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Trends and cycles during the COVID-19 pandemic period

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Abstract
We devise a simple yet versatile strategy to perform trend-cycle decompositions in severe crisis periods, such as the COVID-19 pandemic period. The proposed strategy propels a great deal of volatility during this period into pandemic-specific shocks, with minimal impacts on non-pandemic disturbances. We start by estimating two unobserved components models until 2019:4, for Portugal and the euro area. We then introduce several pandemic-specific disturbances and estimate their variances during the 2020-21 period, keeping fixed all remaining model parameters. Finally, we bring together the information from both estimation stages through a piecewise linear Kalman filter, assuming such heteroskedastic environment. Our strategy has the attractiveness of generating negligible historical revisions when the 2020-2021 period is added to the estimation sample, despite the large pandemic disruption. Results suggest that innovations affecting the cycle are key drivers of GDP during the pandemic period, while yielding negligible historical revisions.

JEL: C11, C30, E32

Keywords: COVID, semi-structural models, unobserved components, potential output, output gap, Bayesian estimation.

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1. Introduction

The social and economic crisis caused by the coronavirus pandemic was characterized by complex demand and supply interactions flowing beneath all health concerns. On the one hand, many consumers decided to postpone spending decisions in the face of unprecedented uncertainty or were simply compelled to stay at home, bringing their everyday spending routines to a halt. On the other hand, many firms were forced to reduce or suspend production, either to deal with the impacts of a new virus or to cope with foreclosure risks due to absent demand. Such environment created a cumulative loop that resulted into a deep collapse in output—totally unexpected if we take into account the available information up to 2019—coupled with a deterioration in labor market conditions. Many firms faced important liquidity shortages that on occasions spilled over into solvency problems. Against this background, it soon become clear that standard textbook models were unfit to cope with the events unfolding during the 2020-21 period.

The huge structural break imposed on second moments by the pandemic crisis is so vast that any structural or semi-structural model estimated throughout the pandemic period either collapses or yields extremely implausible results of some kind. Ascertaining whether output behavior over 2020–21 was driven by cyclical or trend components is key to evaluate if the crisis brought *inter alia* permanent damage to the economy, or simply implied a set of short-lived nefarious effects. There are two extreme views to this conceptual question, as discussed by Bodnár *et al.* (2020) and Thum-Thysen *et al.* (2022). The first view is that trend output was basically "frozen," and thus capacity utilization accounts for the large output downfall. This is the "cycle interpretation." The second view—the "trend interpretation—" suggests a collapse in the full capacity level, namely through firm closure, and thus supply levels reflected lockdowns and virus containment measures.[1]

We shed light on this debate through the estimation of two unobserved components models of different complexities from which classical trend-cycle decompositions of output or unemployment are typically obtained. The first is a parsimonious model—hereinafter termed "P-model"—drawing on the suggestions of Carabenciov *et al.* (2008) and Blagrave *et al.* (2015). The model embodies just two behavioral equations—*viz.* a Phillips curve and an Okun's law. All other equations are either simple definitions or standard time series processes. The second model is the unobserved components model suggested by Duarte *et al.* (2020)—the "U-model—", which builds on the work of Melolinna and Tóth (2019) and Tóth (2021). The latter embodies a richer labor market structure, a Cobb-Douglas technology (relying on total hours worked, capital and total factor productivity to produce trend output), wage and price equations, and an Okun's law. We illustrate

1. Thum-Thysen *et al.* (2022) favors the cycle interpretation, whereas Saunders (2021, 2022) the trend interpretation.

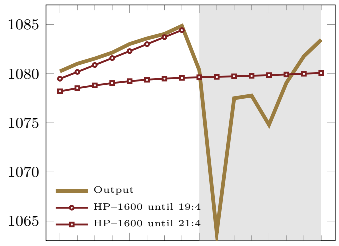
the inappropriateness of the concomitant trend-cycle decomposition brought about by these models when dealing with the pandemic period, although the U-model is better suited to cope with changing economic conditions, and devise a simple but highly versatile strategy to overcome their inadequacy. If models are left untouched when we change the end-of-period sample from 2019:4 to 2021:4 the output gap is revised in 2019:4 by 3.0 and 2.6 percentage points, respectively.

To solve the instability problem, we start by estimating each model until 2019:4. We then include several "pandemic disturbances" that take place during 2020:1-2021:4 and estimate their variances while keeping fixed all previously estimated parameters. This strategy does not pose any computational issue and enables the identification of all pandemic variances. Lastly, we apply a piecewise linear Kalman filter assuming a heteroskedastic environment where pandemic shocks have a zero calibrated variance prior to 2019:4 and the estimated value thereafter. We show that the GDP breakdown into its trend and cycle components is conditional on the number of pandemic disturbances considered in each model. Pandemic shocks impacting the cycle depict much larger standard deviations *vis-à-vis* their non-pandemic counterparts, suggesting that the negative cyclical component dominates the GDP downfall, and systematically emerge as very relevant to deliver negligible historical revisions for the period before 2020:1.[2]

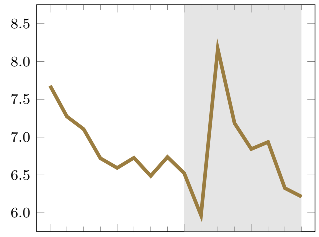
Figure 1 shows the disruptive nature of the pandemic crisis and clarifies how standard identification methodologies fell apart as the recessive period unfolded.[3] Portuguese output fell sharply in the first half of 2020. The recovery period was limited by several factors, including negative impacts of successive infection waves. Identifying and extracting the high frequency content of this output path, which is no different from the one recorded in many countries and the euro area, requires extreme caution and is a canonical example where standard two-sided filters cease to be useful, namely because there is no clear economic reason why the pandemic period—totally unexpected—should carry along a significant revision of potential output historical estimates. For instance, the Hodrick-Prescott filter with a smoothing parameter of 1600 (henceforth "HP–1600 filter") triggers a sharp revision in history if we simply update the end-of-period sample from 2019:4 to 2021:4 (see Figure 2a). The estimated 2019:4 output gap increases from 0.4 to 5.3 percent. In short, the filter ceases to produce reliable contents, a topic that has

2. With the purpose of analyzing policy impacts after the pandemic crisis, Cuadrado *et al.* (2022) avoided the instability problem by assuming that trend output remained unchanged before the crises.

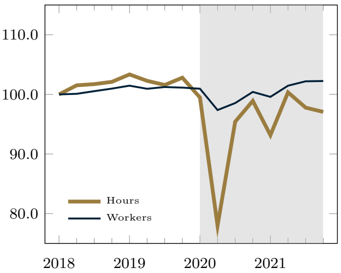
3. The pandemic crisis affected the economy in many other dimensions not covered in this article. The asymmetric impact of the crisis is surely one of the most important characteristics. Bandera *et al.* (2022) show that euro area sectors with an higher degree of personal contacts, and deemed less essential, were more affected. When accessing the disclosed information set, the expert committee of the Fundação Francisco Manuel dos Santos (see *www.ffms.pt*) and of the CEPR-EABCN Euro Area Business Cycle Dating Committee (see *www.cepr.org*) classified 2019:4 as a period where the Portuguese and the euro area economic cycles reached a peak, respectively, and the latter a trough of the crisis in 2021:2.



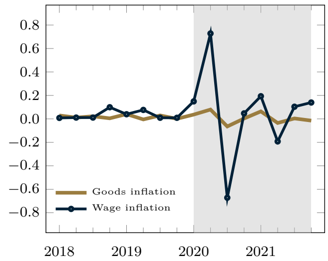
(a) GDP and trend (HP filter).



(b) Unemployment



(c) Employment



(d) Price and wage inflation

Source: Statistics Portugal.

Notes: Portuguese data. GDP and trend output are measured in logs and scaled by a factor of 100. The sample period of HP filters (smoothing parameter of 1600) identified as "HP–1600 until 19:4" and "HP–1600 until 21:4" are 1980:1-2019:4 and 1980:1-2021:4, respectively. Employment, measured in total number of hours or total number of workers, is an index where 2018:1 = 100. Goods and wage inflation are measured by the (annualized) quarter-on-quarter (log) change of the GDP deflator and compensation per hour, respectively. Unemployment is in percentage of the labor force.

Figure 1: Selected variables over the pandemic period.

been extensively discussed in the literature, particularly since the seminal work of Orphanides and van Norden (2002).[4]

Unemployment increased during the crisis, topping at 8.2 percent of the labor force in 2020:2 in the case of Portugal (see Figure 2b). This increase is relatively contained if we take into account Okun's law—the historical relationship between output and unemployment—an outcome shared by the euro area (Kiss *et al.* 2022). This behavior took place against a background where outflows to inactivity were quite expressive and employment relations were significantly supported by policy measures. Relying on the historical relationship to identify unobserved trends and cycles is therefore largely insufficient, even though Okun's law remained informative over the last decades (Ball *et al.* 2017), increasing the stability of real time

4. Hamilton (2018) takes an additional step and claims that we should never use the HP filter. See Rosnick (2016) for the impact of using this filter on a country experiencing a multiyear collapse.

output gap estimates (Barbarino *et al.* 2020). By the end of 2021, the Portuguese unemployment rate had decreased to levels below the 2019:4 figure.

Another important dimension impacted by the crisis concerns the adjustments in average hours worked, both in Portugal and the euro area (Kiss *et al.* 2022). Although the total number of Portuguese employed workers decreased in 2020, the effects over total hours worked were much larger (see Figure 2c). These events are an important part of the pandemic crisis and crucial to understand the disruptive volatility embodied into the trend-cycle identification process. By 2021:4, employed workers had already recovered the 2019:4 level, in contrast with total hours worked.

The relationship between output and the nominal side of the economy—be it a Phillips curve based on product prices or hourly wages—has also been severely impacted by the pandemic crisis. Product prices were barely affected over 2020, despite the sharp downfall in output, but wages per hour registered high volatility levels, conditioned by the evolution of hours worked (see Figure 2d). In annualized terms, compensation per hour increased more than 60 percent in 2020:2. Since product prices were barely affected, the trend interpretation proposes a collapse in full capacity and a relatively contained output gap (which would restrain downward inflationary pressures), whereas the cycle interpretation proposes a frozen trend output, implying that cost-push shocks account for price developments. The same type of question—was it the trend or the cycle?—applies to hourly wages.

This article is organized as follows. The next section presents the P-model model and the U-model separately, as well as the empirical estimates that are required to fulfill our trend-cycle identification strategy. There are several trends in both models, but we focus exclusively on the trend component of GDP. The last section concludes.

2. Trend and cycle contents of GDP

This section first introduces and estimates a small multivariate model—hereinafter termed "parsimonious" or "P-model"—drawing on Carabenciov *et al.* (2008) and Blagrave *et al.* (2015). The model is estimated with just three observed data series—namely output, unemployment and goods price inflation—and two behavioral equations—*viz.* a Phillips curve and an Okun's law. All other equations are either simple definitions or standard time series processes. Although parsimonious and featuring no equations involving hours worked or hourly wage inflation data, which depicted a high volatility during the pandemic period (see Figure 1), this semi-structural model clarifies some problems that researchers face when bringing models to the data over periods characterized by very large disturbances, such as the pandemic crisis.

We then take the medium-size semi-structural unobserved components model named "U-model", suggested in Duarte *et al.* (2020), and bring it to the data. This model considers a richer labor market structure featuring a wage equation, and relies on a Cobb-Douglas technology with total hours worked, capital and total factor productivity to produce trend output, *i.e* featuring equations involving hours worked or hourly wage inflation data. Although designed to better cope with changing economic conditions, we show that the U-model, estimated with ten data series, suffers from the same problems faced by the more parsimonious model.

Finally, we propose and estimate the same models under a simple strategy that greatly suppresses the problems that arise in standard estimation. We focus primarily on the results obtained with Portuguese data.[5] Expectations are backward-looking, and estimation is performed using Bayesian methods. Monetary policy reactions, financial variables and international spillovers are absent in both models.

2.1. A parsimonious semi-structural model

Our estimation strategy consists in enlarging any model with a new set of disturbances, henceforth "pandemic shocks." These are identical to their non-pandemic equivalents except in their estimated standard deviation.

