to a VAR in deviations from its steady states à la Villani (2009) with the notable difference that in this specification steady states are allowed to be time-varying. The vector embedding permanent and transitory innovations is assumed to be i.i.d. and distributed

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

according to a multivariate Normal distribution. This implies, in turn, that permanent and transitory shocks are mutually uncorrelated. The initial conditions of the unobserved states are assumed to be distributed according to:

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

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

where $\underline{y_0}$ is the pre-sample mean and V_0 is the (q x q) identity matrix. The initial condition of the cycles is a vector of zeros, as we assume that cycles symmetrically fluctuate around a zero mean. $V(\Phi, \Sigma_\varepsilon)$ is the unconditional variance of the initial conditions for cyclical components and it is always well defined as we impose stationarity on $\tilde{\chi}_t$.

Finally, the priors of the model's coefficients are distributed according to:

$$\Sigma_e \sim \mathcal{IW}(\kappa_e, (\kappa_e + n + 1)\underline{\Sigma_e}) \tag{6}$$

$$\Sigma_\varepsilon \sim \mathcal{IW}(\kappa_\varepsilon, (\kappa_\varepsilon + n + 1)\underline{\Sigma_\varepsilon}) \tag{7}$$

$$vec(\Phi)|\Sigma_\varepsilon \sim \mathcal{N}(vec(\underline{\Phi}), \Sigma_\varepsilon \otimes \underline{\Omega})\mathcal{I}(vec(\Phi)) \tag{8}$$

$\mathcal{IW}$ is the Inverse-Wishart distribution with κ degrees of freedom and mode equal to $\underline{\Sigma}$. We place a rather tight prior on the covariance matrix of permanent innovations Σ_e being diagonal, by setting the hyperparameter $\kappa_e = 100$. Notice, however, that this does not prevent the data to speak in favour of correlations among permanent innovations, if this is the case. Following Del Negro et al. (2017), the prior on the diagonal elements of Σ_e is conservative in limiting the amount of variance attributable to the trends. We do so by scaling the variances by 1/200, which implies that the standard deviation of the expected change in the trend over five decades is only 1 percentage point.

Turning to the cyclical block, the priors for the lag coefficients are standard Minnesota priors with overall tightness hyperparameter equal to 0.2 with the exception of the own-lag hyperparameter which is set equal to zero instead of 1, as we are characterising the stationary behaviour of the data. $\mathcal{I}(vec(\Phi))$ is an indicator function that is equal to value of one, if all the roots of $\Phi(L)$ are outside the unit circle, equal to zero, if the VAR is explosive. Since data are quarterly, the number of lags p in the stationary VAR is set equal to 4. Finally, the model is linear in its equations and we employ 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). The model samples 10000 draws from the Gibbs algorithm and retains the last 5000 draws.

Data. The model is estimated using the following variables in the vector χ_t : unemployment rate, u_t; real output per capita, y_t, ; real investment per capita, i_t; PCE headline inflation π_t; 10-year ahead PCE headline inflation expectations, π_t^e; wage inflation, π_t^w; imported intermediate inputs price inflation, π_t^m; oil price inflation, π_t^o.[4] Coherently with (1), a bar over a variable indicates its trend component, while a tilde its cyclical component. The sample spans from 1960Q1 to 2019Q4.

4 The Anatomy of Trend Inflation

We distinguish two determinants of the persistent component of inflation, i.e., trend inflation.[5] 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 also be potentially influenced by slow-moving "cost-push" factors, imported from abroad, that are not under full control of monetary policy. This 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 the persistent component of inflation. 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 firms' cost originated domestically and possibly exerts downward pressures to trend inflation, generating persistent deviations from the monetary trend that could not be easily offset by monetary policy. Thus, we propose the following linear decomposition:

$$\bar{\pi}_t = \underbrace{\bar{\pi}_t^*}_{\text{monetary}} + \underbrace{\lambda_\pi \bar{g}_t}_{\text{international}} \tag{9}$$

$$\bar{\pi}_t^m = \bar{\pi}_t^{m,id} + \lambda_{\pi^m} \bar{g}_t \tag{10}$$

$$\bar{\pi}_t^o = \bar{\pi}_t^{o,id} + \lambda_{\pi^o} \bar{g}_t \tag{11}$$

where $\bar{\pi}_t^*$ is the time-varying inflation target, thus we label it as the monetary component of trend inflation. As said above, this also coincides with the trend component in long-term inflation expectations, as usually assumed in this literature. $\bar{\pi}_t^{m,id}$ and $\bar{\pi}_t^{o,id}$ are the idiosyncratic slow-moving components of import prices and oil prices, respectively. $\bar{g}_t$ is the international trend that links the persistent dynamics in international factor prices to

[4]We use the series of industrial supplies and materials as proxy for intermediate inputs. The Appendix A.1 summarises the code for all variables.

[5]We use both terms - persistent component of inflation and trend inflation- interchangeably, as Koester et al. (2021).

domestic inflation. Persistent wedges between $\bar{\pi}_t$ and its monetary trend π_t^* potentially arise from $\bar{g}_t$. The prior for the loading parameters in the Λ matrix in (1), i.e., $\lambda_\pi, \lambda_{\pi^m}$ and λ_{π^o} is assumed to be Gaussian with mean 1 and standard deviation 0.5 - Appendix A.2 shows the Λ matrix.

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 persistent shifts in the long-run component of inflation. λ_π determines the difference between the persistent components of inflation expectations and of inflation. We allow for this de-anchoring between long-term inflation expectations and the statistical measure of trend inflation to depend on the low frequency movements of international factor prices. With this specification, we allow the data to tell us whether international supply side cost-push factors are important in shaping trend inflation dynamics. Nevertheless, it is worth noting that, if λ_π is equal to 0, we are back to the conventional case in which inflation is solely a monetary phenomenon in the long-run and, therefore, under full control of monetary policy.

Figure 1 plots the estimated trend according to (9). 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 the 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.[6] We do not provide here a structural 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.

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, trend in inflation expectations is consistently above the trend in actual infla-

[6] This would not be 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 essentially be adherent to observable data on 10-years expectations.

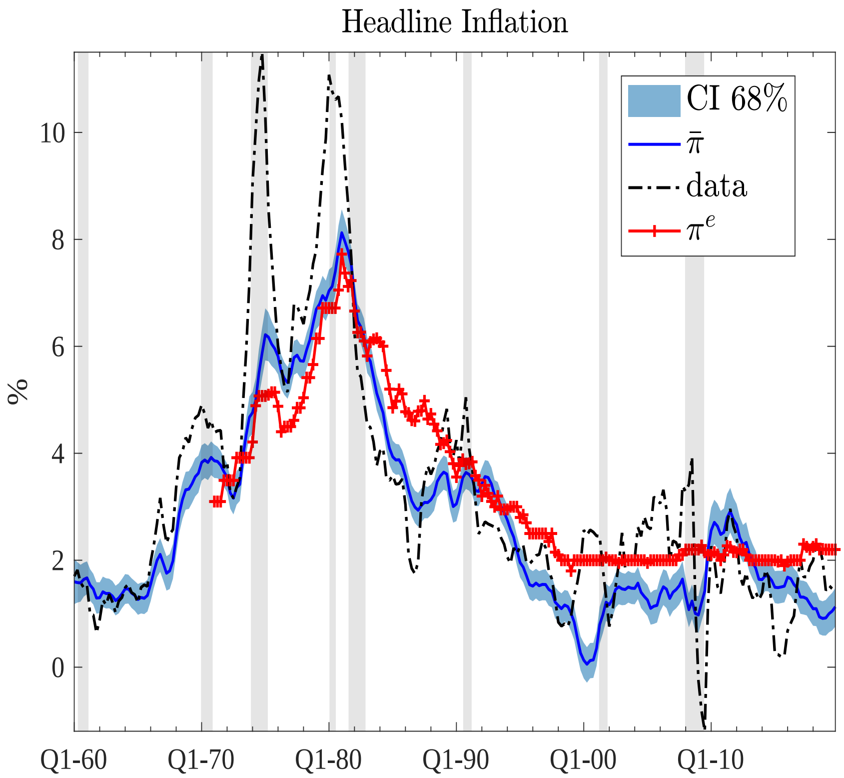

Figure 1: Trend inflation.

tion and from the late '90s it is extremely well-anchored around the inflation target of 2%, showing the power of the inflation target regime in shaping long-term inflation expectations.[7] Second, the estimate of trend inflation falls below 2% from the mid '90s, showing a significant drop until early 2000s and then a steady recovery towards 2% until 2011, followed by a persistent drop thereafter. According to our estimates, the trend in the global cost-push component explains this discrepancy between the persistent component in inflation and the one in inflation expectations. Hence, from the '90s the movements in trend inflation are dominated by movements in the cost-push component, which exerted a deflationary pressure on trend inflation, unanchoring the dynamics of trend inflation from the 2% target and from the trend in inflation expectations.

