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Unit labor costs and inflation in OECD countries during the COVID-19 pandemic

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Abstract:

This paper investigates the drivers of inflation in 34 Organization for Economic Cooperation and Development countries during the COVID-19 pandemic. Using an amplified price equation and two different panel data econometric techniques, we assess the impact of seven key variables on the price level. In this context, unit labor costs are a major source of price instability, whereas massive cash transfers generate demand-pull inflation. Moreover, higher financial costs are potentially inflationary, debt/contract relief policies are deflationary, and pandemic-related variables deliver mixed effects on prices. These findings have clear-cut policy implications.

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> *Inflation may emanate from a number of different sources other than excess demand in the product market. In particular: prices may rise because prices are based on costs of production and costs rise; prices may rise because of shifts in demand from one sector of the economy to another and prices are more flexible in the upward direction than in the downward direction; and prices may rise in a self-reinforcing way because of a loss of confidence in money and the development of a wage-price spiral.*
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> A.P. Thirlwall (1974, p. 37)

This paper investigates the main sources of inflation in 34 (out of the 38) nations of the Organization for Economic Cooperation and Development (OECD) during the COVID-19 pandemic.[1] To that end, we employ a price equation with seven explanatory variables: unit labor costs (ULC), policy-related interest rates, real effective exchange rates, two economic support

[1] Four nations were excluded due to the unavailability of data. The 34 countries included are: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovenia, South Korea, Spain, Sweden, Switzerland, Republic of Türkiye, United Kingdom, and United States.

variables, and two pandemic-related variables. The economic support variables are income support and debt/contract relief, whereas the pandemic-related variables are the stringency index, capturing closure and containment measures, and the number of new COVID-19 cases smoothed per million.

Although the OECD economies are heterogeneous, the global nature of the pandemic and the relative coordination of national economic policies justify the search for empirical regularities across nations. Moreover, OECD countries typically provide high-quality data, resulting in fewer measurement errors. To obtain more reliable evidence and enhance the analytical toolkit of the paper, we use two panel data econometric procedures: Two-stage least squares (2SLS), and difference generalized method of moments (GMM), also known as the Arellano-Bond estimator (Arellano and Bond, 1991). These methodologies complement each other because 2SLS is appropriate for estimating a fixed effects panel data model, which captures the heterogeneity across countries in a static setting. In contrast, the Arellano-Bond estimator is suitable for estimating a dynamic panel data model where country heterogeneity is eliminated by means of first differencing the data. What is more, both procedures are robust to endogeneity problems, meaning that they are consistent under certain conditions. We ensure that these conditions are satisfied and implement efficiency-enhancing measures.

The panel data models involve 34 nations and quarterly data from the first quarter of 2020 to the fourth quarter of 2022, comprising 12 time-series observations.[2] Unfortunately, as of January 1, 2023, the Oxford COVID-19 Government Response Tracker (OxCGRT) stopped providing data for the income support and the debt/contract relief indices, so our sample period cannot go beyond 2022 with the current model specification. The empirical evidence is consistent across econometric methods and remedial measures in showing that:

1) ULC are a major source of inflation. As we shall see, ULC grew more than 17% during the period 2020-2022, mainly because of the pandemic and the great lockdown. In this context, ULC have a strong positive impact on prices, which is statistically significant at the 1% level in every regression.
2) Income support policies generate demand-pull inflation, whereas debt/contract relief measures are deflationary by alleviating financial distress. Lastly, the net effect of closure and containment measures (i.e., school and workplace closings, restrictions to national and international traveling, and prohibition of public events) is deflationary. We use the term “net effect” because these measures generate deflationary effects through reduced consumption on the demand side, and inflationary effects through the disruption of production chains on the supply side.

Secondly, under the Arellano-Bond (AB) estimator, regardless of whether we use quarterly or semi-annual data, we also find that:

1) Interest rates bear a positive relationship with the price level. According to Céspedes et al. (2020) and Cherkasky (2022), in the presence of financial distress, higher financial costs can induce firms to raise prices. This finding is also consistent with the Gibson paradox, which is explained in the next section.
2) The propagation of the virus, like closure and containment measures, brings about demand- and supply-side effects. However, the net effect of the new COVID-19 cases

[2] To deal with the so-called instrument proliferation problem of the Arellano-Bond estimator, we also estimate the model with semi-annual data, compare the findings, and perform Sargan-Hansen tests for overidentifying restrictions. In addition, we conduct Arellano-Bond tests for first- and second-order autocorrelation.

smoothed per million was inflationary, presumably because production chains tend to fail as the number of sick workers rises.