The P-model is fully characterized by the system of equations (1)–(12). The product market equations are described by

$$y_t = \bar{y}_t + \hat{y}_t \tag{1}$$

$$\bar{y}_t = \bar{y}_{t-1} + \Delta^{\bar{y}}_{t-1} \tag{2}$$

$$\Delta^{\bar{y}}_t = \theta^{\bar{y}}\Delta^{\bar{y}} + (1-\theta^{\bar{y}})\Delta^{\bar{y}}_{t-1} + \varepsilon^{\bar{y}}_t + \varepsilon^{\mathbf{\bar{y}_P}}_{\mathbf{t}} \tag{3}$$

$$\hat{y}_t = \alpha^{\hat{y}}_1\hat{y}_{t-1} + \alpha^{\hat{y}}_2\hat{y}_{t-2} + \varepsilon^{\hat{y}}_t + \varepsilon^{\mathbf{\hat{y}_P}}_{\mathbf{t}} \tag{4}$$

These decompose actual output y_t into trend (a measure of potential) output $\bar{y}_t$ and the output gap $\hat{y}_t$, where $0 < \theta^{\bar{y}}, \alpha^{\hat{y}}_1 + \alpha^{\hat{y}}_2 < 1$, and $\Delta^{\bar{y}}$ is the steady-state growth rate of output. In the short run, actual output evolves around the steady-state growth rate $\Delta^{\bar{y}}$. In the long run, the rate of change of both actual and trend output is constant at $\Delta^{\bar{y}}_t = \Delta^{\bar{y}}_{t-1} = \Delta^{\bar{y}}$, and $y_t = \bar{y}_t$ (given that $\hat{y}_t = 0$ by design).

We assume that, outside the pandemic period, zero-mean *iid*-normal disturbances $\varepsilon^{\hat{y}}_t$ affect the output gap $\hat{y}_t$ temporarily and zero-mean *iid* normal shocks $\varepsilon^{\bar{y}}_t$ affect trend output $\bar{y}_t$ permanently. The "pandemic innovations" $\varepsilon^{\bar{y}_P}_t$ and $\varepsilon^{\hat{y}_P}_t$ are calibrated to zero during this period, but are allowed to follow zero-mean *iid*-normal distribution processes during pandemic periods. Let $\sigma^{\hat{y}}$, $\sigma^{\bar{y}}$, $\sigma^{\hat{y}_P}$, $\sigma^{\bar{y}_P}$ be the standard deviation of these shocks, respectively.

5. The appendix reports equivalent outcomes for the euro area. Unreported results are available form the authors upon request. For instance, the trend components of unemployment is omitted to save space.

The labor market equations are

$$U_t = \bar{U}_t + \hat{U}_t \tag{5}$$

$$\bar{U}_t = \gamma^{\bar{u}}\bar{U} + (1-\gamma^{\bar{u}})\bar{U}_{t-1} + \Delta^{\bar{u}}_{t-1} \tag{6}$$

$$\Delta^{\bar{u}}_t = (1-\theta^{\bar{u}})\Delta^{\bar{u}}_{t-1} + \varepsilon^{\bar{u}}_t + \varepsilon^{\mathbf{\bar{u}P}}_{\mathbf{t}} \tag{7}$$

$$\hat{U}_t = \alpha^{\hat{u}}_1\hat{U}_{t-1} - \alpha^{\hat{u}}_2\hat{y}_{t-1} + \varepsilon^{\hat{u}}_t + \varepsilon^{\mathbf{\hat{u}P}}_{\mathbf{t}} \tag{8}$$

These decompose actual unemployment U_t into a trend $\bar{U}_t$ and an unemployment gap $\hat{U}_t$, where $0 < \gamma^{\hat{u}}_1, \theta^{\bar{u}}, \alpha^{\hat{u}}_1 < 1$, $\alpha^{\hat{u}}_2 > 0$, $\bar{u}$ is the steady-state unemployment level and $\Delta^{\bar{y}}_t$ is a zero-mean stationary process. In the short run, unemployment evolves around a constant steady-state rate $\bar{u}$. In the long run, the change in unemployment $\Delta^{\bar{u}}_t$ is nil by design and $U_t = \bar{U}$ (and $\hat{U}_t = \hat{y}_t = 0$).

As before, we assume that zero-mean *iid*-normal disturbances $\varepsilon^{\hat{u}}_t$ and $\varepsilon^{\bar{u}}_t$ affect the unemployment gap $\hat{U}_t$ and the trend unemployment $\bar{u}_t$ in every period. Pandemic disturbances $\varepsilon^{\bar{u}_P}_t$ and $\varepsilon^{\hat{u}_P}_t$ are calibrated to zero outside pandemic years and allowed to follow *iid*-normal distribution processes otherwise. Let $\sigma^{\hat{u}}$, $\sigma^{\bar{u}}$, $\sigma^{\hat{u}_P}$, $\sigma^{\bar{y}_P}$ be the standard deviation of these shocks, respectively.
The price equations are

$$\pi_t = \bar{\pi}_t + \hat{\pi}_t \tag{9}$$

$$\bar{\pi}_t = \gamma^{\bar{\pi}}\bar{\pi} + (1-\gamma^{\bar{\pi}})\bar{\pi}_{t-1} + \Delta^{\bar{\pi}}_{t-1} \tag{10}$$

$$\Delta^{\bar{\pi}}_t = \theta^{\bar{\pi}}(\pi_{t-1} - \pi_{t-2}) + (1-\theta^{\bar{\pi}})\Delta^{\bar{\pi}}_{t-1} + \varepsilon^{\bar{\pi}}_t + \varepsilon^{\mathbf{\bar{\pi}P}}_{\mathbf{t}} \tag{11}$$

$$\hat{\pi}_t = \alpha^{\hat{\pi}}_1\hat{\pi}_{t-1} + \alpha^{\hat{\pi}}_2\hat{y}_{t-1} + \varepsilon^{\hat{\pi}}_t + \varepsilon^{\mathbf{\hat{\pi}P}}_{\mathbf{t}} \tag{12}$$

These decompose goods price inflation π_t into a trend component $\bar{\pi}_t$ and a deviation from trend $\hat{\pi}_t$, where $0 < \gamma^{\hat{\pi}}_1, \theta^{\bar{\pi}}, \alpha^{\hat{\pi}}_1 < 1$, $\alpha^{\hat{\pi}}_2 > 0$, $\bar{\pi}$ is the steady-state inflation and $\Delta^{\bar{\pi}}_t$ is a zero-mean stationary process. In the short run, inflation evolves around the steady-state inflation level $\bar{\pi}$, influenced by actual developments in past inflation figures. In the long run, $\Delta^{\bar{\pi}}_t$ is nil by design and $\pi_t = \bar{\pi}$ (and $\hat{\pi}_t = \hat{y}_t = 0$).

Zero-mean *iid* normal disturbances $\varepsilon^{\bar{\pi}}_t$ and $\varepsilon^{\hat{\pi}}_t$ affect the trend and the cyclical components $\bar{\pi}_t$ and $\hat{\pi}_t$ in every period. Pandemic disturbances $\varepsilon^{\bar{\pi}_P}_t$ and $\varepsilon^{\hat{\pi}_P}_t$ follow identical processes during pandemic years and are calibrated to zero otherwise. Let $\sigma^{\hat{y}}$, $\sigma^{\bar{y}}$, $\sigma^{\hat{\pi}_P}$, $\sigma^{\bar{\pi}_P}$ be the standard deviation of these shocks, respectively.

The model features 6 non-pandemic disturbances, a maximum of 6 pandemic perturbations and 3 observable variables. The estimation database starts in 1999:1 and includes (the log of) real GDP, (annualized quarter-on-quarter log changes of) the GDP deflator, and the total number of unemployed workers, expressed as a percentage of the labor force. The latter was collected from labor force data, whereas the remaining series were collected from the national accounts database.

Our benchmark exercise considers a standard unobserved components filtering procedure, performed until 2019:4 and until 2021:4, under the assumption of absent pandemic shocks (calibrated zero-variance). Next, we apply a simple estimation

Model version	$\sigma^{\hat{y}}$	$\sigma^{\hat{y}_P}$	$\sigma^{\hat{u}}$	$\sigma^{\hat{u}_P}$	$\sigma^{\hat{\pi}}$	$\sigma^{\hat{\pi}_P}$
0 - No pandemic shocks	1.6	-	1.4	-	3.0	-
1 - $\varepsilon_t^{x_P}$, $x \in \{\bar{y}, \hat{y}, \bar{u}, \hat{u}, \bar{\pi}, \hat{\pi}\}$	1.6	12.7	1.4	11.7	3.0	14.2
2 - $\varepsilon_t^{x_P}$, $x \in \{\hat{y}, \hat{u}, \bar{\pi}, \hat{\pi}\}$	1.6	12.6	1.4	11.4	3.0	14.1
3 - $\varepsilon_t^{x_P}$, $x \in \{\bar{y}, \bar{u}, \bar{\pi}, \hat{\pi}\}$	1.6	-	1.4	-	3.0	13.1
4 - $\varepsilon_t^{x_P}$, $x \in \{\bar{y}, \hat{y}, \bar{u}, \hat{u}\}$	1.6	12.9	1.4	11.7	3.0	-

(a) Pandemic and non-pandemic shocks affecting the cycle.

Model version	$\sigma^{\bar{y}}$	$\sigma^{\bar{y}_P}$	$\sigma^{\bar{u}}$	$\sigma^{\bar{u}_P}$	$\sigma^{\bar{\pi}}$	$\sigma^{\bar{\pi}_P}$
0 - No pandemic shocks	0.3	-	0.3	-	0.3	-
1 - $\varepsilon_t^{x_P}$, $x \in \{\bar{y}, \hat{y}, \bar{u}, \hat{u}, \bar{\pi}, \hat{\pi}\}$	0.3	0.5	0.3	0.5	0.3	0.6
2 - $\varepsilon_t^{x_P}$, $x \in \{\hat{y}, \hat{u}, \bar{\pi}, \hat{\pi}\}$	0.3	-	0.3	-	0.3	0.6
3 - $\varepsilon_t^{x_P}$, $x \in \{\bar{y}, \bar{u}, \bar{\pi}, \hat{\pi}\}$	0.3	9.1	0.3	0.4	0.3	0.6
4 - $\varepsilon_t^{x_P}$, $x \in \{\bar{y}, \hat{y}, \bar{u}, \hat{u}\}$	0.3	0.5	0.3	0.5	0.3	-

(b) Pandemic and non-pandemic shocks affecting the trend.

Source: The authors.

Notes: Portuguese data. Parameters σ^i and σ^{i_P} , $i \in \{\hat{y}, \hat{u}, \hat{\pi}, \bar{y}, \bar{u}, \bar{\pi}\}$ refers to non-pandemic and pandemic standard deviations estimated over 1999:1-2019:4 and 2020:1-2021:4, respectively. The term $\varepsilon_t^{x_P}$, $x \in \{\hat{y}, \hat{u}, \hat{\pi}, \bar{y}, \bar{u}, \bar{\pi}\}$, identifies the presence of estimated (pandemic) innovations in each model version. For instance, $x \in \{\bar{y}, \bar{u}, \bar{\pi}, \hat{\pi}\}$ refers to a model where pandemic shocks affecting the output gap $\hat{y}$ and unemployment gap $\hat{u}$ are absent. All results are median posterior estimates computed with 1 million draws, and scaled by a factor of 10. Parameters to the right of the vertical line are also present in the U model (see Section 2.1). Appendix A reports further details.

Table 1. Estimated standard deviations (P-model).

strategy that works around these problems, as follows: *(i)* estimate the model with data until 2019:4 assuming a zero-calibrated variance for pandemic shocks, identified as $\varepsilon_t^{x_P} = \sigma^{x_P} = 0$, $x \in \{\bar{y}, \hat{y}, \bar{u}, \hat{u}, \bar{\pi}, \hat{\pi}\}$; *(ii)* estimate the variances of all pandemic-related components σ^{x_P} over 2020:1–2021:4, keeping fixed (calibrated) all previously estimated parameters and standard deviations of non-pandemic disturbances, *i.e.* the σ^x's; *(iii)* bring together the information from the two-stage estimation procedure by applying a piecewise linear Kalman filter, which settles on the assumption that the σ^{x_P}'s are zero before 2020:1 and equal to their estimated value thereafter.