Our analysis provides a measurement of the relative importance of the global trend feeding into trend inflation. Figure 3 provides strong evidence in favour of a state of the world in which the slow-moving dynamics in international factor prices, i.e., $\bar{g}_t$, non-negligibly affect the low-frequency movements in inflation. The data could in principle reject that assumption by estimating a negligible role for this component of trend inflation, pushing λ_π towards zero.

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

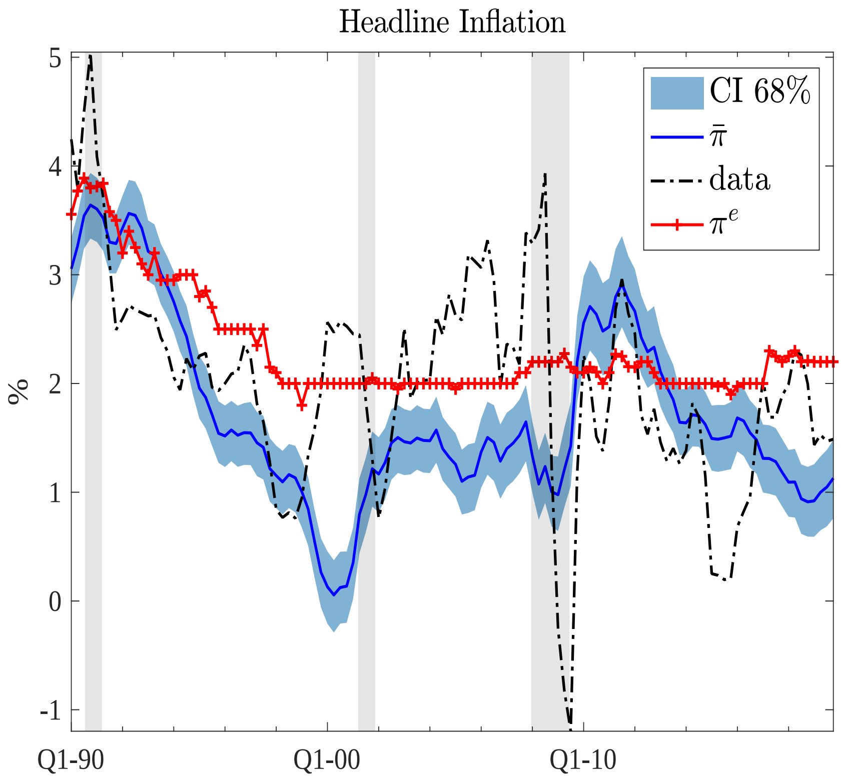

Figure 2: Trend inflation 1991Q1-2019Q4.

Table 1

	Bayes Factor
$log(\mathcal{M}_0) - log(\mathcal{M}_1)$	-6.70

The posterior distribution (blue) of λ_π, instead, moves decisively rightward and tightens, such that it does not include values smaller than 1. The posterior distributions for the other two loadings, λ_π^m and λ_π^o, tightens too, but they remain centered in 1. Overall, the posterior distributions show a strong identification and refuse the possibility that $\lambda_\pi = 0$. Further corroborating evidence is provided by the Bayes factor in Table 1 that shows that the specification $\mathcal{M}_1$, allowing for the possibility of $\lambda_\pi \neq 0$ is strongly preferred to a benchmark "monetarist" model $\mathcal{M}_0$, which imposes $\lambda_\pi = 0$.[8]

Furthermore, we find no evidence of significant time variation in these coefficients when we estimate the model for the pre- and post-Volcker sample. The strong deflationary pressure in Figure 1 derives entirely from the international component, and starts already from mid-

[8]See Jeffreys (1998) for the thresholds values.

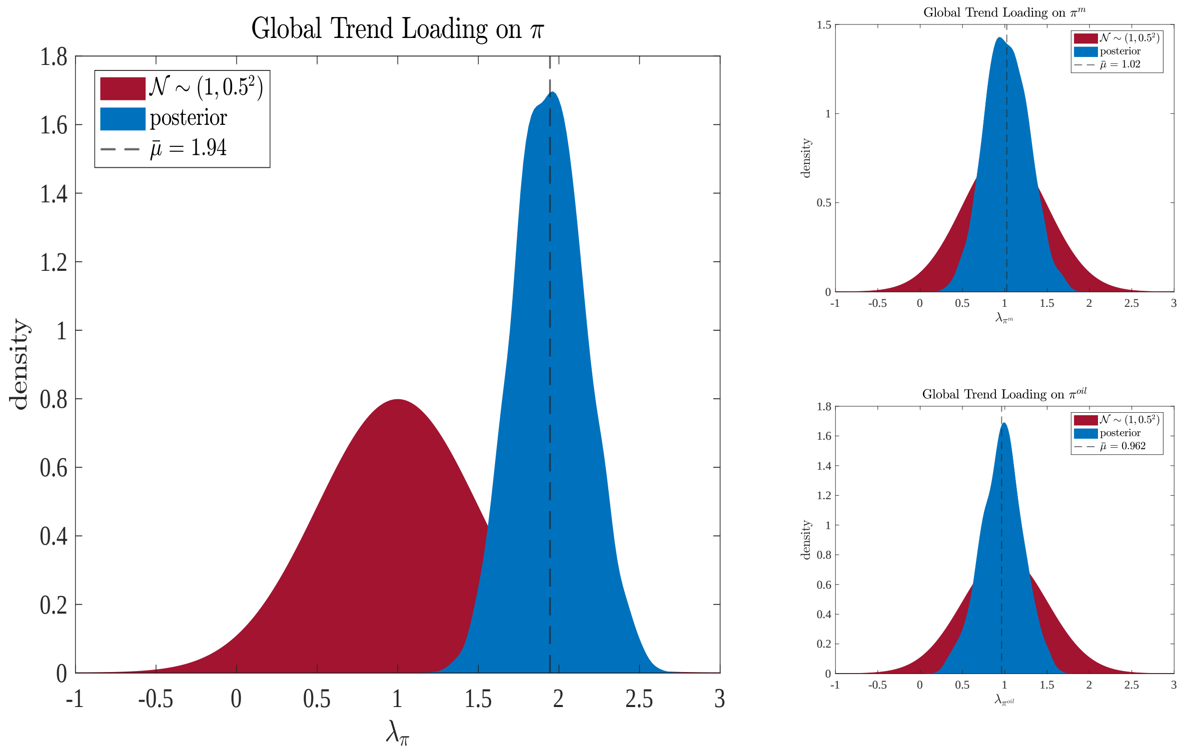

Figure 3: Prior and posterior distributions of the loadings

'80s and particularly so from the mid-'90s onward. This is roughly the period in which China embraced globalisation becoming an increasingly important hub in international trade - the China shock. Branstetter 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 in 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 inflation expectations, and by a deflationary pressure of the international price of intermediate goods.

[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).

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.