3) Inflation is an inertial phenomenon to a certain degree, given the influence of past inflation on current inflation.

Therefore, to the best of our knowledge, this paper fills a small gap in the empirical literature by showing the significant impact of ULC on inflation during the COVID-19 pandemic. Among other things, our paper provides empirical support to Céspedes et al.'s (2020) theoretical assertion regarding the behavior of ULC during the pandemic and the consequences of it. Based on a theoretical model for a small open economy, these authors show that the COVID-19 pandemic can contribute to reduced labor productivity. The rationale is that workers who lose their jobs during the pandemic are forced to migrate to industries where their expertise is not as useful as before, so labor productivity falls and ULC tend to rise.

Furthermore, the inflationary episodes taking place after the great lockdown are mainly attributed, in the current literature, to countercyclical policies running into capacity constraints. As we explain in detail in the next section, Erdoğan et al. (2020) provide evidence that pandemic-related inflationary pressures in 28 European Union countries and candidate nations were the result of monetary growth, among other factors. Examining 32 emerging economies and 7 advanced economies, de Soyres et al. (2022) conclude that the surge in inflation was caused by a combination of fiscal expansion and an insufficient output response. Using ten nations as a benchmark (five from Latin America and five from Asia), Abdelkafi et al. (2023) offer some evidence that income support measures and government-backed loans were key sources of inflation. For four Asian economies, Rizvi et al. (2023) contend that monetary expansion played a pivotal role in fostering price instability during the pandemic. Lastly, according to Jordà et al. (2022), Gharehgozli and Lee (2022), and Kliesen and Wheelock (2023), the recent inflationary outburst in the US was the result of a substantial increase in government spending. Against this backdrop, our paper highlights the role played by ULC while acknowledging the influence of income support programs, debt/contract relief packages, and other variables.

The rest of the paper is organized as follows. Section 1 briefly reviews the recent econometric literature. Section 2 specifies the theoretical model, explains the econometric methods, and describes the data. Section 3 presents the empirical evidence. Finally, we summarize the findings and make some policy recommendations.

1. Literature review

The world economy has gone through an unprecedented episode. As opposed to previous crises originated either in the financial or the real sector, the recent economic imbalances stem from a worldwide health crisis (Susskind and Vines, 2020), leading to the great lockdown and then to expansionary fiscal and monetary policies aimed at revitalizing economic activity. Moreover, although closure and containment measures saved lives and reduced the number of hospitalizations, they had two undesirable outcomes:

1) A contractionary demand-side effect, causing a downward pressure on prices. The closing of public places, the full or partial interruption of air and land transportation services, the stoppage of recreation and entertainment activities, and the stay-at-home mandates had a devastating effect on the service sector (Yeh, 2021). The consumption of durable goods also fell during the first quarter of 2020 and subsequently managed to recover (Tauber

and Van Zandweghe, 2021). In any event, retail and wholesale commerce endured a substantial negative impact in the early stages of the pandemic (Yeh, 2021).

2) A contractionary supply-side effect, given the initial downfall in economic activity and the massive bankruptcy of enterprises (Makin and Layton, 2021). In fact, worldwide quarantine measures gave rise to an "acute overall disruption" (Devereux et al., 2020, p. S226), given that lots of businesses were forced either to temporarily close or drastically limit their operations. Barlow et al. (2021) point out that international trade flows as well as global supply chains (GSC) were interrupted. This, in turn, caused the lack of numerous electrical and electronic components used in the manufacturing industry and the service sector (Akbulaev et al., 2020).