Table 1 reports the estimated standard deviations of pandemic and non-pandemic disturbances, for alternative model specifications differing on the number of allowed disturbances. Each model version n, $n \in \{0, 1, 2, 3, 4\}$ is designed with a pre-defined number of disturbances, which clarifies from the outset that our estimation strategy can be implemented in a variety of specifications. In particular, Model 0 has no pandemic shock, whereas Model 1 features the maximum number of disturbances considered in this exercise (6 pandemic shocks). Standard deviations for non-pandemic components are identical across all versions, since they are based on the estimated model until 2019:4 and kept fixed during the pandemic period. The controlled number of estimated parameters during pandemic years, jointly with the Bayesian approach, is sufficient to prevent any estimation issues—such as non-identification or corner solutions—from occurring.

Pandemic disturbances depict much larger median standard deviations *vis-à-vis* their non-pandemic counterparts, particularly for the product and labor market cycle components of the model (they are around eight times higher than their non-pandemic counterparts, whereas those affecting prices are five times higher). An exception is $\sigma^{\bar{y}_P}$ in Model 3, where we only allow for pandemic shocks affecting the non-cyclical real elements $\bar{y}$ and $\bar{u}$, in addition to $\bar{\pi}$ and $\hat{\pi}$. The absence of some cycle components leaves the model with no alternative but to adjust in the trend component.

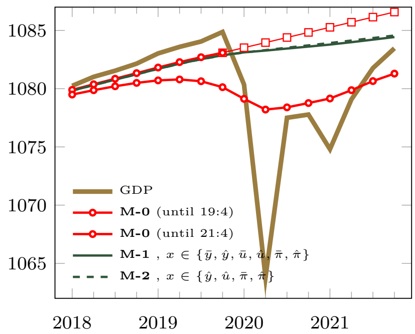
In all model versions, the median standard deviation of all pandemic shocks affecting the cycle are outside the 90 percent Highest Posterior Density (HPD) intervals depicted by Model 0—the benchmark model.[6] In the case of pandemic shocks affecting trend components, estimates are close or above the upper limit of the interval. These results suggest that the negative cyclical component dominates the GDP downfall during pandemic years (even if we admit no pandemic shocks affecting the nominal side of the economy, as in Model 4), and that homoskedastic models can hardly mimic implied volatility levels, leading to erroneous trend-cycle decompositions, sometimes of difficult economic interpretation.

Figure 2 reports smoothed trend components according to different model versions. Albeit less severe than the impact of using an HP–1600 filter (recall Figure 2a), the model without pandemic shocks—Model 0—continues to revise historical trend estimates sharply when we filter the data until 2019:4 or 2021:4 (henceforth named "Model 0 (until 19:4)" and "Model 0 (until 21:4)"), *i.e.* when we bring data from the pandemic period into the model in an homoskedastic environment (with standard deviations estimated with data until 2019:4). In 2019:4, trend output is revised around -3.0 percent. In short, history changes if the observer is looking before or after the unexpected COVID-19 pandemic.

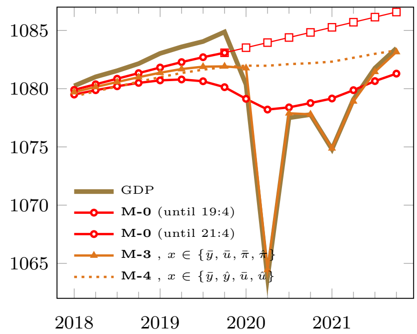
The two-step estimation strategy coupled with the piecewise linear Kalman filter broadly maintains the previous trend estimate of the benchmark Model 0 (until 19:4) once we allow for pandemic shocks in gaps and in the nominal side of the model (Models 1 and 2).[7] The percentage difference between trend output of

6. Standard deviations are in general higher in Portugal as compared with the euro area, which reflects a traditionally higher instability of the Portuguese economy, both in real and nominal terms. Table A.1 and Table A.2 in Appendix A present prior and posterior distributions for both economies, as well as the HPD intervals.

7. The natural environment to bring together the two-step estimation procedure is through a piecewise linear Kalman filter. However, results would be similar if we fix the standard deviations of pandemic shocks and estimate the model between 1999.1 and 2021.4. Results are available from the authors upon request.



(a) Trend $\bar{y}_t$ of model versions M-0, M-1 and M-2.



(b) Trend $\bar{y}_t$ of model versions M-0, M-3 and M-4

Source: The authors.

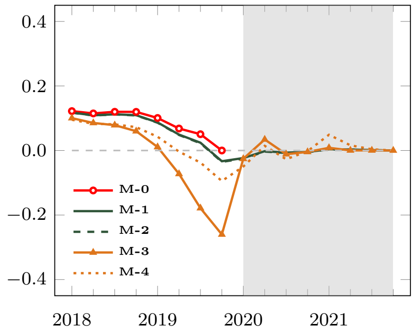
Notes: Notes: Portuguese data. GDP and trend output are in logarithm scale and multiplied by a factor of 100. "Model 0 (until 19:4)" refers to a model version without pandemic shocks, estimated until 2019:4 and where the unobserved trend components are computed with a database until 2019:4. White squares—the naive projection of this model over 20:1-21:4—extend trend output using the average growth rate recorded in 2019. Model 0 (until 21:4)" is the same model but data is filtered until 2021:4. All unobserved components are computed with median posterior estimates. See Appendix A for further details.

Figure 2: GDP and trends across model versions (P-model).

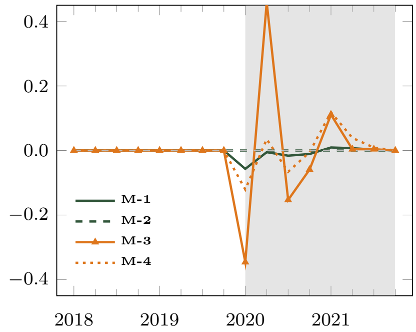
Model 1 and Model 2 *vis-à-vis* a naive projection of the benchmark Model 0 (also reported in Figure 2), which provides an estimate of the pandemic crises impact, stands close to -2.0% by 2021:4.[8] Unsurprisingly, allowing for shocks solely on trends alongside disturbances affecting $\bar{\pi}$ and $\hat{\pi}$ (Model 3) places GDP fluctuations fundamentally in the trend component, which is in line with the view that the output gap remained relatively stable (against a background where goods inflation also remained relatively contained). This results in a historical revision around 1.2 percent in 2019:4 trend output *vis-à-vis* Model 0 (until 19:4). Withdrawing pandemic disturbances from the nominal side of the model (Model 4) implies a historical revision of identical magnitude, but a smoother behavior after the crisis' inception. Without the pandemic cost-push shocks $\varepsilon_t^{\bar{\pi}P}$ and $\varepsilon_t^{\hat{\pi}P}$, both the trend and the cycle components of inflation can only be exogenously driven by non-pandemic shocks.

Figure 3 depicts the implied pandemic ($\varepsilon_t^{\bar{y}P}$) and non-pandemic smoothed trend shocks ($\varepsilon_t^{\bar{y}}$) of alternative model versions. When we filter the database with information up to 2021:4, Model 1 and Model 2 exhibit almost identical innovations prior to the crisis inception, and both are relatively close to those implicit by

8. The percentage difference stands close to -0.3% in the euro area.



(a) Non-pandemic trend disturbances (innovation $\varepsilon_t^{\bar{y}}$)



(b) Pandemic trend disturbances (innovation $\varepsilon_t^{\bar{y}_P}$)

Source: The authors.

Notes: Portuguese data. Pandemic trend disturbances of M-3 are scaled by a factor of 50. All unobserved disturbances are computed with median posterior estimates. See Appendix A for further details.

Figure 3: Exogenous shocks affecting trend output $\bar{y}_t$ (P-model).

the benchmark Model 0 (until 19:4). All other model versions carry along visible historical revisions, more emphatic in Model 3.[9]

Pandemic trend disturbances vary between nil in Model 2 (by design, given that they are absent from this version), and reach the largest value in Model 3 (by design as well, given that shocks on the deviations from trend are absent, and only trend disturbances are allowed to drive the model).

2.2. The U-model

The U-model features behavioral equations for real and nominal developments in product and labor markets, an Okun's law linking these markets, and relies on a Cobb-Douglas technology to produce trend output.[10] The growth rate of trend output

$$\Delta\bar{y}_t \quad = \quad \Delta\overline{tfp}_t + \iota\Delta\bar{l}_t + (1-\iota)\Delta\bar{k}_t \tag{13}$$

depends on the unobserved total factor productivity $\overline{tfp}_t$, on total hours worked $\bar{l}_t \approx \bar{h}_t - \bar{U}_t$ (where $\bar{h}_t$ is the labor force measured in hours), and on the observed capital stock $\bar{k}_t = k_t$. The element Δ is the first difference operator, and $0 \leq \iota \leq 1$. We allow for additional disturbances to affect unobserved productivity and labor inputs during the pandemic period, namely

9. We omit the innovations of Model 0 when the data is filtered until 2021:4, but estimates also imply historical revisions.

10. See Appendix B for a more comprehensive overview of the model and estimation details.

$$\Delta\overline{tfp}_t = \rho_1 \Delta I_t^{tfp} + (1-\rho_1)\Delta\overline{tfp}_{t-1} + \varepsilon_t^{\Delta\overline{tfp}} + \varepsilon_{\mathbf{t}}^{\mathbf{\Delta\overline{tfp}_P}} \quad (14)$$
$$\Delta_t^{\bar{U}} = \rho_2 \Delta I_t^U + (1-\rho_2)\Delta_{t-1}^{\bar{U}} + \varepsilon_t^{\bar{U}} + \varepsilon_{\mathbf{t}}^{\mathbf{\bar{U}_P}} \quad (15)$$
$$\Delta_t^{\bar{h}} = \rho_3 \Delta I_t^h + (1-\rho_3)\Delta_{t-1}^{\bar{h}} + \varepsilon_t^{\bar{h}} + \varepsilon_{\mathbf{t}}^{\mathbf{\bar{h}_P}} \quad (16)$$

where ΔI_t^{tfp}, ΔI_t^U and ΔI_t^h are low-frequency indicators affecting changes in productivity $\Delta\overline{tfp}_t$, trend unemployment $\Delta_t^{\bar{U}}$ and trend labor force $\Delta_t^{\bar{h}}$, respectively, and $0 \leq \{\rho_1, \rho_2, \rho_3\} \leq 1$. Zero-mean iid-normal shocks $\varepsilon_t^{\Delta\overline{tfp}}, \varepsilon_t^{\bar{U}}, \varepsilon_t^{\bar{h}}$ affect the complete time span, whereas $\varepsilon_t^{\Delta\overline{tfp}_P}, \varepsilon_t^{\bar{h}_P}, \varepsilon_t^{\bar{U}_P}$ are only allowed to have a non-nil variance during pandemic years. Let σ^i, $i \in \{\varepsilon^{\Delta\overline{tfp}}, \varepsilon^{\bar{U}}, \varepsilon^{\bar{h}}, \varepsilon^{\Delta\overline{tfp}_P}, \varepsilon^{\bar{U}_P}, \varepsilon^{\bar{h}_P}\}$ denote the corresponding standard deviations