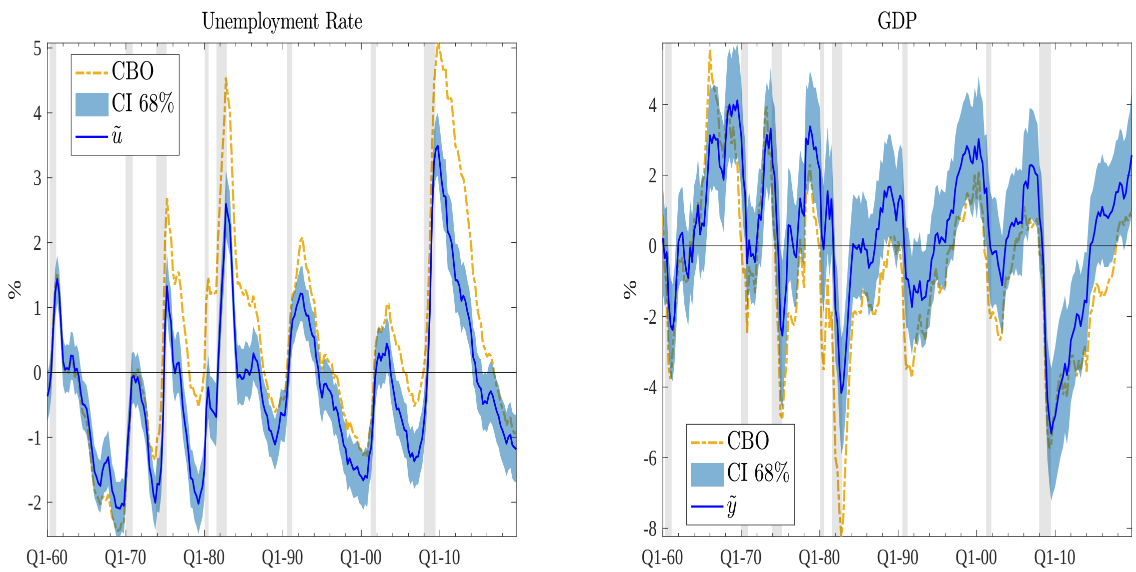

Figure 4

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 and output - clearly share a common pattern, suggesting that business cycle fluctuations are originated from a common propagation mechanism. The model retrieves two business cycle measures that are directly comparable and highly correlated with the CBO estimates of unemployment gap and output gap - yellow dashed lines in Figure 4.

5.2 The Flattening of the Phillips Curve

Figure 5 displays the reduced-form slope of the Phillips curve obtained by projecting the model consistent inflation gap onto the space spanned by unemployment gap for pre- and Great Moderation time windows. When comparing the two periods, we find that the estimated reduced-form slope has significantly declined (in absolute value) at 68% credibility level from approximately 0.73 (median of the red density) down to 0.4 (see the blue density).

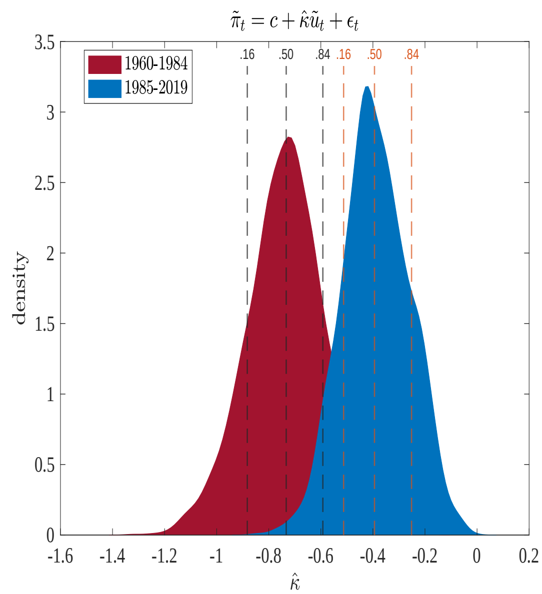

Figure 5: Distribution of the reduced-form slope of the Phillips Curve.

Additional support is provided from the two scatter plots in Figure 6, showing the relationship between the inflation gap and the unemployment gap in the two sub-periods. The scatter plot in the right-hand panel of Figure 6 exhibits a flatter relationship, in accordance with the evidence in the literature about the flattening of the Phillips Curve for the Great Moderation period. While we do not perform a structural estimation of a Phillips curve, 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, given that our approach has already filtered out the low frequencies.[10] While the results clearly shows evidence of a flattening of the Phillips curve, the next Section takes a step further to analyze its causes.

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

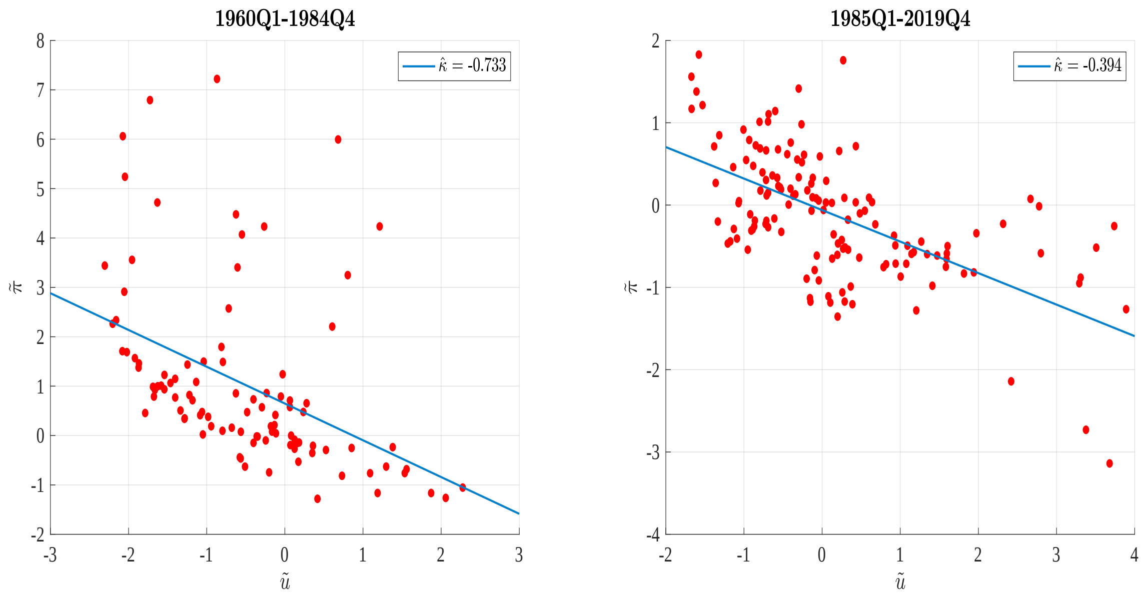

Figure 6: Scatter plot of the cyclical components of unemployment. Left panel: 1960Q1-1984Q4 ; right panel: 1985Q1-2019Q4.

5.3 The Inflation Rate Disconnect Puzzle

To shed further light on the Phillips Curve relationship, 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 convolution of reduced-form shocks which maximizes the forecast error variance (FEV) of one specific variable over some interval horizon. In a recent work, Angeletos et al. (2020) revisit Uhlig's (2003) methodology to identify a "main business cycle shock" (MBC shock) as major contributor of the co-movement in all the main real variables - output, consumption, investment and hours - at business cycle frequencies.[11] The empirical MBC shock supports the existence a common propagation mechanism in the data, because the estimated IRFs are highly interchangeable and share the same patterns, no matter which real variable's FEV is targeted. This methodology naturally applies to our identified cyclical components.[12] The high correlations displayed in Figure 4 between the cyclical measures of real variables suggest we might be able to find similar results to Angeletos et al. (2020). In contrast with Angeletos et al. (2020), however, our main purpose is to use this template to investigate the evolution of the relationship between inflation dynamics and the domestic real business cycle over time. More specifically, we are interested in understanding if the propagation mechanism linking inflation to the real side of the economy has been subject to a break leading to an "inflation rate disconnect puzzle" over the last

[11]They estimate a VAR in the frequency domain and focus on business cycle bands 6Q-32Q. We use the same business cycle band 6Q-32Q to identify the shocks in our analysis.

[12]Angeletos et al. (2020) do not explicitly model trend and cycles.