In this context, governments implemented stimulus packages to soften the effects of the health and economic crisis on firms and households. Broadly speaking, economic support programs consisted of:

1) Income support measures (i.e., fiscal expansion) to businesses and households. Businesses with working capital problems, especially in the hardest-hit industries, benefited from government subsidies in exchange for employment retention assurances. In fact, governments were seeking to preserve production capacities and help firms retain workers, especially those difficult to replace given their qualifications (Akbulaev et al., 2020; Makin and Layton, 2021). Direct cash transfers were also made to unemployed people and informal workers.
2) Debt/contract relief measures, aimed at alleviating the financial situation of households and small-business owners. To that end, many governments resorted to offering loans with below-market interest rates to the needy, granting grace periods to individuals and firms owing taxes and utility payments, and temporarily freezing mortgages (Akbulaev et al., 2020; Makin and Layton, 2021).
3) Cuts in interest rates and reserve requirements (i.e., monetary expansion). To stimulate private investment and consumers' demand for durable goods, many central banks reduced the policy-related interest rate (Maital and Barzani, 2020). At the same time, to improve liquidity in the financial markets, some central banks brought down legal reserve requirements (Economic Commission for Latin America and the Caribbean, 2020).

In summary, the COVID-19 pandemic and the social distancing measures generated demand-side contractions, which were deflationary, and supply-side contractions, which were inflationary. That is why Christensen et al. (2020) and Shapiro (2020) assert that widespread lockdowns lowered not only consumer demand but also aggregate supply. However, in their view, the demand-side effect was stronger than the supply-side effect, so the net impact of social distancing on inflation was negative. Nonetheless, to keep economic activity from falling further, governments resorted to countercyclical policies that ultimately drove inflation up amid a persistent underperformance of GSC.

In this context, several studies regarding the drivers of price instability have been conducted. Erdoğan et al. (2020) analyze the sources of inflation in the 28 European Union countries and candidate nations during the period January-July 2020. Based on a panel data model, these authors find that price increases are due to monetary expansion, exchange rate depreciation, and external shocks. They explain that exchange rate depreciation in some nations was caused by economic uncertainty, prompting private agents to buy foreign currencies to protect their savings. The resulting capital outflows led to currency depreciation which, in turn, made imported intermediate inputs more expensive. The most important contribution here is to show the influence of external shocks on the domestic economy, underscoring the relevance of international cooperation. However, little consideration is paid to the role of fiscal policy and pandemic-related variables in generating price instability.

By contrast, de Soyres et al. (2022) focus on the link between easy fiscal policies and inflation using cross-country regressions involving 39 economies: 32 emerging market economies and seven advanced economies. They emphasize that: 1) Growing fiscal spending raised consumer demand for goods during 2021; and 2) fiscal support packages in some countries could have enhanced excess demand in others through international trade. Nonetheless, firms continued to face production restraints during that time, even as quarantine measures were being relaxed and people's mobility rebounded. Therefore, they conclude that inflationary pressures built up because of the insufficient output response to fiscal loosening, albeit this policy prevented many economies from sinking into a persistent recession. Capturing the exposure of countries to domestic and foreign fiscal expansion is an important contribution here. Nonetheless, while acknowledging that models must be parsimonious, this study does not account for other relevant sources of inflation.

Another multi-country study of inflation is Abdelkafi et al. (2023). To analyze the impact of the COVID-19 pandemic and four policy variables on the price level, they utilize panel data involving ten nations (five Latin American and five Asian) and monthly observations from January to September of 2020. The empirical evidence stems from the use of four model specifications and the AB methodology. Broadly speaking, their conclusion is that price instability was caused by income support measures, debt/contract relief initiatives, and the number of COVID-19 cases interacting with social distancing measures. The rationale for using four model specifications is to conduct a separate examination of the effects of four subsets of variables. While this approach may reduce multicollinearity problems, it carries the risk of excluding relevant variables in some or all the four models.

Rizvi et al. (2023) employ a fixed effects panel data model consisting of monthly data from January 2020 to December 2021 from four ASEAN economies (i.e., Indonesia, Malaysia, Singapore, and Thailand) to assess the inflationary impact of the broad monetary aggregate M3, the policy-related interest rate, the exchange rate, and the stringency index. These authors provide evidence that M3 is positively related to the consumer price index, whereas the interest rate is negatively related. The implication is that higher interest rates can be effective in alleviating the price instability caused by the countercyclical monetary policies implemented during the COVID-19 crisis.