In the nominal side, the changes in the trend components of price and wage inflation are

$$\Delta_t^{\bar{\pi}^p} = \rho_4 \Delta I_t^{\pi^p} + (1-\rho_4)\Delta_{t-1}^{\bar{\pi}^p} + \varepsilon_t^{\bar{\pi}^p} + \varepsilon_{\mathbf{t}}^{\mathbf{\bar{\pi}_P^P}} \quad (17)$$
$$\Delta_t^{\bar{\pi}^w} = \rho_5 \Delta I_t^{\pi^w} + (1-\rho_5)\Delta_{t-1}^{\bar{\pi}^w} + \varepsilon_t^{\bar{\pi}^w} + \varepsilon_{\mathbf{t}}^{\mathbf{\bar{\pi}_P^w}} \quad (18)$$

where $\Delta I_t^{\pi^p}$ and $\Delta I_t^{\pi^w}$ are indicators affecting the changes in trend price inflation $\Delta_t^{\bar{\pi}^p}$ and trend wage inflation $\Delta_t^{\bar{\pi}^w}$, and $0 \leq \{\rho_4, \rho_5\} \leq 1$. Zero-mean iid-normal shocks $\varepsilon_t^{\bar{\pi}^p}, \varepsilon_t^{\bar{\pi}^w}$ exists in every period, while $\varepsilon_t^{\bar{\pi}_P^p}, \varepsilon_t^{\bar{\pi}_P^w}$ have a nil calibrated variance outside the pandemic period. Let σ^j, $j \in \{\varepsilon^{\bar{\pi}^p}, \varepsilon^{\bar{\pi}^w}, \varepsilon^{\bar{\pi}_P^p}, \varepsilon^{\bar{\pi}_P^w}\}$ denote the corresponding standard deviations

The decomposition of output, unemployment and inflation between trend and cycle is identical to that in Equations (1), (5) and (9), respectively. We allow for additional disturbances to affect all deviations from trend during the pandemic period, namely

$$A_1(L)(y_t - \bar{y}_t) = \varepsilon_{1,t} + \varepsilon_{\mathbf{1,t}}^{\mathbf{P}} \quad (19)$$
$$A_2(L)(U_t - \bar{U}_t) = -B_2(L)(y_t - \bar{y}_t) + \varepsilon_{2,t} + \varepsilon_{\mathbf{2,t}}^{\mathbf{P}} \quad (20)$$
$$A_3(L)(h_t - \bar{h}_t) = -B_3(L)(U_t - \bar{U}_t) + \varepsilon_{3,t} + \varepsilon_{\mathbf{3,t}}^{\mathbf{P}} \quad (21)$$
$$A_4(L)(\pi_t^p - \bar{\pi}_t^p) = B_4(L)(y_t - \bar{y}_t) + \varepsilon_{4,t} + \varepsilon_{\mathbf{4,t}}^{\mathbf{P}} \quad (22)$$
$$A_5(L)(\pi_t^w - \bar{\pi}_t^w) = B_5(L)(l_t - \bar{l}_t) + \varepsilon_{5,t} + \varepsilon_{\mathbf{5,t}}^{\mathbf{P}} \quad (23)$$

where $A_i(L)$ and $B_i(L)$ denote lag polynomials of order p_i and q_i, $\bar{X}_t = \bar{X}_{t-1} + \Delta_{t-1}^{\bar{X}}$, $X \in \{U, h, \pi^p\}$, and $\bar{\pi}_t^w = \bar{\pi}_t^p + 4 * (\Delta\bar{y}_{t-1} - \Delta\bar{l}_{t-1}) + \Delta_{t-1}^{\bar{\pi}^w}$. All shocks follow zero-mean iid-normal distributions with standard deviations σ^{ε_i} and $\sigma^{\varepsilon_i^P}$, with $i \in \{1, ..., 5\}$.

The model's steady state depicts nil gaps in output, unemployment, labor force, price inflation, and wage inflation. Capital grows in line with output, the latter due to the presence of a balanced growth path assumption, defined as $A_6(L)\Delta k_t = B_6(L)\Delta y_t + \varepsilon_t^k$, where $A_6(L) = B_6(L)$ denote lag polynomials respectively of order p_6 and q_6, and ε_t^k is an zero mean iid-normal error term with σ^{ε^k} variance.

As in the P-model, the number of exogenous shocks is higher than the number of observed variables. In addition to real GDP, quarter-on-quarter changes in the GDP deflator, and the unemployment rate, we now include the labor force (measured in hours), wage inflation (per hour), and the capital stock of the whole economy—all taken from the national accounts database. We consider also four indicators to influence trend components estimation, namely ΔI_t^i, $i = \{tfp, U, h, \pi^p\}$.[11] The model is more flexible than the one presented in the previous subsection, since output, unemployment and price inflation cease to gravitate around constant values over the sample, and low frequency indicators cope more easily with changing economic conditions.

Table 2 reports the estimated pandemic and non-pandemic standard deviations, using Bayesian methods, for the Portuguese case.[12] We follow the same steps as in the previous subsection to identify all model parameters. As before, Model 0 has no pandemic shock, whereas Model 1 features the maximum number of disturbances considered in this exercise (ten pandemic shocks). Standard deviations for non-pandemic components are identical in all versions since they are based on the same estimated model (with a database ending in 2019:4). In terms of notation, $\varepsilon_t^{x_P}$, $x \in \{\hat{y}, \hat{u}, \hat{\pi}, \bar{y}, \bar{u}, \bar{\pi}\}$, identifies pandemic innovations in each model version n. The elements $\hat{\pi}$ and $\bar{\pi}$ refer to price and wage inflation (namely $\hat{\pi}^p$, $\hat{\pi}^w$, $\bar{\pi}^p$ and $\bar{\pi}^w$), $\bar{y}$ groups $\bar{tfp}$ and $\bar{h}$, and $\hat{y}$ refers to the output gap $\hat{y}$ and the cyclical component of the labor force measured in hours $\hat{h}$. Trend output $\bar{y}_t$ directly accumulates the impact of innovations affecting $\bar{u}_t$ (in contrast with the P-model), $\bar{h}_t$ and $\bar{tfp}$ (both absent in the P-model), which spillover to the rest of the model, and is no longer impacted by idiosyncratic shocks (there is no $\varepsilon_t^{\bar{y}}$, as in the P-model).

Conclusions are in many respects qualitatively identical to the ones already mentioned for the P-model. As before, the median standard deviations of pandemic shocks are substantially higher than non-pandemic counterparts, particularly when these shocks affect the cycle components.

Disturbances in the wage Equation (23) are particularly large as compared with those in other components. This is required for the model to cope with the volatility of actual wage data (see Figure 2d). When pandemic shocks affecting the cycle are excluded (Model 3), trend output $\bar{y}$ becomes highly influenced by the

11. Indicators I_t^{tfp}, I_t^h and I_t^U are computed from Solow's residual, the labor force, and the ratio of short- to long-run unemployment, respectively, from which we remove short-run fluctuations using HP filters (calculated with standard smoothing parameters); finally, we set $\Delta I_t^{\pi^p} = \Delta \pi_t^p$. Appendix B provides further details. The presence of low-frequency indicators in the estimation database maintains the approach proposed by Duarte *et al.* (2020), but the two-sided nature of these filters may lead to some underestimation of trend output levels before the pandemic period.

12. Table B.1 reports the lag structure of the model and Table B.2 prior and posterior distributions. For further details on the model, see Duarte *et al.* (2020).

Model version	$\sigma^{\hat{h}}$	$\sigma^{\hat{h}_P}$	$\sigma^{\hat{\pi}^w}$	$\sigma^{\hat{\pi}^w_P}$	$\sigma^{\hat{y}}$	$\sigma^{\hat{y}_P}$	$\sigma^{\hat{u}}$	$\sigma^{\hat{u}_P}$	$\sigma^{\hat{\pi}^p}$	$\sigma^{\hat{\pi}^p_P}$
0 - No pandemic shocks	1.7	-	7.4	-	1.5	-	1.4	-	3.2	-
1 - $\varepsilon_t^{x_P}$, $x \in \{\bar{y}, \hat{y}, \bar{u}, \hat{u}, \bar{\pi}, \hat{\pi}\}$	1.7	15.8	7.4	36.4	1.5	10.9	1.4	10.7	3.2	13.1
2 - $\varepsilon_t^{x_P}$, $x \in \{\hat{y}, \hat{u}, \bar{\pi}, \hat{\pi}\}$	1.7	15.8	7.4	36.7	1.5	10.8	1.4	10.6	3.2	13.1
3 - $\varepsilon_t^{x_P}$, $x \in \{\bar{y}, \bar{u}, \bar{\pi}, \hat{\pi}\}$	1.7	-	7.4	51.1	1.5	-	1.4	-	3.2	13.7
4 - $\varepsilon_t^{x_P}$, $x \in \{\bar{y}, \hat{y}, \bar{u}, \hat{u}\}$	1.7	15.5	7.4	-	1.5	13.2	1.4	10.7	3.2	-

(a) Pandemic and non-pandemic shocks affecting the cycle.

Model version	$\sigma^{\bar{tfp}}$	$\sigma^{\bar{tfp}_P}$	$\sigma^{\bar{\pi}^w}$	$\sigma^{\bar{\pi}^w_P}$	$\sigma^{\bar{h}}$	$\sigma^{\bar{h}_P}$	$\sigma^{\bar{u}}$	$\sigma^{\bar{u}_P}$	$\sigma^{\bar{\pi}^p}$	$\sigma^{\bar{\pi}^p_P}$
0 - No pandemic shocks	0.2	-	0.3	-	0.3	-	0.2	-	0.2	-
1 - $\varepsilon_t^{x_P}$, $x \in \{\bar{y}, \hat{y}, \bar{u}, \hat{u}, \bar{\pi}, \hat{\pi}\}$	0.2	0.5	0.3	0.6	0.3	0.4	0.2	0.4	0.2	0.5
2 - $\varepsilon_t^{x_P}$, $x \in \{\hat{y}, \hat{u}, \bar{\pi}, \hat{\pi}\}$	0.2	-	0.3	0.6	0.3	-	0.2	-	0.2	0.6
3 - $\varepsilon_t^{x_P}$, $x \in \{\bar{y}, \bar{u}, \bar{\pi}, \hat{\pi}\}$	0.2	0.5	0.3	0.6	0.3	13.3	0.2	0.4	0.2	0.5
4 - $\varepsilon_t^{x_P}$, $x \in \{\bar{y}, \hat{y}, \bar{u}, \hat{u}\}$	0.2	6.2	0.3	-	0.3	0.4	0.2	0.4	0.2	-

(b) Pandemic and non-pandemic shocks affecting the trend.

Source: The authors.

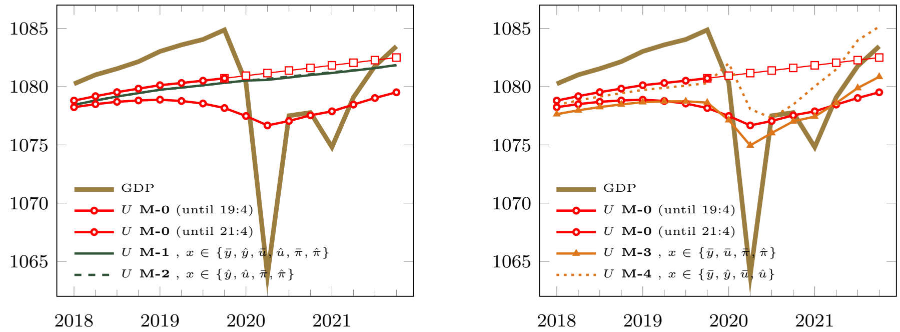
Notes: Portuguese data. Parameters σ^i and σ^{i_P} , $i \in \{\hat{y}, \hat{h}, \hat{u}, \hat{\pi}, \bar{tfp}, \bar{h}, \bar{u}, \bar{\pi}\}$, refers to non-pandemic and pandemic standard deviations estimated over 1999:1-2019:4 and 2020:1-2021:4, respectively. The term $\varepsilon_t^{x_P}$, $x \in \{\hat{y}, \hat{u}, \hat{\pi}, \bar{y}, \bar{u}, \bar{\pi}\}$, identifies the estimated (pandemic) innovations in each model version, where identifiers $\hat{\pi}$ and $\bar{\pi}$ refer to price and wage inflation (namely $\hat{\pi}^p$, $\hat{\pi}^w$, $\bar{\pi}^p$ and $\bar{\pi}^w$), identifier $\bar{y}$ to $\bar{tfp}$ and $\bar{h}$, and identifier $\hat{y}$ to the output gap $\hat{y}$ and $\hat{h}$. Standard deviations of each model version are median posterior estimates computed with 1000000 draws, and scaled by a factor of 10. The parameters after the vertical line are also present in the small model (see Table 1). Appendix B reports further details.