30 years. For this purpose, we retrieve and analyse the IRFs resulting from the convolution of innovations responsible for the main bulk of business cycle fluctuations of unemployment gap and inflation gap. Finally, it is worth stressing out that our approach is consistent with theory as we study the variables in deviations from their long-run equilibrium, thus, explicitly cleaning them out of their low frequency features.

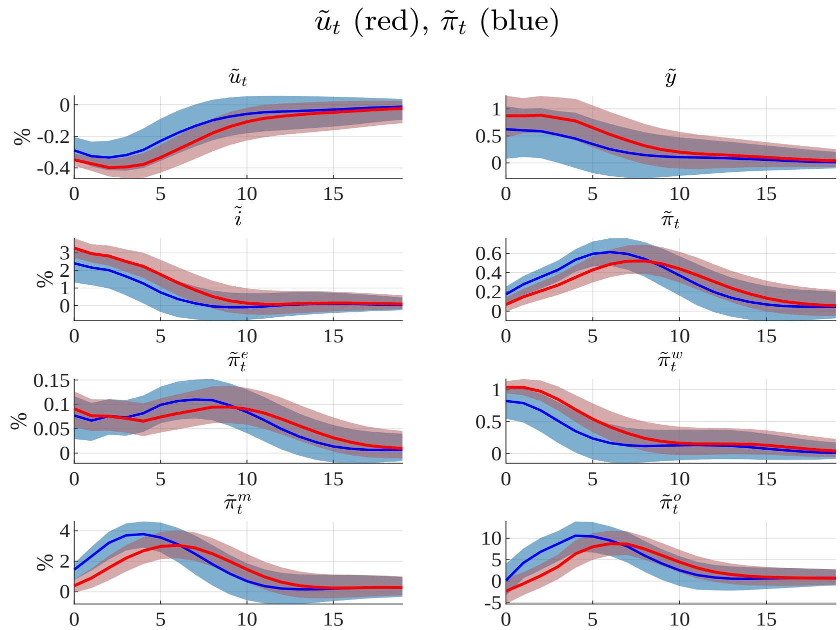

Figure 7: IRFs maximising the FEVD of $\tilde{u}$ and $\tilde{\pi}$. Sample 1960Q1-1984Q4; median response and 68% uncertainty band.

Consider the 1960Q1-1984Q4 subsample in Figure 7 first. The red lines visualise the responses with respect to the unemployment shock. This shock shares similar features with the MBC shock in Angeletos et al. (2020). Therefore, we will refer to the unemployment shock and the MBC shock interchangeably hereafter. The blue lines, instead, refer to the IRFs of the shock maximising the business cycle FEV of inflation gap. The two set of impulse responses describe a common propagation mechanism that is not only responsible for the co-movement among real variables, but that also transmits to inflation. The shock can be labelled as a demand-type shock, as it generates an opposite co-movement between unemployment and inflation. Furthermore, it also draws a clear lead-lag relationship between domestic slack and inflation. Real variables strongly move together and tend to converge back to the steady state in approximately two years. For both the domestic real variables and wage inflation the peak of the shock realizes within one year. Instead, for inflation and inflation expectations the peak materialises after approximately two years before being entirely absorbed approximately 4 years after the shock. The MBC shock generates wage inflationary pressures that encourage agents to revise the expectations upward and that passes-through inflation. To show this, similarly to Conti et al. (2019) and Forbes et al. (2018), we compute the ratio of the cumulative response of inflation over the cumulative response of wage inflation conditional to the MBC shock. We define this ratio as the wage pass-through stemming from the "main business cycle shock" to inflation. Figure 8 shows the dynamic wage pressures feeding into inflation over the two subsample. In the pre-Great Moderation period, the wage response almost fully passes-through to inflation after 15 quarters, consistent with the timing of the response of inflation.

Table 2 displays how much of the forecast error variance of the variables in our BVAR is explained by the unemployment shock. As expected the MBC shock explains a large fraction of the volatility of real variables - 39% for the output gap and 67% for the investment gap.[13] Table 2 confirms the sound link between real slack and inflation, as the MBC shock is responsible for approximately 84% and 60% of the business cycle fluctuations of $\tilde{\pi}^w$ and $\tilde{\pi}$, respectively. In addition, the shock also significantly contributes to inflation expectations dynamics. The third and fourth rows in Table 2 refer to the FEVD of the shock maximising the business cycle fluctuations of inflation gap. This "inflation shock" identifies again a strong link between labour market and inflation gap, as it explains roughly 66% and 50% of the FEV of the unemployment gap and wage inflation gap, respectively. This first set of results shows that, in the pre-Great Moderation era, our econometric analysis points to well-functioning wage and price Phillips curves, linking the domestic labour market to inflation via wage inflationary pressures.

Let us now move to the subsample spanning from 1985Q1 to 2019Q4. The responses to the "unemployment shock" (red) and "inflation shock" (blue) are jointly collected in Figure 9. The procedure identifies again what could be interpreted as demand-type of shock as the MBC shock. Although wages soundly react to the MBC, this time the responses of inflation and inflation expectations are muted. By comparing the impulse responses of all variables with respect to the two shocks, we no longer observe a common propagation mechanism driving both the real side and the nominal side of the economy. As a matter of fact, by just looking at Figure 9, we can clearly distinguish two facets of the business cycle. On the one hand, our procedure identifies a MBC shock that drives the real domestic variables and wage inflation, but that no longer feeds into inflationary pressures - both actual inflation and inflation expectations are muted. On the other hand, our procedure identifies a shock maximising the business cycle fluctuations of inflation, which yields a strong positive co-movement with international prices - see the (blue) responses in the last row of Figure 9 -,

[13]In section A.6.1 of the Appendix, we show that, similarly, a shock that maximize the FEV of the output gap or the investment gap explains a substantial fraction of the volatility of the other two real variables, respectively.

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

1960Q1-1984Q4			
$\tilde{u}_t$ shock			
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{\pi}_t$
0.9071	0.3900	0.6743	0.5920
[0.8806,0.9285]	[0.3081,0.4868]	[0.6246,0.7227]	[0.5119,0.6636]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{\pi}_t^o$
0.5668	0.8382	0.4731	0.3148
[0.4835,0.6461]	[0.7996,0.8723]	[0.3987,0.5501]	[0.2536,0.3806]
$\tilde{\pi}_t$ shock			
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{\pi}_t$
0.6556	0.2474	0.4043	0.7996
[0.5529,0.7498]	[0.1705,0.3455]	[0.3164,0.5039]	[0.7564,0.8385]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{\pi}_t^o$
0.6654	0.5025	0.7093	0.4715
[0.5972,0.7278]	[0.3883,0.6134]	[0.6524,0.7640]	[0.4175,0.5330]
1985Q1-2019Q4			
$\tilde{u}_t$ shock			
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{\pi}_t$
0.9264	0.4428	0.8655	0.2797
[0.9082,0.9422]	[0.3180,0.5570]	[0.8355,0.8914]	[0.2064,0.3603]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{\pi}_t^o$
0.1880	0.8502	0.0663	0.0593
[0.1181,0.2860]	[0.8093,0.8858]	[0.0451,0.0929]	[0.0398,0.0849]
$\tilde{\pi}_t$ shock			
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{\pi}_t$
0.1431	0.1079	0.1221	0.7172
[0.0855,0.2451]	[0.0720,0.1638]	[0.0768,0.2057]	[0.6642,0.7701]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{\pi}_t^o$
0.1557	0.2336	0.59404	0.7485
[0.1098,0.2154]	[0.16812,0.3329]	[0.5230,0.6511]	[0.6836,0.7965]