Jordà et al. (2022) address the inflationary differentials between the US and other advanced economies that recently emerged. Although supply-side disruptions, coupled with countercyclical economic policies, caused an inflationary outburst across the world, in 2021 US inflation noticeably surpassed inflation in other advanced nations. According to these authors, this can be explained by the magnitude of the US fiscal stimulus aimed at offsetting the pandemic-related recessionary effects. Such a conclusion is based on a counterfactual analysis for the US economy, which compares an ex-post forecast of inflation assuming no fiscal stimulus with its actual evolution. Nonetheless, other investigations also conclude that the recent inflation in the US was the result of a substantial increase in government spending (Gharehgozli and Lee, 2022; Kliesen and Wheelock, 2023).

Victor et al. (2021) rely on generalized additive models (GAMs) to study the inflation-unemployment trade-off in the United Kingdom and India during the period January 2016-December 2020. They explain that the GAM technique allows for a non-normal distribution of the regression residuals by removing outliers, thereby mitigating the macroeconomic volatility generated by the COVID-19 pandemic. Their evidence for the United Kingdom is consistent with conventional economic theory, as it points to a negative relationship between inflation and unemployment in the short-term horizon. In the case of India, however, these authors make a counterintuitive finding, given that inflation and unemployment are positively related. While the outlier removal technique employed here is helpful to mitigate residual departures from normality, the higher volatility in India is likely to cause a more significant information loss in that country than in the United Kingdom. Therefore, the empirical evidence for India might not be as robust as that for the United Kingdom.

Cherkasky (2022) analyzes the influence of international inflation on Latin American inflation during 2021 and 2022. To that end, however, the author works with a historical approach, since he estimates two panel data models with annual data from 2000 to 2019. His main model involves 13 Latin American nations and annual observations for the period. Using the AB estimator, Cherkasky concludes that the dominant inflationary factors are nominal wages, nominal exchange rates, and international food prices. Although Cherkasky's empirical work is based on a plausible cost approach, two potential concerns arise. One is the use of wages as a proxy for ULC, ignoring labor productivity (perhaps because of lack of data). The other is that the reliability of the AB estimator rests on having more cross-section units (i.e., countries) than time periods, which does not happen in this case.

To study the impact of interest rates and inflation on industrial production in Pakistan, Hayat et al. (2021) resort to cointegration and Granger-causality tests, coupled with the wavelet transformation approach. Along these lines, they utilize monthly data from January 1991 through May 2020, so that their sample period includes the beginning of the COVID-19 pandemic. Combining the wavelet transformation approach with Granger causality tests (which measure predictive power), these authors indicate that there is a feedback system between interest rates and inflation in the short run (i.e., 2 to 4 months) as well as in the long run (i.e., more than 32 months). The policy implication is that the negative impact of the COVID-19 pandemic on the Pakistani economy could be softened by keeping interest rates (and inflation) low in the short- and long-term horizons. A salient aspect of this paper is its connection with the Gibson paradox or price puzzle, which underscores the long-run positive relationship between interest rates and inflation (Gibson, 1923; Keynes, 1930; Shiller and Siegel, 1977).[3] Various theories attempt to clarify why prices and interest rates can fall and rise together over extended periods (Sargent, 1973, p. 385). However, a compelling explanation within this literature posits that the interest rate is a component of unit production costs (Barth and Ramey, 2001; Céspedes et al., 2020; Cherkasky, 2022; Cucciniello et al., 2022). According to Barth and Ramey (2001), restrictive monetary policy may exert a robust supply-side effect by elevating the cost of working capital financing. In a similar vein, Céspedes et al. (2020) and Cherkasky (2022) indicate that raising interest rates can be detrimental in the presence of financial distress. Lastly, Cucciniello et al. (2022) conduct multiple robustness tests to show that the positive link between interest rates and prices is a common phenomenon rather than a paradox.