Table 2. Estimated standard deviations (U model).

higher volatility of labor variables (see Figure 2c), particularly the labor force trend component.

When we exclude pandemic shocks affecting the trend components of prices and wages (Model 4), developments in GDP during the pandemic crisis are still envisaged to be conditional on large standard deviations of innovations affecting the cyclical content of the model, as in the P-model. The main difference is that the model shifts the adjustment not only to $\varepsilon_t^{\hat{y}_P}$ and $\varepsilon_t^{\hat{u}_P}$, but also to $\varepsilon_t^{\hat{h}_P}$ and $\varepsilon_t^{\bar{tfp}_P}$, the latter conditioned by the absence of shocks affecting the "productivity gap."[13] The median standard deviation of all pandemic shocks affecting the cycle

13. As discussed by Duarte *et al.* (2020), productivity levels are a residual in the model, and productivity gaps should be seen as deviations of labor and capital utilization rates from their trend levels. This means that positive productivity (or utilization) gaps translate into positive output gaps and higher inflation pressures.



(a) Trend $\bar{y}_t$ of model versions M-0, M-1 and M-2.

(b) Trend $\bar{y}_t$ of model versions M-0, M-2 and M-3.

Source: The authors.

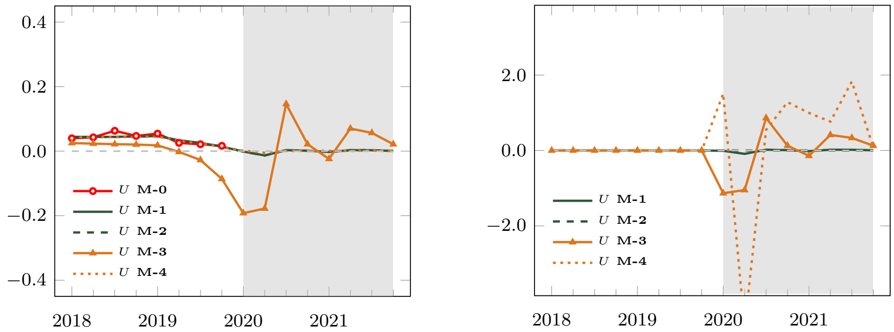
Notes: Portuguese data. "U M-0 (until 19:4)" and "U M-0 (until 21:4)" refers to a model version without pandemic shocks, estimated until 2019:4, where the unobserved trend components are computed with information until 2019:4 and until 2021:4, respectivey. White squares report projections of "U M-0 (until 19:4)" over 20:1-21:4. All unobserved components are computed with median posterior estimates. See Appendix B for further details.

Figure 4: GDP and trends across model versions (U model).

are outside the 90 percent HPD intervals depicted by the benchmark model, as before.[14]

Figure 4 plots the trend component of output according to different model versions. All U-models filter the database ending in 2021:4, except the benchmark version "U M-0 (until 19:4)", which finishes the filtering process in 2019:4. Without pandemic shocks, the unobserved trend estimates of the benchmark version register important revisions when the last data point of the information set is simply updated from 2019:4 to 2021:4 in an homoskedastic environment. These revisions are limited by the presence of low-frequency data series ΔI^i, $i = \{tfp, U, h, \pi^p\}$, which help to cope with changing economic conditions (as discussed in Duarte *et al.* 2020), and partly explain why they are smaller than the ones from the P-model and the HP–1600 filter. Nevertheless, revisions remain high—in 2019:4, trend output of the benchmark version is revised around -2.6 percent when the disruptions caused by the COVID-19 pandemic are imported into the model. The piecewise linear Kalman filter applied herein solves this problem and broadly maintains the trend estimate of the benchmark version "U M-0 (until 19:4)" when we allow pandemic shocks to affect all trend and cycle components, as well as price and wage dynamics (Model 1), or when we include all but pandemic trend disturbances affecting the real side of the economy (Model 2). The pandemic crises impact on trend output, measured by the percentage difference between of

14. See Table B.2 of Appendix B.



(a) Non-pandemic disturbances affecting productivity (innovation $\varepsilon_t^{\Delta \overline{tfp}}$)

(b) Pandemic disturbances affecting productivity (innovation $\varepsilon_t^{\Delta \overline{tfp}_P}$)

Figure 5: Selected exogenous shocks affecting trend output $\bar{y}_t$ (U model).

Source: The authors.

Notes: Portuguese data. Pandemic trend disturbances of M-3 are scaled by a factor of 50. All unobserved disturbances are computed with median posterior estimates. See Appendix B for further details.

Model 1 and Model 2 *vis-à-vis* a naive projection of the benchmark Model 0, stands close to -0.6% by 2021:4.[15]

When we allow pandemic shock to impact solely the trend components and the nominal side (Model 3), GDP volatility becomes highly influenced by the labor force trend component ($\bar{h}$), and to a lesser extent by the unemployment and total factor productivity trends ($\bar{U}$ and $\overline{tfp}$, respectively). Estimates feature noteworthy historical revisions—trend output is revised around -2.0 percent in 2019:4 *vis-à-vis* the reported U M-0 (until 19:4)—confirming that innovations affecting the cycle still play a high-level role.

When pandemic disturbances affecting the nominal side are absent, as in Model 4, trend price and trend wage inflation, and concomitant gaps, can only be exogenous driven by non-pandemic disturbances. In contrast with the results obtained for the P-model, historical revisions appear negligible, but the trend component of output looses some of its low frequency characteristics over the pandemic period and even increases in 2020:1, led primarily by a productivity push, before receding afterwards.

Figure 5 depicts the pandemic and non-pandemic shocks affecting productivity trends across all model versions.[16] Historical non-pandemic trend disturbances are relatively clustered, with the exception of those computed with

15. The percentage difference stands close to -0.3% in the euro area.

16. We refrain from reporting the impacts of $\varepsilon_t^{\Delta \bar{h}_P}$ and $\varepsilon_t^{\Delta \bar{U}_P}$ to save space, but results are available form the authors upon request.

Model 3. In this case, only the trend components of output are allowed to exist, by design.

Pandemic trend disturbances affecting productivity are also relatively clustered arround similar values, with the exception of models 3 and 4. In these cases, trend productivity needs to adjust sharply as a response to the high volatility registered in the product and labour market, both in nominal and real terms.

3. Conclusion

This article proposes an estimation strategy based on the piecewise linear Kalman filter that largely overcomes the problem of large historical revisions when the pandemic period of called into the estimation sample. The strategy consists in estimating the model until the beginning of the crisis, and then add pandemic shocks where desirable and estimate their standard deviations during the pandemic period, keeping fixed all previously estimated parameters. The two estimations stages are brought together *via* the piecewise Kalman filter, which considers a heteroskedastic environment where pandemic shocks have a zero calibrate variance prior to the crisis and the estimated value thereafter.

The strategy is applied to two standard unobserved component models commonly used to perform trend-cycle decompositions of key macroeconomic variables. Our results suggest that innovations affecting the cycle are key drivers of GDP during the pandemic period, while yielding negligible historical revisions.

Appendix A: Small model details

This appendix reports the main Bayesian estimates behind the estimation of the small model, both with Portuguese and euro area data, including prior and posterior distributions, as well as several unobserved components of interest.

In both economies, we set the prior mean of $\Delta^{\bar{y}}$ and $\bar{U}$ equal to the average growth rate of GDP and to the average unemployment rate over 1995:2019:4, respectively, and set high penalties to large deviations from the mean. Steady-state inflation is $\bar{\pi} = 2\%$, in line with the policy objectives of the European Central Bank.

We also set a low prior mean and a tight prior around $\gamma^{\bar{u}}$ in both economies—slightly tigher than Carabenciov *et al.* (2008)—which allows us to obtain a more volatile trend component of unemployment. Setting the prior mean to 0.5 would yield an almost constant trend component.

In the Portuguese case, the upward movement of the unemployment rate up to 2013 produces trend levels in the first part of the sample that are at odds with most empirical estimates (see Duarte *et al.* (2020) for references). We overcome this problem by setting $\bar{U}_{2002Q1} = 6\%$ in the estimation of Model 0. This working assumption has no material influence in our conclusions.

Table A.1 reports Bayesian estimates for the Portuguese case, and Table A.2 for the euro area case.

	Prior distribution						Selected parametrization: ε_t^{xP}			
Parameters	Form	Mean	std				Model 1	Model 2	Model 3	Model 4
					Model 0		$x \in$	$x \in$	$x \in$	$x \in$
				5%	50%	95%	$\{\bar{y},\hat{y},\bar{u},\hat{u},\bar{\pi},\hat{\pi}\}$	$\{\hat{y},\hat{u},\bar{\pi},\hat{\pi}\}$	$\{\bar{y},\bar{u},\bar{\pi},\hat{\pi}\}$	$\{\bar{y},\hat{y},\bar{u},\hat{u}\}$
Product market										
$\theta^{\bar{y}}$	β	0.5	0.1	0.3	0.443	0.6	0.443	0.443	0.443	0.443
$\alpha_1^{\hat{y}}$	β	0.5	0.1	0.4	0.583	0.7	0.583	0.583	0.583	0.583
$\alpha_2^{\hat{y}}$	β	0.4	0.2	0.2	0.312	0.5	0.312	0.312	0.312	0.312
$\Delta^{\bar{y}}$	N	0.006	0.05	0.0	0.002	0.0	0.002	0.002	0.002	0.002
Labor market										
$\gamma^{\bar{u}}$	β	0.03	0.02	0.0	0.022	0.1	0.022	0.022	0.022	0.022
$\theta^{\bar{u}}$	β	0.5	0.1	0.3	0.489	0.6	0.489	0.489	0.489	0.489
$\alpha_1^{\hat{u}}$	β	0.5	0.1	0.5	0.624	0.8	0.624	0.624	0.624	0.624
$\alpha_2^{\hat{u}}$	Γ	0.5	0.1	0.3	0.424	0.6	0.424	0.424	0.424	0.424
$\bar{u}$	Γ^{-1}	0.066	0.05	0.0	0.065	0.1	0.065	0.065	0.065	0.065
Price equations										
$\gamma^{\bar{\pi}}$	β	0.25	0.1	0.1	0.367	0.8	0.367	0.367	0.367	0.367
$\theta^{\bar{\pi}}$	β	0.5	0.1	0.3	0.470	0.6	0.470	0.470	0.470	0.470
$\alpha_1^{\hat{\pi}}$	β	0.5	0.1	0.2	0.347	0.5	0.347	0.347	0.347	0.347
$\alpha_2^{\hat{\pi}}$	β	0.5	0.1	0.3	0.377	0.5	0.377	0.377	0.377	0.377
$\bar{\pi}$	-	0.02	0.02	-	0.02	-	0.02	0.02	0.02	0.02
Std. deviations										
$\varepsilon_t^{\bar{y}}$	Γ^{-1}	1	∞	0.2	0.3	0.5	0.3	0.3	0.3	0.3
$\varepsilon_{\mathbf{t}}^{\bar{\mathbf{y}}\mathbf{P}}$	Γ^{-1}	1	∞	-	-	-	**0.5**	-	**9.1**	**0.5**
$\varepsilon_t^{\hat{y}}$	Γ^{-1}	100	∞	1.3	1.6	1.9	1.6	1.6	1.6	1.6
$\varepsilon_{\mathbf{t}}^{\hat{\mathbf{y}}\mathbf{P}}$	Γ^{-1}	100	∞	-	-	-	**12.7**	**12.6**	-	**12.9**
$\varepsilon_t^{\bar{u}}$	Γ^{-1}	1	∞	0.2	0.3	0.4	0.3	0.3	0.3	0.3
$\varepsilon_{\mathbf{t}}^{\bar{\mathbf{u}}\mathbf{P}}$	Γ^{-1}	1	∞	-	-	-	**0.5**	-	**0.4**	**0.5**
$\varepsilon_t^{\hat{u}}$	Γ^{-1}	100	∞	1.2	1.4	1.7	1.4	1.4	1.4	1.4
$\varepsilon_{\mathbf{t}}^{\hat{\mathbf{u}}\mathbf{P}}$	Γ^{-1}	100	∞	-	-	-	**11.7**	**11.4**	-	**11.7**
$\varepsilon_t^{\bar{\pi}}$	Γ^{-1}	1	∞	0.2	0.3	0.6	0.3	0.3	0.3	0.3
$\varepsilon_{\mathbf{t}}^{\bar{\pi}\mathbf{P}}$	Γ^{-1}	1	∞	-	-	-	**0.6**	**0.6**	**0.6**	-
$\varepsilon_t^{\hat{\pi}}$	Γ^{-1}	100	∞	2.6	3.0	3.5	3.0	3.0	3.0	3.0
$\varepsilon_{\mathbf{t}}^{\hat{\pi}\mathbf{P}}$	Γ^{-1}	100	∞	-	-	-	**14.2**	**14.1**	**13.1**	-

Source: The authors.