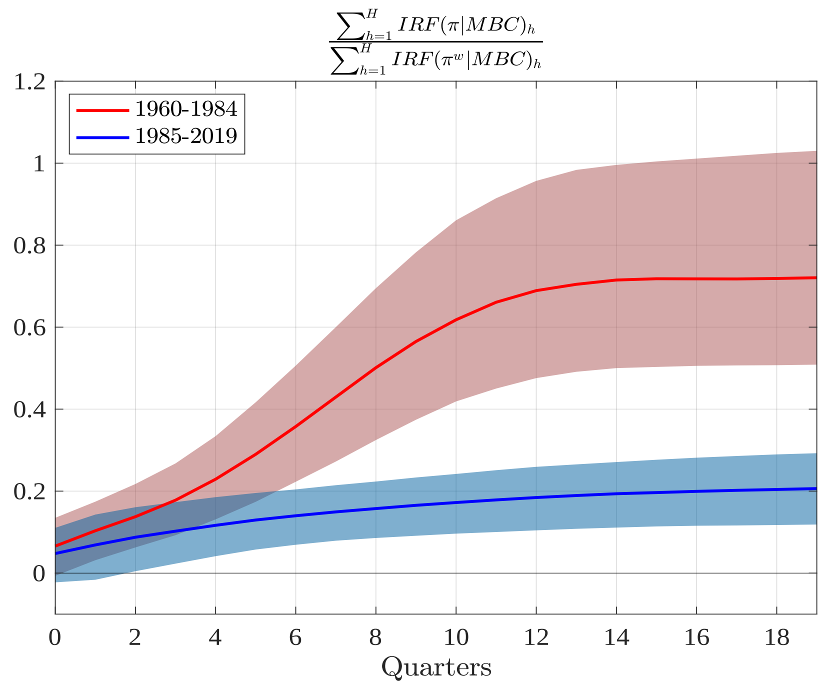

Figure 8: Median response of inflation to the MBC shock over the median response of wage inflation

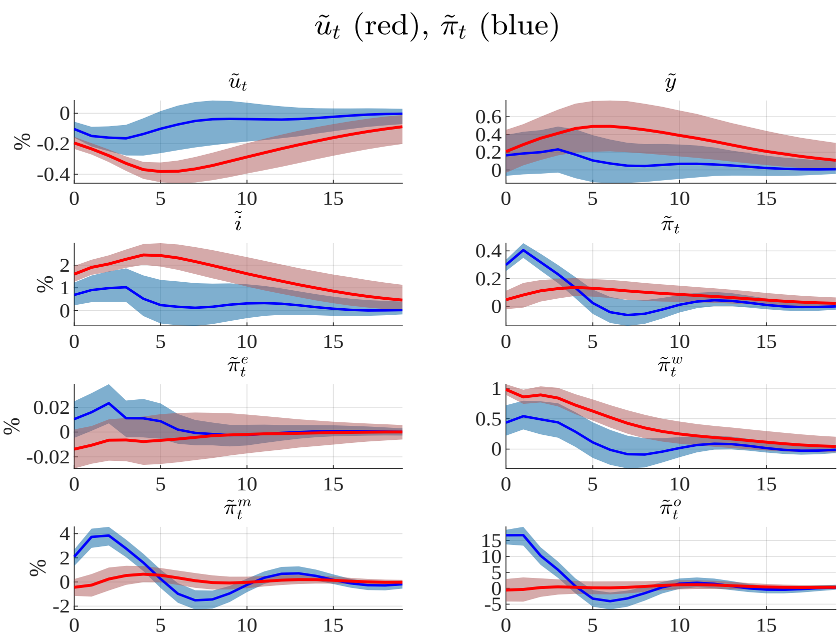

Figure 9: IRFs maximising the FEVD of $\tilde{u}$ and $\tilde{\pi}$. Sample 1985Q1-2019Q4; median response and 68% uncertainty band.

but that affects only slightly the domestic real variables.

This *disconnection* is confirmed by Table 2. The MBC shock, in fact, characterises approximately 93% of the total volatility of the unemployment gap, 87% of the investment gap, 44% of output gap. Furthermore, it accounts for 85% of wage inflation total volatility, therefore generating a strong wage inflationary pressures as in the pre-Great Moderation period. However, the MBC shock explanation of FEV of domestic inflation and inflation expectations has declined by more than a half. It seems that the main transmission channel, via wage pressure, no longer passes-through inflation. This is, in fact, confirmed by Figure 8, which shows as our measure of wage pass-through has declined substantially in the second subsample and no longer produce the inflationary pressures observed in the first subsample. The pass-through is now four times smaller than before, in fact. This, in turn, explains the muted response of inflation. Other studies report 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 (demand-type) MBC shock, if an improved monetary policy was the reason behind the poor response of inflation.

Inflation, therefore, seems to have become increasingly exogenous to the domestic business cycle behaviour of measure of economic slack, suggesting a disconnection with the local labour market. And yet it moves: how? Figure 9 plots the impulse responses (blue lines) to the shock that maximises the variance of inflation gap over the business cycle. The responses to this shock reveal a clear disconnection between the real side and the price side over the business cycle. This shock is essentially orthogonal to the real side of the economy because none of the real variables significantly move. Second, there is a strong positive - and precisely estimated - co-movement between domestic inflation, imported intermediate inputs inflation and oil inflation. Third, despite the latter, the responses of both wage inflation and inflation expectations are short-lived a mildly significant only for one year after the shock. The results in Table 2 are even more striking: the shock generates a large part of the international components of prices inflation, i.e., 59% of the variance of imported intermediate goods inflation - $\tilde{\pi}_t^m$ - and 75% of the one of oil prices - $\tilde{\pi}_t^o$, however it generates a small fraction of the volatility of the wage inflation (23%) and an even smaller fraction of the volatility of inflation expectation (16%), unemployment (14%), output (11%) and investment (12%) gaps.

To further corroborate this evidence, we estimate the impulse responses generated from a shock maximising the cyclical variance of either imported intermediate inputs inflation or

[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.

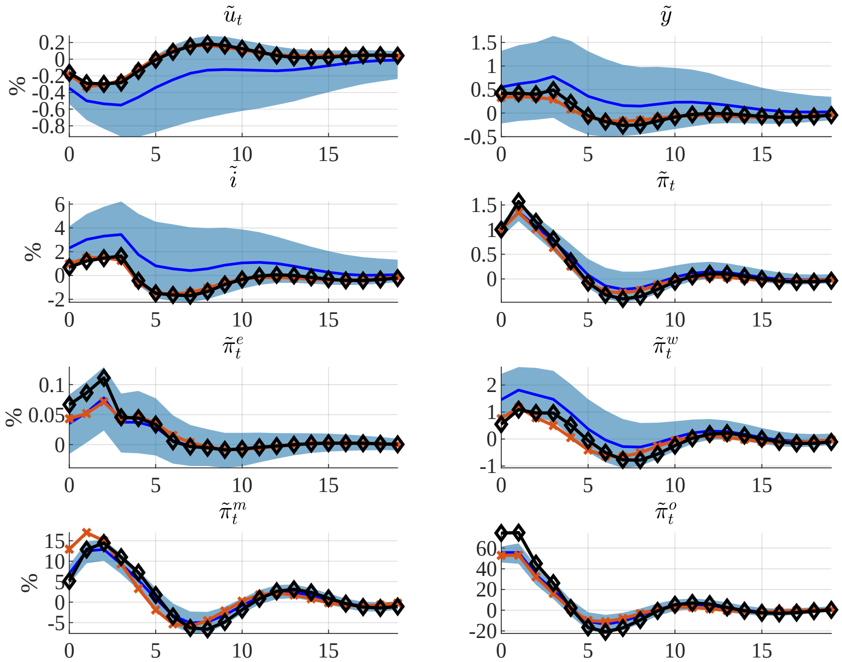

Figure 10: IRFs maximising the FEVD of $\tilde{\pi}$ (blue –), $\tilde{\pi}^m$ (orange -×-) and $\tilde{\pi}^o$ (black -◇-). Sample 1985Q1-2019Q4; median response and 68% uncertainty band.

oil inflation. If the strong co-movement originates from a common international propagation channel, then the impulse responses should be interchangeable to the blue ones in Figure 9 and the underlying shocks should explain approximately the same amount of business cycle volatility of these three variables. The three sets of impulse responses are jointly plotted in Figure 10. Strikingly, they draw the same patterns and are almost perfectly correlated - not surprisingly, domestic variables react relatively more to the domestic inflation shock. The results, thus, validate our hypothesis of a common international mechanism characterising the cyclical behaviour of all the three measures of prices. Both identifications explains around 60% of total fluctuations in domestic inflation and less than 10% of the real block of the model (see Appendix A.6.1).