Apergis and Apergis (2021) investigate the impact of the COVID-19 pandemic on inflation expectations and inflation uncertainty in the US economy. Using a generalized autoregressive conditional heteroscedasticity model with exogenous variables (GARCHX) and daily data spanning from January 2, 2019, to July 31, 2020, they show that the COVID-19 pandemic raised

[3] While Keynes (1930) attributed the positive correlation between interest rates and inflation to Alfred Herbert Gibson, this apparent paradox was first documented by Thomas Tooke (1838).

inflation uncertainty as well as inflation expectations. Such a finding is relevant because expected inflation and its volatility influence private consumption and investment and, therefore, ex-post inflation and economic activity. In this context, Apergis and Apergis underscore the pandemic-related risk of inflationary expectations going far beyond the central banks' targets. However, their study is restricted to the case of the US economy.

In summary, the prevailing view is that inflation is mostly driven by demand-side variables in a number of countries. Through fiscal and monetary loosening, many countries were able to make cash transfers to households and enterprises, thereby lessening unemployment and financial hardship. Public spending escalation was financed through a combination of debt and money supply growth, given that central banks conducted massive purchases of government bonds and other financial assets, implemented interest rate cuts, and granted loans with subsidized interest rates (Clarida et al., 2021; Agur, 2022). Regrettably, worldwide social distancing measures and the spread of the virus itself gave rise to a variety of supply-side disruptions (Barlow et al., 2021; Akbulaev et al., 2020; Santacreu and LaBelle, 2022), so aggregate supply was outpaced by the rising demand. In this context, our investigation is one of the earliest efforts to assess the supply-side sources of inflation during the COVID-19 pandemic in a panel data setting. To the best of our knowledge, one novelty of the present work is to show that ULC are a major driver of price instability over this period. What is more, this evidence holds at the highest significance level across two econometric procedures and their corresponding remedial measures, thereby leading to clear-cut policy recommendations. On the other hand, our research offers some empirical support to the idea, which largely remains in the theoretical domain thus far, that higher interest rates can be inflationary with widespread financial distress across industries (Céspedes et al., 2020; Cherkasky, 2022). Lastly, we provide evidence that cost-push inflation coexists with demand-pull and inertial inflation.

2. Model, estimation methods, and data description

2.1 Model and estimation procedures

The starting point to conduct the empirical analysis is the following price equation, based on the model developed by Gordon and Stock (1998, p. 302):

$$p_t = \alpha_0 + \alpha_1 ulc_t + \alpha_2 d_t + \alpha_3 s_t \tag{1}$$

where p_t is the price level, ulc_t are unit labor costs, and d_t and s_t are vectors of variables. While d_t includes demand variables, s_t incorporates cost variables other than unit labor costs (ULC).[4] The lowercase letters mean that the variables are stated in natural logarithms and the subscript t stands for the period. Moreover, $lnULC_t = ulc_t = lnW_t - lnLP_t = w_t - lp_t$, meaning that ULC are directly related to wages (W_t) and inversely related to labor productivity (LP_t). In theoretical and applied work, we often find that some variables render demand- and supply-side effects. For instance, closure and containment measures and the spread of the virus reduce consumption by keeping people at home (the demand-side effect) and, at the same time, they lower production by abruptly cutting back working hours in factories (the supply-side effect). This means that such

[4] Just like in Gordon and Stock's paper (1998), we will incorporate a lagged dependent variable; however, this will be done as part of a subsequent model re-specification.

variables are simultaneously related to d_t and s_t. Based on our benchmark model (i.e., equation (1)), the literature review and the availability of data, we specify the following extended equation:

$$p_t = \beta_0 + \beta_1 ulc_t + \beta_2 i_t + \beta_3 q_t + \beta_4 dcr_t + \beta_5 isu_t + \beta_6 covid_t + \beta_7 si_t + u_t \quad (2)$$

where i_t is the policy-related interest rate, q_t is the real effective exchange rate, dcr_t is the index of debt/contract relief for households, isu_t is the income support index, $covid_t$ is the number of new COVID-19 cases smoothed per million, si_t is the stringency index, and u_t is a disturbance term. Except for the interest rate, all the variables are in natural logarithms. This set of variables keeps the model relatively parsimonious, is theoretically plausible, and allows for capturing the inflationary effects of ULC, fiscal and monetary policies, exchange rate fluctuations, closure and containment measures, and the spread of the virus. On the other hand, such an equation performs better than alternative specifications from the empirical standpoint. Rewriting equation (2) in panel form, we get:

$$p_{it} = \beta_0 + \beta_1 ulc_{it} + \beta_2 i_{it} + \beta_3 q_{it} + \beta_4 dcr_{it} + \beta_5 isu_{it} + \beta_6 covid_{it} + \beta_7 si_{it} + u_{it} \quad (3)$$

where subscripts *i* and *t* denote the country and the period, respectively. Equation (3) is a pooled regression model, which assumes that nations are homogeneous. However, there are two standard specifications dealing with heterogeneous nations: the fixed effects (FE) and the random effects (RE) panel data models (Greene, 2008, p. 183). The FE model allows the intercept term to vary from one nation to another,[5] so we write β_{0i} instead of β_0 in equation (4). To estimate β_{0i} for 34 nations, we utilize 33 dummy variables. In this manner, $\beta_{0i} = \beta_0 + \sum_{i=2}^{34} \gamma_i d_{ij}$, where β_0 is the intercept term of country 1 serving as a reference point, d_{ij} is the dummy variable of the country *i*, and γ_i is the corresponding intercept term differential. So, for instance, d_{2j} equals 1 when dealing with country 2 and remains at 0 otherwise, whereas γ_2 is the change in the intercept as we shift from country 1 to country 2. This means that the intercept term of country 2 is given by $\beta_0 + \gamma_2$, and so on. Thus, the FE model can be written as:

$$p_{it} = \beta_0 + \sum_{i=2}^{34} \gamma_i d_{ij} + \beta_1 ulc_{it} + \beta_2 i_{it} + \beta_3 q_{it} + \beta_4 dcr_{it} + \beta_5 isu_{it} + \beta_6 covid_{it} + \beta_7 si_{it} + u_{it} \quad (4)$$

According to Kmenta (1986, p. 633), the heterogeneity across countries under the RE model takes the following form: $\beta_{0i} = \beta_0 + \varepsilon_i$, where $E(\varepsilon_i) = 0$ and $E(\varepsilon_i^2) = \sigma^2$. The RE model is appropriate only when the heterogeneity among countries is uncorrelated with the seven explanatory variables, in which case it can be incorporated as part of the disturbance term.[6] However, this assumption is difficult to satisfy (Greene, 2008, p. 182). In fact, following Kmenta (1986), the RE model is valid only when the sample countries are obtained randomly from a much broader population, which is not the case here.

To address endogeneity under the FE panel data model, we use 2SLS. Put differently, 2SLS eliminates the correlation between the regressors and the error term (w_{it}), a problem that brings about biased and inconsistent estimations. To verify that 2SLS is robust to endogeneity, we evaluate the validity of the instruments. We do so by showing that the instrumental variables are basically uncorrelated with the residuals of the two models estimated by 2SLS. Lastly, we enhance efficiency through feasible generalized least squares weights, on the one hand, and panel-corrected standard errors, on the other.

[5] But it is constant over time.
[6] In this case, we would have a compound error term given by $\varepsilon_i + u_{it}$.

Our second estimation procedure is the AB estimator, which requires some changes to equation (4). The first change is to replace $\beta_0 + \sum_{i=2}^{34} \gamma_i d_{ij}$ with a cross-sectional error term, μ_i, representing the heterogeneity among countries as well. The second is to incorporate a lagged dependent variable to achieve a dynamic panel data model, written as:

$$p_{it} = \gamma p_{it-1} + \beta_1 ulc_{it} + \beta_2 i_{it} + \beta_3 q_{it} + \beta_4 dcr_{it} + \beta_5 isu_{it} + \beta_6 covid_{it} + \beta_7 si_{it} + \mu_i + u_{it} \quad (5)$$

where γ is an autoregressive parameter, given that it multiplies the lagged dependent variable (p_{it-1}) in equation (5). Moreover, now we have a compound error term, μ_i+u_{it}, where μ_i varies only across countries and u_{it} is a combined error term that changes across countries and across time. To begin suppressing any potential correlation between the error terms and the regressors, which is the source of endogeneity, the AB methodology first gets rid of μ_i. This is because μ_i influences the dependent variable and thus could be correlated with the lagged dependent variable, which is one of the regressors. Under this procedure, μ_i is eliminated by first differencing, which gives us:

$$\Delta p_{it} = \gamma \Delta p_{it-1} + \beta_1 \Delta ulc_{it} + \beta_2 \Delta i_{it} + \beta_3 \Delta q_{it} + \beta_4 \Delta dcr_{it} + \beta_5 \Delta isu_{it} + \beta_6 \Delta covid_{it} + \beta_7 \Delta si_{it} + \Delta u_{it} \quad (6)$$

Notice that endogeneity could still take place if one or more regressors in equation (6) are correlated with the combined error term in first differences, Δu_{it}. Therefore, now we must generate a set of valid instruments, given by the right lags of the regressors "in levels" (i.e., by the right lags of p_{it-1}, ulc_{it}, i_{it}, q_{it}, dcr_{it}, is_{it}, $covid_{it}$, and si_{it}). According to Arellano and Bond (1991), endogeneity is resolved insofar as the instruments chosen are valid. Put differently, the instruments must be highly correlated with the regressors (Δp_{it-1}, Δulc_{it}, Δi_{it}, Δq_{it}, ,Δdcr_{it}, Δisu_{it}, $\Delta covid_{it}$, and Δsi_{it}) and uncorrelated with the error term, Δu_{it}. According to Windmeijer (2005), one possible drawback of the AB estimator is that the number of instruments increases significantly with the number of time-series observations (T), potentially leading to finite sample bias. Moreover, this author shows through Monte Carlo simulations that lowering the instrument count is an effective measure to bring down the bias of the two-step AB estimator, which is precisely the one used here. To lower the instrument count, we estimate equation (6) with quarterly and semi-annual data, compare the results, and perform Sargan-Hansen tests.

One crucial criterion that the AB estimator must fulfill is that the number of cross-section units (N=34) exceeds the number of periods (T=12), which is satisfied here. In fact, Arellano and Bond (1991) and Baltagi (2008, p. 150) assert that when N>T, the AB estimator is consistent, is robust to endogeneity problems, and essentially needs no information regarding the distribution of the residuals.

2.2 Data description

The price level, p_{it}, is measured through the consumer price index (CPI) and is a function of the following seven explanatory variables:

1) The unit labor costs (ulc_{it}) index, measuring the cost of labor per unit of production. Such a variable reflects the variations of wages and labor productivity.
2) The policy-related interest rate (r_{it}), which captures the impact of monetary policy. In the case of Norway and Sweden, we used the short-term interest rate.

3) The real effective (or multilateral) exchange rate (q_{it}) index, based on the CPI of 64 countries. We expressed this index so that an increase must be construed as a real depreciation and vice versa.
4) The index of debt contract relief for households (dcr_{it}), encompassing transitory measures to alleviate the financial situation of vulnerable population groups and small-business owners, such as granting more time to taxpayers to fulfil their obligations, extending government-backed loans with low interest rates, rescheduling the payment of some government services, and freezing mortgage payments (OxCGRT Coding Interpretation Guide, 2022).
5) The income support (isu_{it}) index, which captures cash transfers to needy households and subsidies to the private sector aimed at preventing bankruptcies and layoffs, especially during the lockdowns. This index is a good measure of the fiscal stance of governments in the face of the COVID-19 pandemic (OxCGRT Coding Interpretation Guide, 2022).
6) The number of new COVID-19 cases smoothed per million ($covid_{it}$). This variable works as a proxy for the negative labor supply shock generated by the pandemic, given that sick workers had to stop working and undergo an isolation period.
7) The stringency index (si_{it}), reflecting the extent to which each nation enforces the following actions: on-line teaching and remote work, public event cancellations, restraints on domestic and international traveling, closure of public transportation services, stay-at-home policies, gathering size regulations, and information campaigns (Hale et al., 2021, p. 530).

In this context, for each variable (of each nation) we gathered quarterly data from the first quarter of 2020 to the fourth quarter of 2022. It is worth noting that there is no monthly data for ULC and, beyond 2022, no more data is available for the income support and the debt/contract relief indices on the part of the OxCGRT. Before undertaking the econometric analysis, it is useful to briefly analyze the behavior of the variables involved.