Notes: The prior distribution functional form is given by the Beta (β), Gamma (Γ), Normal (N) and inverse-Gamma (Γ^{-1}) functions. The selected parametrization corresponds to posterior median estimates, computed with one million draws, from which we discard the initial 40%. The sample period covers the 1995:1-2019:4 period in model 0 and 2020:1-2021:4 in the remaining models. Identifier ε_t^{xP} clarifies the model version, as in Table 1. Models $1-4$ use the posterior median estimates of model 0 as fixed values.

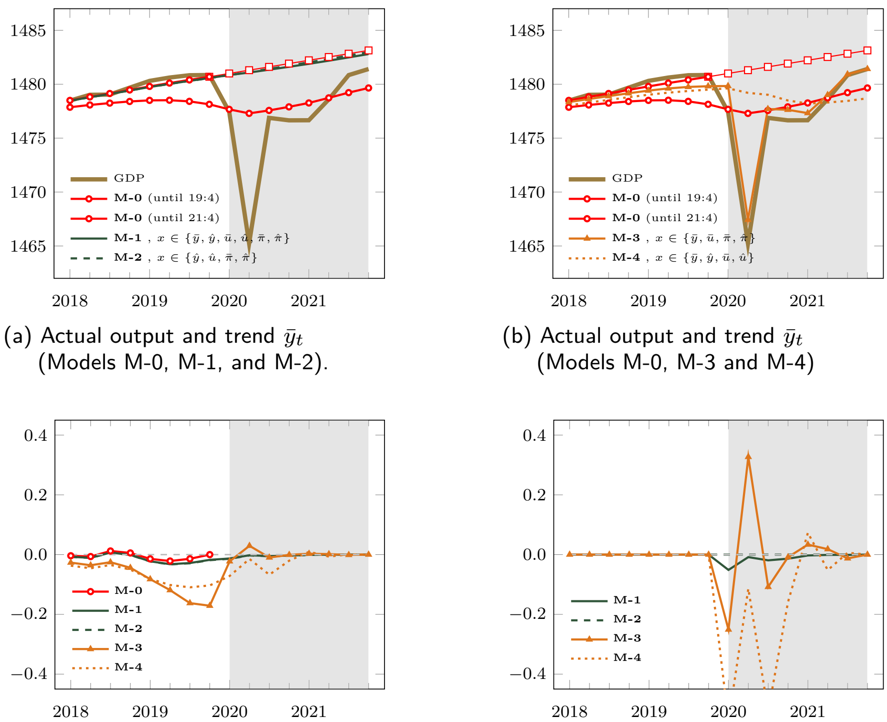
Table A.1. Priors and posteriors using Portuguese data (P-model)

	Prior distribution						Selected parametrization: ε_t^{xP}			
Parameters	Form	Mean	std				Model 1	Model 2	Model 3	Model 4
					Model 0		$x \in$	$x \in$	$x \in$	$x \in$
				5						
Product market										
$\theta^{\bar{y}}$	β	0.5	0.1	0.3	0.495	0.7	0.495	0.495	0.495	0.495
$\alpha_1^{\hat{y}}$	β	0.5	0.1	0.4	0.582	0.7	0.582	0.582	0.582	0.582
$\alpha_2^{\hat{y}}$	β	0.4	0.2	0.1	0.269	0.4	0.269	0.269	0.269	0.269
$\Delta^{\bar{y}}$	N	0.006	0.05	0.0	0.003	0.0	0.003	0.003	0.003	0.003
Labor market										
$\gamma^{\bar{u}}$	β	0.03	0.02	0.0	0.030	0.1	0.030	0.030	0.030	0.030
$\theta^{\bar{u}}$	β	0.5	0.1	0.4	0.543	0.7	0.543	0.543	0.543	0.543
$\alpha_1^{\hat{u}}$	β	0.5	0.1	0.4	0.572	0.7	0.572	0.572	0.572	0.572
$\alpha_2^{\hat{u}}$	Γ	0.5	0.1	0.3	0.401	0.5	0.401	0.401	0.401	0.401
$\bar{u}$	Γ^{-1}	0.093	0.05	0.1	0.084	0.1	0.084	0.084	0.084	0.084
Price equations										
$\gamma^{\bar{\pi}}$	β	0.25	0.1	0.1	0.414	0.8	0.414	0.414	0.414	0.414
$\theta^{\bar{\pi}}$	β	0.5	0.1	0.3	0.435	0.6	0.435	0.435	0.435	0.435
$\alpha_1^{\hat{\pi}}$	β	0.5	0.1	0.3	0.434	0.6	0.434	0.434	0.434	0.434
$\alpha_2^{\hat{\pi}}$	β	0.5	0.1	0.3	0.355	0.5	0.355	0.355	0.355	0.355
$\bar{\pi}$	-	0.02	0.02	-	0.02	-	0.02	0.02	0.02	0.02
Std. deviations										
$\varepsilon_t^{\bar{y}}$	Γ^{-1}	1	∞	0.2	0.3	0.4	0.3	0.3	0.3	0.3
$\boldsymbol{\varepsilon_t^{\bar{y}P}}$	Γ^{-1}	1	∞	-	-	-	**0.5**	-	**6.4**	**0.8**
$\varepsilon_t^{\hat{y}}$	Γ^{-1}	100	∞	1.3	1.5	1.8	1.5	1.5	1.5	1.5
$\boldsymbol{\varepsilon_t^{\hat{y}P}}$	Γ^{-1}	100	∞	-	-	-	**11.8**	**11.7**	-	**15.4**
$\varepsilon_t^{\bar{u}}$	Γ^{-1}	1	∞	0.1	0.2	0.3	0.2	0.2	0.2	0.2
$\boldsymbol{\varepsilon_t^{\bar{u}P}}$	Γ^{-1}	1	∞	-	-	-	**0.5**	-	**0.4**	**0.5**
$\varepsilon_t^{\hat{u}}$	Γ^{-1}	100	∞	1.1	1.3	1.6	1.3	1.3	1.3	1.3
$\boldsymbol{\varepsilon_t^{\hat{u}P}}$	Γ^{-1}	100	∞	-	-	-	**11.2**	**10.9**	-	**11.5**
$\varepsilon_t^{\bar{\pi}}$	Γ^{-1}	1	∞	0.1	0.2	0.4	0.2	0.2	0.2	0.2
$\boldsymbol{\varepsilon_t^{\bar{\pi}P}}$	Γ^{-1}	1	∞	-	-	-	**0.6**	**0.6**	**0.6**	-
$\varepsilon_t^{\hat{\pi}}$	Γ^{-1}	100	∞	1.4	1.6	1.9	1.6	1.6	1.6	1.6
$\boldsymbol{\varepsilon_t^{\hat{\pi}P}}$	Γ^{-1}	100	∞	-	-	-	**12.3**	**12.2**	**11.7**	-

Source: The authors.

Notes: For details, see Table A.1.

Table A.2. Priors and posteriors using euro area data (P-model)



(a) Actual output and trend $\bar{y}_t$ (Models M-0, M-1, and M-2).

(b) Actual output and trend $\bar{y}_t$ (Models M-0, M-3 and M-4)

(c) Non-pandemic trend disturbances (innovation $\varepsilon_t^{\bar{y}}$)

(d) Pandemic trend disturbances (innovation $\varepsilon_t^{\bar{y}P}$)

Figure A.1: Output and exogenous shocks affecting trend output $\bar{y}_t$ (P-model)

Source: The authors.

Notes: Euro area data. For further details, see Figure 2.

Appendix B: U model details

This appendix recalls key features of the U model—for all details, see Duarte *et al.* (2020). The model features a production function $Y = \mathcal{A}\mathcal{L}^{\iota}\mathcal{K}^{1-\iota}$ with productivity $\mathcal{A}$, total labour services $\mathcal{L} \equiv (U_L E_L)L$ and total capital services $\mathcal{K} \equiv (U_K E_K)K$, where U_i and E_i, $i = \{L, K\}$ are utilization rates and efficiency levels, respectively, and $0 \leqslant \iota \leqslant 1$.

Output is produced with technology $Y = (TFP)L^{\iota}K^{1-\iota}$, where $TFP \equiv \mathcal{A}(U_L E_L)^{\iota}(U_K E_K)^{1-\iota}$, and potential output with $\bar{Y} = (\overline{TFP})\bar{L}^{\iota}\bar{K}^{1-\iota}$, where all inputs are at their trend levels.

The (log) growth rate of potential output is given by

$$\Delta\bar{y}_t = \Delta\overline{tfp}_t + \iota\Delta\bar{l}_t + (1-\iota)\Delta\bar{k}_t \tag{B.1}$$

where $\Delta\bar{l}_t = \Delta\bar{h}_t + \Delta ln(1 - \bar{U}_t)$ is the change of trend labour, $\Delta\bar{k}_t = \Delta k_t$ is the change in the observed capital stock; $\Delta\bar{h}_t$ is the change in trend labour force (measured in hours) and $\bar{U}_t$ is the trend unemployment rate.[17] Assuming nil deviations from trend of both $\mathcal{A}$ and E_i, $i = \{L, K\}$, then $(TFP - \overline{TFP})$ measures the deviation of utilization rates from their trend levels.

The growth rate

$$\Delta\overline{tfp}_t = \rho_1\Delta I_t^{tfp} + (1-\rho_1)\Delta\overline{tfp}_{t-1} + \varepsilon_t^{\Delta\overline{tfp}} \tag{B.2}$$

is informed by I_t^{tfp} (defined as the trend component of Solow's residual and computed with an HP filter with a smoothing parameter of 1600), where $0 \leq \rho_1 \leq 1$, and is subject to iid shocks $\varepsilon_t^{\Delta\overline{tfp}}$, following a normal distribution $N(0, \sigma^{\varepsilon^{\Delta\overline{tfp}}})$.

The output gap

$$A_1(L)(y_t - \bar{y}_t) = \varepsilon_{1,t} \tag{B.3}$$

follows an autoregressive process, where $A_1(L)$ denotes a lag polynomial of order p_1 and $\varepsilon_{1,t}$ is an iid shock following a normal distribution $(0, \sigma^{\varepsilon_1})$.

The unemployment gap

$$A_2(L)(U_t - \bar{U}_t) = -B_2(L)(y_t - \bar{y}_t) + \varepsilon_{2,t}, \tag{B.4}$$

follows an Okun's law, where $A_2(L)$ and $B_2(L)$ denote lag polynomials of order p_2 and q_2, respectively, and $\varepsilon_{2,t}$ is an iid $(0, \sigma^{\varepsilon_2})$ error term. Furthermore,

$$\bar{U}_t = \bar{U}_{t-1} + \Delta_{t-1}^{\bar{U}} \tag{B.5}$$

$$\Delta_t^{\bar{U}} = \rho_2\Delta I_t^U + (1-\rho_2)\Delta_{t-1}^{\bar{U}} + \varepsilon_t^{\bar{U}} \tag{B.6}$$

$$\bar{h}_t = \bar{h}_{t-1} + \Delta_{t-1}^{\bar{h}}, \tag{B.7}$$

$$\Delta_t^{\bar{h}} = \rho_3\Delta I_t^h + (1-\rho_3)\Delta_{t-1}^{\bar{h}} + \varepsilon_t^{\bar{h}} \tag{B.8}$$

17. A residual term, omitted from the labor input definition, ensures an exact decomposition of L_t, namely to account for the differences between total employment in national accounts and total employment in the Labour Force Survey.

where I_t^U is the trend component of unemployment (initially computed with an HP filter on the ratio of short- and long-run unemployment (annual data), with a smoothing parameter of 100, and then transformed into quarterly data), and I_t^h is the labor force trend component (computed with an HP–1600 filter), $\varepsilon_t^{\bar{U}}$ and $\varepsilon_t^{\bar{h}}$ are iid-normal terms, given by $N(0, \sigma^{\varepsilon^{\bar{U}}})$ and $N(0, \sigma^{\varepsilon^{\bar{h}}})$, and $0 \leq \rho_2, \rho_3 \leq 1$.