In Appendix A.5, we provide additional evidence of this *disconnection* by inspecting the spectral densities of the estimated cycles. In the 1960Q1-1984Q4 period, both unemployment and inflation cyclical variance peaks after approximately 25 quarters, within the conventional 6-32 business cycle window. However, in the 1985Q1-2019Q4 period we observe a timing disconnection between the cycle of unemployment and inflation. On the one hand, similarly to what documented by Beaudry et al. (2020), the cycle of unemployment becomes more persistent peaking after 40 quarters and does not display other significant peaks within the usual business cycle windows. On the other hand, the cycle of inflation peaks within the 6-32 frequency band, and is characterised by multiple local peaks sharing the same timing of the cyclical peaks observed in the spectral densities of international factor prices.

Therefore, this analysis delivers an additional explanation about why inflation has been exogenous to the domestic business cycle. Heise et al. (2020) focus on a demand side channel, whereby the decrease of the wage pass-through to U.S. inflation is due 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. 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, therefore, should be seen as complementary to the ones in Heise et al. (2020).

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, with a common propagation mechanism driving inflation and the real business cycle. Second, in the 1985Q1-2019Q4 sample, the procedure identifies a MBC shock - as in Angeletos et al. (2020) - that generates most of the volatility in the real block and in the labour market variables. This no longer feeds into inflationary pressures. The reason for this has to be found in the limited wage pass-through, despite the sound response of wage inflation. The lower responsiveness of inflation cannot thus be attributed to structural breaks in the labour markets, because wages are still tightly linked to the other measures of economic slack, as we also show in the next Section. Third, while disconnected from the 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 the cost-push component generated internationally via international linkages has grown in importance. 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 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 and stable also in the second subsample, that is, had the slope of the wage Phillips Curve remained steep and constant, we should observe wage dynamics to share the same main sources of fluctuations of the unemployment gap in both subsamples. Figure 11 and 12 plot the responses to the shock that maximises the FEVD of $\tilde{\pi}_t^w$ for the 1960Q1-1984Q4 and the 1985Q1-2019Q4 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 the change in the functioning of the labour market as being responsible for the flattening of the Phillips curve.

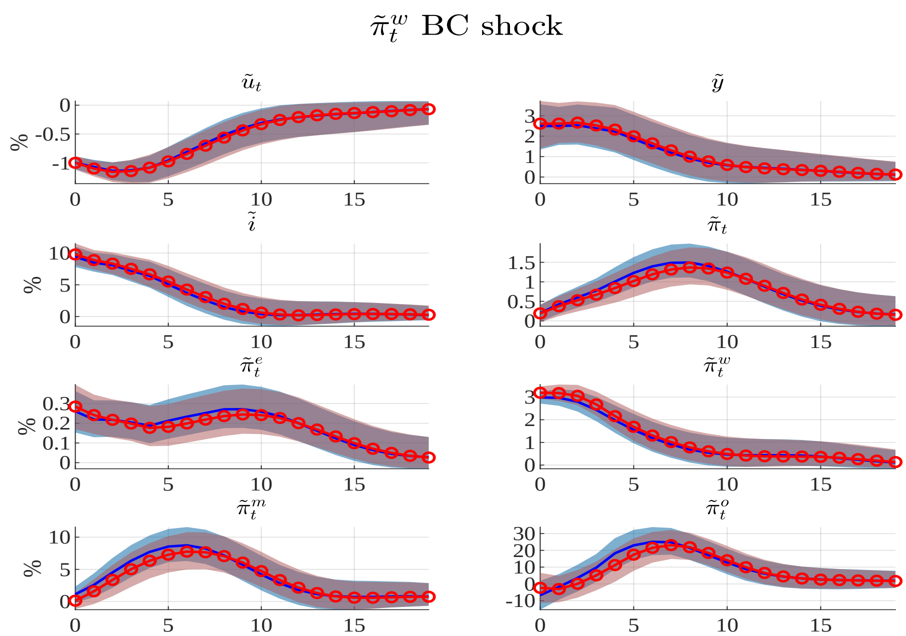

Figure 11: IRFs maximising the FEVD of $\tilde{\pi}^w$ (red -○-) and $\tilde{u}$ (blue –). Sample 1960Q1-1984Q4; median response and 68% uncertainty band.

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.

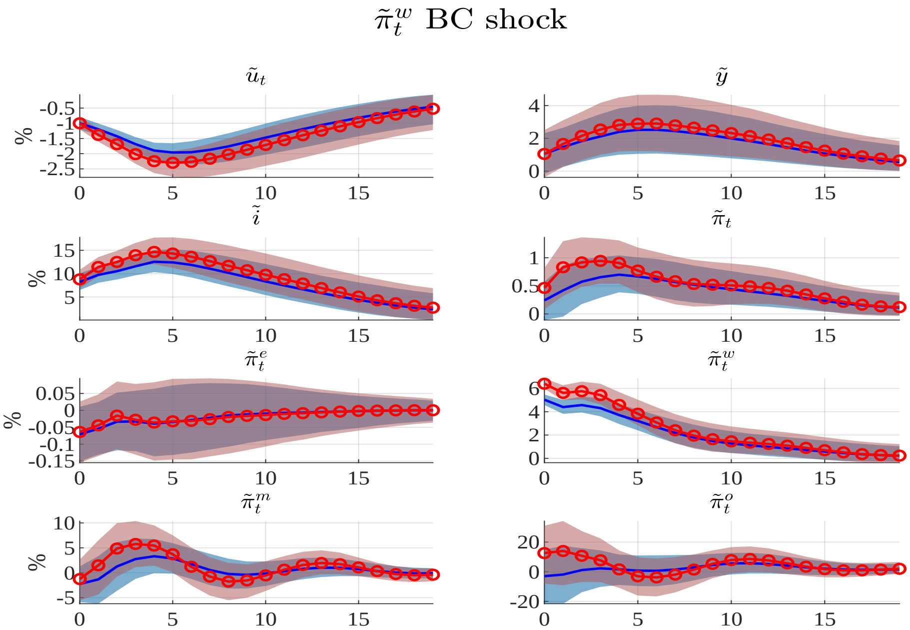

Figure 12: IRFs maximising the FEVD of $\tilde{\pi}^w$ (red -○-) and $\tilde{u}$ (blue –). Sample 1985Q1-2019Q4; median response and 68% uncertainty band.

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, decomposing it into two distinct low-frequency components. Our anatomy distinguishes between (domestic) monetary and international - imported intermediate goods - determinants of trend inflation. The results attribute the decline in trend inflation observed from the mid-'80s to both the monetary policy regime switch toward explicit targeting and the dynamics of international prices of imported intermediate goods.

From the analysis on the cyclical block of the model several facts emerge. First, the Phillips Curve relationship between the unemployment gap and the inflation gap shows a strong flattening over time. Second, the impulse response analysis in the 1985Q1-2019Q4 sample uncovers two main facets 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 a demand 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 analysis on the wage Phillips curve relationship in Section 5.4 shows that the relationship between wage inflation and unemployment has remained relatively stable over time and, thus, the labour market continues to be a reliable barometer of business cycle pressure. The muted response of inflation is, thus, neither due to an aggressive monetary policy reaction, nor to a structural change in the local labour market dynamics. In fact, our analysis relies on conditional correlations and, therefore, the unemployment gap should have also remained closed had it been monetary policy the reason behind the muted response of inflation.

Second, the business cycle behaviour of inflation in the 1985Q1-2019Q4 sample is mainly characterised by a shock originating abroad, which generates the main bulk of volatility in international prices of intermediate goods and is almost orthogonal to the domestic slack. Therefore, we conclude that, in the sample 1985Q1-2019Q4, 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, our results suggest that the international component of inflation should not only be considered a business cycle phenomenon, but it could also leave long-run scars on the level of inflation. These results pose some new and crucial challenges for the ability of monetary policy to govern both the persistent component and cyclical behaviour of inflation. Central banks should be aware that an external factor beyond their direct control could potentially undermine both the long-run mandate of the central bank, in terms of achieving the inflation target, and the stabilization of inflation dynamics around the target, because of the insensitivity of inflation to the domestic business cycle conditions.