The labor force gap

$$A_3(L)(h_t - \bar{h}_t) = -B_3(L)(U_t - \bar{U}_t) + \varepsilon_{3,t} \tag{B.9}$$

depends on the unemployment gap, where $A_3(L)$ and $B_3(L)$ denote lag polynomials of order p_3 and q_3, respectively, and $\varepsilon_{3,t}$ is an iid-normal $(0, \sigma^{\varepsilon_3})$ error term.

The price and wage equations

$$A_4(L)(\pi_t^p - \bar{\pi}_t^p) = B_4(L)(y_t - \bar{y}_t) + \varepsilon_{4,t} \tag{B.10}$$

$$A_5(L)(\pi_t^w - \bar{\pi}_t^w) = B_5(L)(l_t - \bar{l}_t) + \varepsilon_{5,t} \tag{B.11}$$

depend on the output gap and on $l_t - \bar{l}_t = (h_t - \bar{h}_t) - (U_t - \bar{U}_t)$—a labour market tightness indicator—, where $A_4(L)$, $A_5(L)$, $B_4(L)$ and $B_5(L)$ denote lag polynomials of order p_4, p_5, q_4 and q_5, and $\varepsilon_{4,t}$ and $\varepsilon_{5,t}$ are iid-normal $(0, \sigma^{\varepsilon_4})$ and $(0, \sigma^{\varepsilon_5})$ error terms, respectively. Price and wage inflation are defined in annualized terms and their trend components as

$$\bar{\pi}_t^p = \bar{\pi}_{t-1}^p + \Delta_{t-1}^{\bar{\pi}^p}, \tag{B.12}$$

$$\Delta_t^{\bar{\pi}^p} = \rho_4 \Delta I_t^{\pi^p} + (1 - \rho_4)\Delta_{t-1}^{\bar{\pi}^p} + \varepsilon_t^{\bar{\pi}^p} \tag{B.13}$$

$$\bar{\pi}_t^w = \bar{\pi}_t^p + 4 * (\Delta\bar{y}_{t-1} - \Delta\bar{l}_{t-1}) + \Delta_{t-1}^{\bar{\pi}^w}, \tag{B.14}$$

$$\Delta_t^{\bar{\pi}^w} = \rho_5 \Delta I_t^{\pi^w} + (1 - \rho_5)\Delta_{t-1}^{\bar{\pi}^w} + \varepsilon_t^{\bar{\pi}^w} \tag{B.15}$$

where $\Delta I_t^{\pi^p} = {\pi^p}_t - {\pi^p}_{t-1}$ and $\varepsilon_t^{\bar{\pi}^p}, \varepsilon_t^{\bar{\pi}^w}$ are iid-normal shocks following $N(0, \sigma^{\varepsilon^{\bar{\pi}^p}})$ and $N(0, \sigma^{\varepsilon^{\bar{\pi}^w}})$, respectively. Trend output growth per hour worked is annualized, $4 * (\Delta\bar{y}_{t-1} - \Delta\bar{l}_{t-1})$, since price and wage inflation are also measured in annualized terms. Although the general model allows $\Delta I_t^{\pi^w}$ to play a role, we set $\rho_5 = 0$, as in Duarte *et al.* (2020), to cope with labour share dynamics over the sample.

The model posits that capital and output growth will be equal in the long run, absent any shocks. More precisely,

$$\begin{aligned} A_6(L)\Delta k_t &= B_6(L)\Delta y_t + \varepsilon_t^k \\ A_6(1) &= B_6(1), \end{aligned} \tag{B.16}$$

where $A_6(L)$ and $B_6(L)$ denote lag polynomials of order p_6 and q_6, respectively, and ε_t^k is an iid $(0, \sigma^{\varepsilon^k})$ error term.

Finally, regarding indicators ΔI^i, $i = \{tfp, U, h, \pi^p, \pi^w\}$, their general form is given by standard zero mean processes

$$A_i(L)\Delta I_t^i = \varepsilon_t^{I^i}, \tag{B.17}$$

	Equations	Parameters	**Portugal**	**Euro area**
A polynomial				
p_1	(B.3)	α_1, α_2	2	2
p_2	(B.4)	γ_1	1	1
p_3	(B.9)	η_1	1	1
p_4	(B.10)	β_1	1	1
p_5	(B.11)	β_3	1	1
p_6	(B.16)	–	–	–
p_i	(B.17)	–	–	–
B polynomial				
q_2	(B.4)	γ_2, γ_3	2	2
q_3	(B.9)	η_2	1	1
q_4	(B.10)	β_2	1	1
q_5	(B.11)	β_4	1	1
q_6	(B.16)	–	–	–

Table B.1. The model's lag structure

Note: Polynominals of type B omit the contemporaneous term, reducing the degree of endogeneity of the model. Identifiers p_i consider $i = \{tfp, U, h, \pi^p, \pi^w\}$.

where $A_i(L)$ denote lag polynomials of order p_i and $\varepsilon_t^{I^i}$ is an iid $(0, \sigma^{\varepsilon^{I^i}})$ shock.

The polynominal lag structure, presented in Table B.1, is identical to the one chosen by Duarte *et al.* (2020).

Table B.2 and Table B.3 report priors and posteriors using Portuguese and euro area data, respectively.

Model structure	Param.	Prior Dist. Mean	Dist.	s.d.	Selected parametrization 5%	Model 0 50%	95%	Model 1 50%	Model 2 50%	Model 3 50%	Model 4 50%
Economic relationships											
Output gap equation: $y_t - \bar{y}_t$											
$(y_{t-1} - \bar{y}_{t-1})$	α_1	0.50	β	0.15	0.4	0.65	0.8	0.65	0.65	0.65	0.65
$(y_{t-2} - \bar{y}_{t-2})$	α_2	0.40	β	0.20	0.1	0.27	0.5	0.27	0.27	0.27	0.27
Output elasticity of labour	ι	0.63	β	0.05	0.6	0.64	0.7	0.64	0.64	0.64	0.64
Okun's law: $U_t - \bar{U}_t$											
$(U_{t-1} - \bar{U}_{t-1})$	γ_1	0.50	β	0.15	0.4	0.62	0.8	0.62	0.62	0.62	0.62
$(y_{t-1} - \bar{y}_{t-1})$	γ_2	0.50	Γ	0.30	0.1	0.21	0.4	0.21	0.21	0.21	0.21
$(y_{t-2} - \bar{y}_{t-2})$	γ_3	0.50	Γ	0.30	0.1	0.16	0.3	0.16	0.16	0.16	0.16
Price equation: $\pi_t^p - \bar{\pi}_t^p$											
$(\pi_{t-1}^p - \bar{\pi}_{t-1}^p)$	β_1	0.50	β	0.10	0.2	0.30	0.4	0.30	0.30	0.30	0.30
$(y_{t-1} - \bar{y}_{t-1})$	β_2	0.50	Γ	0.30	0.1	0.27	0.6	0.27	0.27	0.27	0.27
Wage equation: $\pi_t^w - \bar{\pi}_t^w$											
$(\pi_{t-1}^w - \bar{\pi}_{t-1}^w)$	β_3	0.50	β	0.15	0.1	0.13	0.2	0.13	0.13	0.13	0.13
$(l_{t-1} - \bar{l}_{t-1})$	β_4	0.50	Γ	0.15	0.3	0.49	0.7	0.49	0.49	0.49	0.49
Labour force equation: $h_t - \bar{h}_t$											
$(h_{t-1} - \bar{h}_{t-1})$	η_1	0.50	β	0.20	0.3	0.54	0.8	0.54	0.54	0.54	0.54
$(U_{t-1} - \bar{U}_{t-1})$	η_2	0.20	Γ	0.10	0.1	0.13	0.3	0.13	0.13	0.13	0.13
Unobserved components' law of motion											
Trend TFP $(I_t^{t\bar{f}p})$	ρ_1	0.50	Γ	0.20	0.3	0.63	1.1	0.63	0.63	0.63	0.63
NAWRU $(I_t^{\bar{U}})$	ρ_2	0.50	Γ	0.20	0.2	0.50	0.9	0.50	0.50	0.50	0.50
Trend labour force $(I_t^{\bar{h}})$	ρ_3	0.50	Γ	0.20	0.2	0.42	0.7	0.42	0.42	0.42	0.42
Trend inflation $(I_t^{\bar{\pi}^P})$	ρ_4	0.50	Γ	0.20	0.1	0.25	0.4	0.25	0.25	0.25	0.25
Standard errors of innovations: economic relationships											
Non-COVID shocks											
Output gap: $y_t - \bar{y}_t$	σ^{ε_1}	1.00	Inv-Γ	∞	0.013	0.0152	0.018	0.0152	0.0152	0.0152	0.0152
Okun's law: $U_t - \bar{U}_t$	σ^{ε_2}	1.00	Inv-Γ	∞	0.012	0.0139	0.017	0.0139	0.0139	0.0139	0.0139
Price equation: $\pi_t^p - \bar{\pi}_t^p$	σ^{ε_4}	1.00	Inv-Γ	∞	0.028	0.0324	0.038	0.0324	0.0324	0.0324	0.0324
Wage equation: $\pi_t^w - \bar{\pi}_t^w$	σ^{ε_5}	1.00	Inv-Γ	∞	0.065	0.0745	0.086	0.0745	0.0745	0.0745	0.0745
Lab. force equation: $h_t - \bar{h}_t$	σ^{ε_3}	1.00	Inv-Γ	∞	0.015	0.0172	0.020	0.0172	0.0172	0.0172	0.0172
COVID shocks											
Output gap: $y_t - \bar{y}_t$	$\sigma^{\varepsilon_1^P}$	1.00	Inv-Γ	∞	-	-	-	0.1091	0.1079	-	0.1322
Okun's law: $U_t - \bar{U}_t$	$\sigma^{\varepsilon_2^P}$	1.00	Inv-Γ	∞	-	-	-	0.1068	0.1058	-	0.1068
Price equation: $\pi_t^p - \bar{\pi}_t^p$	$\sigma^{\varepsilon_4^P}$	1.00	Inv-Γ	∞	-	-	-	0.1308	0.1311	0.1369	-
Wage equation: $\pi_t^w - \bar{\pi}_t^w$	$\sigma^{\varepsilon_5^P}$	1.00	Inv-Γ	∞	-	-	-	0.3644	0.3667	0.5109	-
Lab. force equation: $h_t - \bar{h}_t$	$\sigma^{\varepsilon_3^P}$	1.00	Inv-Γ	∞	-	-	-	0.1577	0.1579	-	0.1550
Standard errors of innovations: unobserved components											
Non-COVID shocks											
TFP growth: $\Delta t\bar{f}p$	$\varepsilon_t^{\Delta \overline{tfp}}$	0.01	Inv-Γ	∞	0.001	0.0020	0.003	0.0020	0.0020	0.0020	0.0020
NAWRU: $\bar{U}$	$\sigma^{\varepsilon^{\bar{U}}}$	0.01	Inv-Γ	∞	0.001	0.0022	0.004	0.0022	0.0022	0.0022	0.0022
Expected price inflation: $\bar{\pi}^p$	$\sigma^{\varepsilon^{\bar{\pi}^p}}$	0.01	Inv-Γ	∞	0.001	0.0020	0.003	0.0020	0.0020	0.0020	0.0020
Expected wage inflation: $\bar{\pi}^w$	$\sigma^{\varepsilon^{\bar{\pi}^w}}$	0.01	Inv-Γ	∞	0.002	0.0032	0.007	0.0032	0.0032	0.0032	0.0032
Trend labour force: $\bar{h}$	$\sigma^{\varepsilon^{\bar{h}}}$	0.01	Inv-Γ	∞	0.002	0.0026	0.004	0.0026	0.0026	0.0026	0.0026
COVID shocks											
TFP growth: $\Delta t\bar{f}p$	$\varepsilon_t^{\Delta \overline{tfp}^P}$	0.01	Inv-Γ	∞	-	-	-	0.0052	-	0.0048	0.0623
NAWRU: $\bar{U}$	$\sigma^{\varepsilon^{\bar{U}^P}}$	0.01	Inv-Γ	∞	-	-	-	0.0040	-	0.0035	0.0041
Expected price inflation: $\bar{\pi}^p$	$\sigma^{\varepsilon^{\bar{\pi}^{p^P}}}$	0.01	Inv-Γ	∞	-	-	-	0.0055	0.0055	0.0054	-
Expected wage inflation: $\bar{\pi}^w$	$\sigma^{\varepsilon^{\bar{\pi}^{w^P}}}$	0.01	Inv-Γ	∞	-	-	-	0.0059	0.0059	0.0059	-
Trend labour force: $\bar{h}$	$\sigma^{\varepsilon^{\bar{h}^P}}$	0.01	Inv-Γ	∞	-	-	-	0.0041	-	0.1330	0.0041

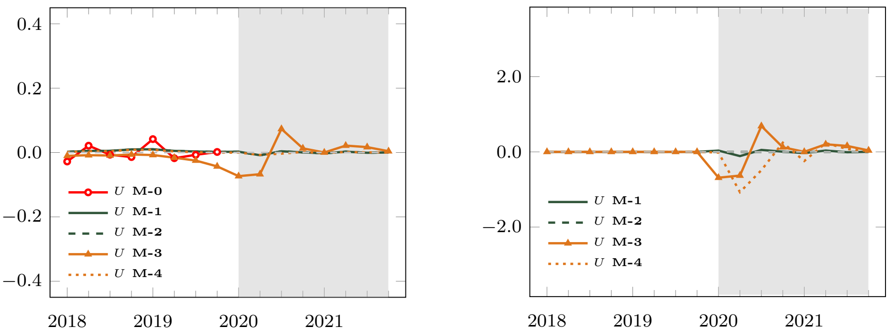
Table B.2. Priors and posteriors using Portuguese data (U model)

Note: All selected parametrizations are median posterior estimates, computed as in the small model exercise (see Table A.1 for further details).

	Param.	Prior Dist.			Selected parametrization						
Model structure		Mean	Dist.	s.d.	5	Model 0		Model 1	Model 2	Model 3	Model 4
Economic relationships											
Output gap equation: $y_t - \bar{y}_t$											
$(y_{t-1} - \bar{y}_{t-1})$	α_1	0.50	β	0.15	0.4	0.64	0.8	0.64	0.64	0.64	0.64
$(y_{t-2} - \bar{y}_{t-2})$	α_2	0.40	β	0.20	0.1	0.23	0.4	0.23	0.23	0.23	0.23
Output elasticity of labour	ι	0.63	β	0.05	0.6	0.63	0.7	0.63	0.63	0.63	0.63
Okun's law: $U_t - \bar{U}_t$											
$(U_{t-1} - \bar{U}_{t-1})$	γ_1	0.50	β	0.15	0.3	0.56	0.8	0.56	0.56	0.56	0.56
$(y_{t-1} - \bar{y}_{t-1})$	γ_2	0.50	Γ	0.30	0.1	0.17	0.3	0.17	0.17	0.17	0.17
$(y_{t-2} - \bar{y}_{t-2})$	γ_3	0.50	Γ	0.30	0.0	0.15	0.3	0.15	0.15	0.15	0.15
Price equation: $\pi_t^p - \bar{\pi}_t^p$											
$(\pi_{t-1}^p - \bar{\pi}_{t-1}^p)$	β_1	0.50	β	0.10	0.3	0.46	0.6	0.46	0.46	0.46	0.46
$(y_{t-1} - \bar{y}_{t-1})$	β_2	0.50	Γ	0.30	0.1	0.23	0.4	0.23	0.23	0.23	0.23
Wage equation: $\pi_t^w - \bar{\pi}_t^w$											
$(\pi_{t-1}^w - \bar{\pi}_{t-1}^w)$	β_3	0.50	β	0.15	0.2	0.34	0.5	0.34	0.34	0.34	0.34
$(l_{t-1} - \bar{l}_{t-1})$	β_4	0.50	Γ	0.15	0.2	0.39	0.6	0.39	0.39	0.39	0.39
Labour force equation: $h_t - \bar{h}_t$											
$(h_{t-1} - \bar{h}_{t-1})$	η_1	0.50	β	0.20	0.4	0.71	0.9	0.71	0.71	0.71	0.71
$(U_{t-1} - \bar{U}_{t-1})$	η_2	0.20	Γ	0.10	0.1	0.15	0.3	0.15	0.15	0.15	0.15
Unobserved components' law of motion											
Trend TFP $(I_t^{t\bar{f}p})$	ρ_1	0.50	Γ	0.20	0.4	0.63	1.0	0.63	0.63	0.63	0.63
NAWRU $(I_t^{\bar{U}})$	ρ_2	0.50	Γ	0.20	0.3	0.60	1.0	0.60	0.60	0.60	0.60
Trend labour force $(I_t^{\bar{h}})$	ρ_3	0.50	Γ	0.20	0.3	0.50	0.8	0.50	0.50	0.50	0.50
Trend inflation $(I_t^{\bar{\pi}^p})$	ρ_4	0.50	Γ	0.20	0.2	0.38	0.6	0.38	0.38	0.38	0.38
Standard errors of innovations: economic relationships											
Non-COVID shocks											
Output gap: $y_t - \bar{y}_t$	σ^{ε_1}	1.00	Inv-Γ	∞	0.012	0.0142	0.017	0.0142	0.0142	0.0142	0.0142
Okun's law: $U_t - \bar{U}_t$	σ^{ε_2}	1.00	Inv-Γ	∞	0.011	0.0129	0.015	0.0129	0.0129	0.0129	0.0129
Price equation: $\pi_t^p - \bar{\pi}_t^p$	σ^{ε_4}	1.00	Inv-Γ	∞	0.014	0.0168	0.020	0.0168	0.0168	0.0168	0.0168
Wage equation: $\pi_t^w - \bar{\pi}_t^w$	σ^{ε_5}	1.00	Inv-Γ	∞	0.018	0.0217	0.026	0.0217	0.0217	0.0217	0.0217
Lab. force equation: $h_t - \bar{h}_t$	σ^{ε_3}	1.00	Inv-Γ	∞	0.011	0.0134	0.016	0.0134	0.0134	0.0134	0.0134
COVID shocks											
Output gap: $y_t - \bar{y}_t$	$\sigma^{\varepsilon_1^P}$	1.00	Inv-Γ	∞	-	-	-	0.0978	0.0967	-	0.1106
Okun's law: $U_t - \bar{U}_t$	$\sigma^{\varepsilon_2^P}$	1.00	Inv-Γ	∞	-	-	-	0.1049	0.1044	-	0.1056
Price equation: $\pi_t^p - \bar{\pi}_t^p$	$\sigma^{\varepsilon_4^P}$	1.00	Inv-Γ	∞	-	-	-	0.1151	0.1171	0.1205	-
Wage equation: $\pi_t^w - \bar{\pi}_t^w$	$\sigma^{\varepsilon_5^P}$	1.00	Inv-Γ	∞	-	-	-	0.1615	0.1658	0.2745	-
Lab. force equation: $h_t - \bar{h}_t$	$\sigma^{\varepsilon_3^P}$	1.00	Inv-Γ	∞	-	-	-	0.1285	0.1304	-	0.1292
Standard errors of innovations: unobserved components											
Non-COVID shocks											
TFP growth: $\Delta t\bar{f}p$	$\varepsilon_t^{\Delta\overline{tfp}}$	0.01	Inv-Γ	∞	0.001	0.0014	0.002	0.0014	0.0014	0.0014	0.0014
NAWRU: $\bar{U}$	$\sigma^{\varepsilon^{\bar{U}}}$	0.01	Inv-Γ	∞	0.001	0.0017	0.003	0.0017	0.0017	0.0017	0.0017
Expected price inflation: $\bar{\pi}^p$	$\sigma^{\varepsilon^{\bar{\pi}^p}}$	0.01	Inv-Γ	∞	0.001	0.0016	0.003	0.0016	0.0016	0.0016	0.0016
Expected wage inflation: $\bar{\pi}^w$	$\sigma^{\varepsilon^{\bar{\pi}^w}}$	0.01	Inv-Γ	∞	0.001	0.0025	0.005	0.0025	0.0025	0.0025	0.0025
Trend labour force: $\bar{h}$	$\sigma^{\varepsilon^{\bar{h}}}$	0.01	Inv-Γ	∞	0.001	0.0019	0.003	0.0019	0.0019	0.0019	0.0019
COVID shocks											
TFP growth: $\Delta t\bar{f}p$	$\varepsilon_t^{\Delta\overline{tfp}^P}$	0.01	Inv-Γ	∞	-	-	-	0.0050	-	0.0042	0.0162
NAWRU: $\bar{U}$	$\sigma^{\varepsilon^{\bar{U}^P}}$	0.01	Inv-Γ	∞	-	-	-	0.0041	-	0.0032	0.0046
Expected price inflation: $\bar{\pi}^p$	$\sigma^{\varepsilon^{\bar{\pi}^{p^P}}}$	0.01	Inv-Γ	∞	-	-	-	0.0051	0.0051	0.0052	-
Expected wage inflation: $\bar{\pi}^w$	$\sigma^{\varepsilon^{\bar{\pi}^{w^P}}}$	0.01	Inv-Γ	∞	-	-	-	0.0053	0.0057	0.0059	-
Trend labour force: $\bar{h}$	$\sigma^{\varepsilon^{\bar{h}^P}}$	0.01	Inv-Γ	∞	-	-	-	0.0037	-	0.0806	0.0041

Table B.3. Priors and posteriors using euro area data (U model)

Note: All selected parametrizations are median posterior estimates, computed as in the small model exercise (see Table A.1 for further details).



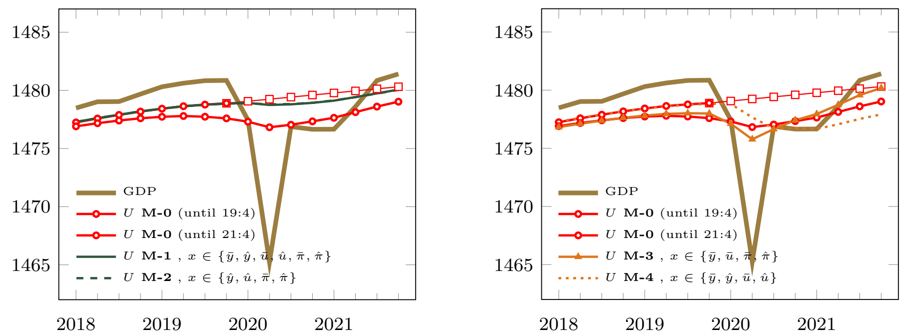
(a) Non-pandemic disturbances affecting productivity (innovation $\varepsilon_t^{\Delta \overline{tfp}}$)

(b) Pandemic disturbances affecting productivity (innovation $\varepsilon_t^{\Delta \overline{tfp}_P}$)

Figure B.1: Selected exogenous shocks affecting trend output $\bar{y}_t$ (U model).

Source: The authors.

Notes: Euro area data. All unobserved disturbances are computed with median posterior estimates.



(a) Trend $\bar{y}_t$ of model versions M-0, M-1 and M-2.

(b) Trend $\bar{y}_t$ of model versions M-0, M-2 and M-3.

Source: The authors.

Notes: Euro area data. “U M-0 (until 19:4)” and “U M-0 (until 21:4)” refers to a model version without pandemic shocks, estimated until 2019:4, where the unobserved trend components are computed with information until 2019:4 and until 2021:4, respectivey. White squares report projections of “U M-0 (until 19:4)” over 20:1-21:4. All unobserved components are computed with median posterior estimates.

Figure B.2: GDP and trends across model versions (U model).

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