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A Appendix

A.1 Data

All data are available in FRED website with the exception of long-run inflation expectations. 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.[15] All nominal 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. Finally, all variables but unemployment rate are in logs.

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
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

A.2 Model in Matrix Notation

$$\begin{bmatrix} u_t \\ y_t \\ i_t \\ \pi_t \\ \pi_t^e \\ \pi_t^w \\ \pi_t^m \\ \pi_t^o \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} c_t + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & \lambda_{4,2} \\ 1 & 0 \\ 0 & 0 \\ 0 & \lambda_{7,2} \\ 0 & \lambda_{8,2} \end{bmatrix} \begin{bmatrix} \bar{\pi}_t^e \\ \bar{g}_t \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \bar{u}_t \\ \bar{y}_t^{id} \\ \bar{i}_t^{id} \\ \bar{\pi}_t^{w,id} \\ \bar{\pi}_t^{m,id} \\ \bar{\pi}_t^{o,id} \end{bmatrix} + \Phi(L) \begin{bmatrix} \tilde{u}_t \\ \tilde{y}_t \\ \tilde{i}_t \\ \tilde{\pi}_t \\ \tilde{\pi}_t^e \\ \tilde{\pi}_t^w \\ \tilde{\pi}_t^m \\ \tilde{\pi}_t^o \end{bmatrix}$$

[15] 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.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 $\lambda | c, \phi, \Sigma_e, \Sigma_\varepsilon, y_{1:T}$:

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

The posterior distribution of λ is approximated implementing a Metropolis Hastings step within the Gibbs sampler. 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 posterior distribution of 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

The identification of structural shocks follows Uhlig (2003). The reduced-form VAR of cyclical components is given by:

$$\tilde{\chi}_t = C(L)\varepsilon_t \qquad \varepsilon_t \sim N(0_n, \Sigma_\varepsilon) \tag{A1}$$

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:

$$A = \hat{A}Q \tag{A2}$$

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

$$\epsilon_{t+k} = \sum_{i=0}^{k} \hat{B}_i Q v_{t+k-i} \tag{A3}$$

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:

$$\Sigma_\varepsilon(k, j) = \sum_{i=0}^{k} (\hat{B}_i q_j)(\hat{B}_i q_j)' \tag{A4}$$

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:

$$\sigma_\varepsilon^2(\underline{k}, \overline{k}; q_1) = q_1' \left(\sum_{k=\underline{k}}^{\overline{k}} \sum_{i=0}^{k} \hat{B}_i' \hat{B}_i \right) q_1$$

$$\sigma_\varepsilon^2(\underline{k}, \overline{k}; q_1) = q_1' \mathcal{S} q_1 \tag{A5}$$

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 Further Evidence From Spectral Analysis

A.5.1 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. 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[16]. Once the window smoothing is applied to the periodogram, the estimator looks like:

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

A.5.2 Results From Spectral Analysis

Cycles are by construction zero-mean covariance stationary processes, thus they are suitable candidates for spectral analysis. We, therefore, perform the spectral analysis to further corroborate the above results. First, the analysis provides an additional robustness check of the loosening of 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 13 plots the spectral densities for unemployment and inflation gap over the two samples. The first row compares the spectral densities over the 1960Q1-1984Q4 sample.

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

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 1985Q1-2019Q4 sample (second row), 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 higher frequencies compared with unemployment gap, with a local peak around Q25.

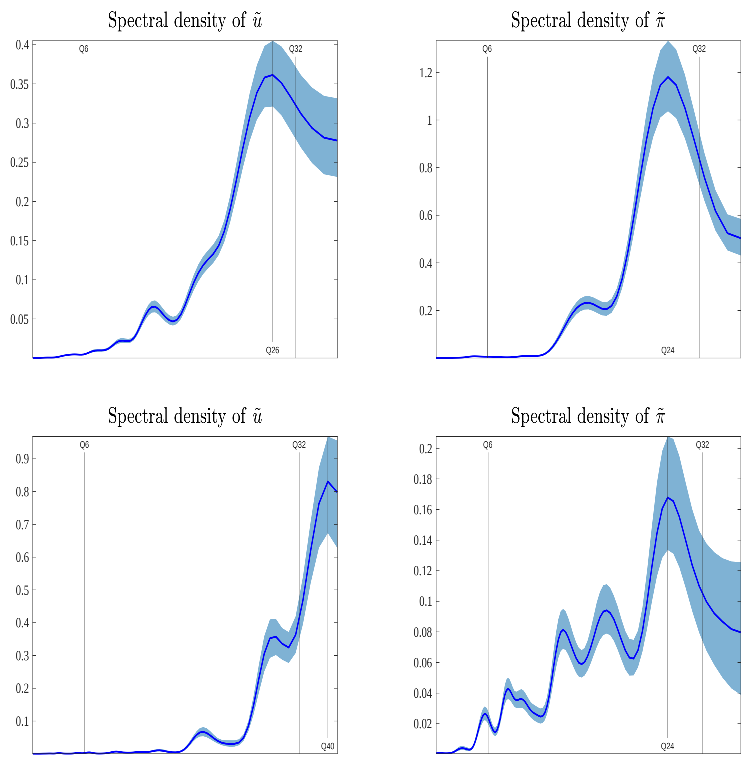

Figure 13: First row: sample 1960Q1-1984Q4; the second row: sample 1985Q1-2019Q4.

Figure 17 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.

Finally, the spectral densities of real variables in the second subsample corroborates once more the hypothesis of a common propagation mechanism. 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 36Q, 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 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 pressure.

A.6 Additional Figures

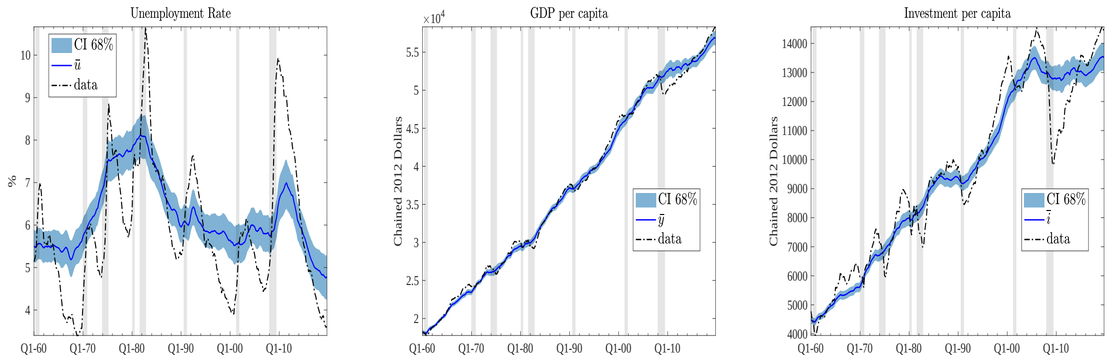

Figure 14: Trends of real variables.

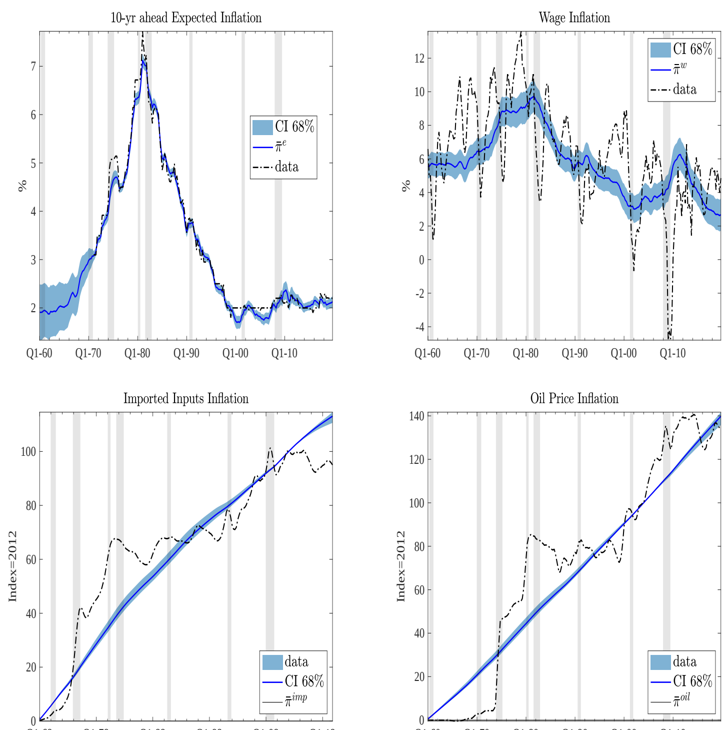

Figure 15: Trends of nominal variables.

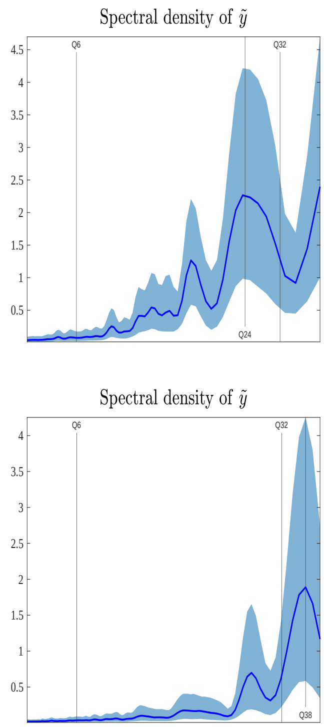

Figure 16: First row: sample 1960Q1-1984Q4; the second row: sample 1985Q1-2019Q4.

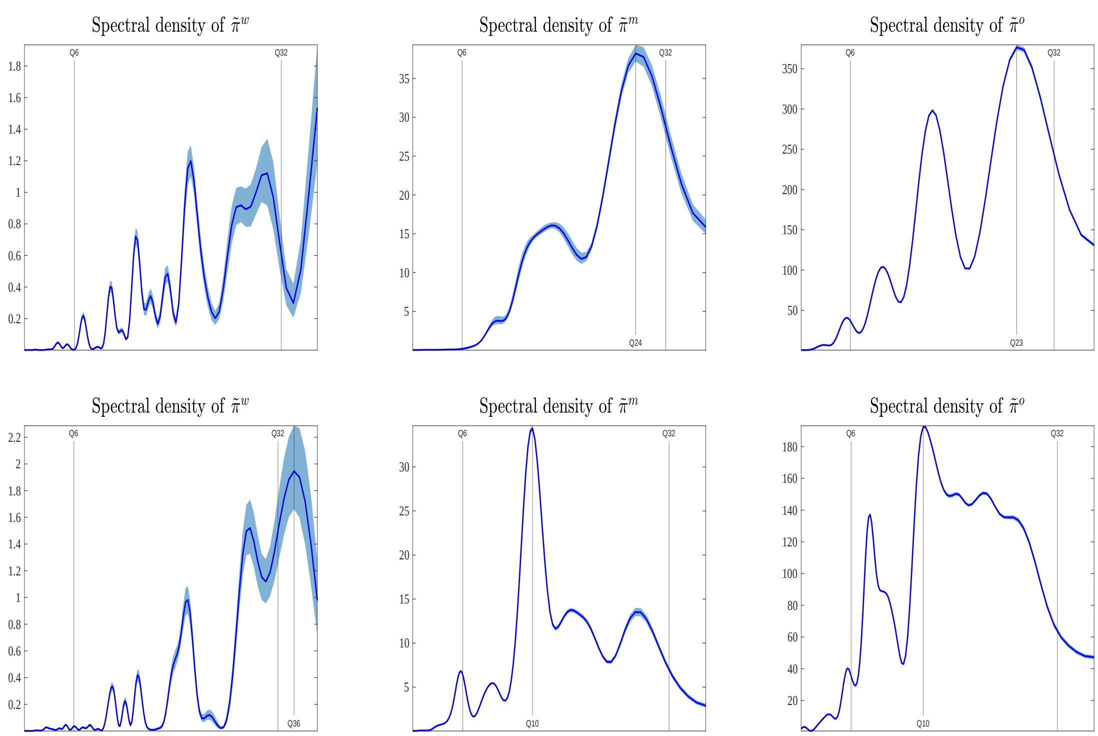

Figure 17: First row: sample 1960Q1-1984Q4; the second row: sample 1985Q1-2019Q4.

A.6.1 Additional Tables

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

1985Q1-2019Q4			
	$\tilde{\pi}_t^m$ **shock**		
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{\pi}_t$
0.0566	0.0679	0.0568	0.5498
[0.0378,0.0843]	[0.0461,0.0972]	[0.0378,0.0840]	[0.4665,0.6248]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{\pi}_t^o$
0.1288	0.0981	0.7507	0.5611
[0.0902,0.1815]	[0.0706,0.1319]	[0.7073,0.7894]	[0.4739,0.6427]
	$\tilde{\pi}_t^o$ **shock**		
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{\pi}_t$
0.0501	0.0738	0.0548	0.5963
[0.0332,0.0756]	[0.0522,0.1034]	[0.0357,0.0794]	[0.5318,0.6572]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{\pi}_t^o$
0.1753	0.0994	0.5221	0.9198
[0.1264,0.2374]	[0.0725,0.1310]	[0.4712,0.5693]	[0.8970,0.9394]
	$\tilde{\pi}_t^w$ **shock**		
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{\pi}_t$
0.8776	0.4148	0.8145	0.3127
[0.8451,0.9055]	[0.2978,0.5195]	[0.7746,0.8539]	[0.2396,0.3845]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{\pi}_t^o$
0.1673	0.8984	0.0786	0.0672
[0.1074,0.2550]	[0.8685,0.9222]	[0.0550,0.1087]	[0.0468,0.0951]

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

1960Q1-1984Q4			
$\tilde{y}_t$ shock			
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{\pi}_t$
0.3444	0.6689	0.3156	0.1880
[0.1946,0.5594]	[0.6330,0.7061]	[0.1838,0.4947]	[0.0989,0.3343]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{\pi}_t^o$
0.1862	0.3403	0.1556	0.1109
[0.1003,0.3386]	[0.1914,0.5422]	[0.0822,0.2730]	[0.0613,0.1885]
$\tilde{i}_t$ shock			
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{\pi}_t$
0.7867	0.3886	0.7657	0.4367
[0.7369,0.8326]	[0.3116,0.4812]	[0.7299,0.7979]	[0.3466,0.5258]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{\pi}_t^o$
0.4305	0.7715	0.3585	0.2549
[0.3462,0.5209]	[0.7194,0.8184]	[0.2823,0.4369]	[0.1979,0.3217]

1985Q1-2019Q4			
$\tilde{y}_t$ shock			
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{\pi}_t$
0.4479	0.6315	0.4309	0.1073
[0.0765,0.8416]	[0.5839,0.6901]	[0.0788,0.8080]	[0.0434,0.2233]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{\pi}_t^o$
0.0611	0.3925	0.0440	0.0409
[0.0261,0.1414]	[0.0677,0.7328]	[0.0232,0.0721]	[0.0215,0.0700]
$\tilde{i}_t$ shock			
$\tilde{u}_t$	$\tilde{y}_t$	$\tilde{i}_t$	$\tilde{\pi}_t$
0.9161	0.4465	0.8742	0.2661
[0.8938,0.9348]	[0.3405,0.5583]	[0.8471,0.8976]	[0.1214,0.3479]
$\tilde{\pi}_t^e$	$\tilde{\pi}_t^w$	$\tilde{\pi}_t^m$	$\tilde{\pi}_t^o$
0.1926	0.8382	0.0667	0.0609
[0.1087,0.2920]	[0.7778,0.8748]	[0.0468,0.0926]	[0.0415,0.0869]

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De Nederlandsche Bank N.V.
Postbus 98, 1000 AB Amsterdam
020 524 91 11
dnb.nl