Table 1 – *Average evolution of the variables of the model (34 OECD countries)*

Period	P_t	ULC_t	i_t	Q_t	DCR_t	ISU_t	$COVID_t$	SI_t
2020Q1	100.00	100.00	0.774	100.00	0.207	0.263	2.79	18.07
2020Q2	99.67	105.16	0.513	100.26	1.277	1.416	44.35	64.81
2020Q3	100.33	100.02	0.449	99.99	1.375	1.643	82.19	59.75
2020Q4	100.8	101.52	0.608	98.79	1.277	1.665	262.53	58.61
2021Q1	101.78	102.68	0.664	98.56	1.454	1.924	141.77	64.95
2021Q2	102.81	102.29	0.750	98.44	1.019	1.458	263.67	56.74
2021Q3	104.35	103.55	0.792	98.92	0.982	1.376	353.14	52.93
2021Q4	106.84	104.72	0.907	99.38	0.815	1.159	399.54	41.48
2022Q1	110.95	107.13	1.036	99.38	0.872	1.227	949.16	34.98
2022Q2	115.56	109.86	1.841	99.71	0.563	0.809	916.18	18.77
2022Q3	119.44	114.17	2.839	99.98	0.451	0.677	1197.47	17.75
2022Q4	122.47	117.75	3.472	98.89	0.385	0.561	506.56	11.89

Notes: Q=quarter. Variables are denoted in capital letters because they are in levels rather than in natural logarithms. DCR_t and ISU_t are ordinal variables taking on three possible values: 0, 1 and 2. SI_t is a normalized index ranging from 0 to 100.
Source: authors' calculations based on data from the data sources depicted in table A1.

Table 1 shows that ULC experienced a sizable increase in the second quarter of 2020, presumably because the spread of the virus and the great lockdown brought down labor productivity. Notice that, from the first to the second quarter of 2020, the stringency index, and the number of new COVID-19 cases smoothed per million, climbed sharply. Moreover, after a downward correction in ULC in the third quarter of 2020, this variable displayed a rising trend, and the same applies to prices and interest rates. What is more, starting from the third quarter of 2021, ULC, prices, and interest rates underwent a more noticeable growth.

Debt/contract relief (DCR_t) and income support (ISU_t) rose rapidly from the first to the second quarter of 2020 and continue to grow on average during the rest of the year, albeit at a slower pace. In the first quarter of 2021, these two variables peaked and then declined in an oscillatory fashion. The stringency index reflects a drastic policy shift from the first to the second quarter of 2020, when this indicator escalated to reach its second-highest value in the reference period. From the second quarter of 2020 to the first quarter of 2021, when this indicator peaked, we saw the highest stringency levels (i.e., the great lockdown). After that period, there was a noticeable downward trend in stringency. For its part, the number of COVID-19 cases smoothed per million rises in an oscillatory fashion during 2020 and 2021. In 2022, the number of reported cases surged, presumably because of the relative success of massive testing policies and public information campaigns, which raised awareness about the need to identify and isolate asymptomatic individuals.

Lastly, we must highlight that all the variables of the model are seasonally adjusted. Moreover, before estimating the panel data models, we expressed all variables in natural logarithms, except for the interest rates. Table A1 describes the data sources and measurement units for each variable.

3. Econometric evidence

The next step is to estimate equation (4) through 2SLS and equation (6) through the AB estimator. Table 2 displays two FE panel data models estimated through 2SLS.

Panel data models suffer from four basic sources of inefficiency: contemporaneous correlation, time series correlation, cross-section heteroscedasticity, and time series heteroscedasticity. There are two basic tools to deal with those challenges: feasible generalized least squares (FGLS) weights[7] and robust coefficient covariance estimation procedures. As shown in table 2, estimated regression 1 makes no use of FGLS weights and relies only on cross-section seemingly unrelated (SUR) equations panel-corrected standard errors (PCSE). Such a coefficient covariance method takes account of the interconnection structure across the 34 OECD countries and is robust to contemporaneous correlation and cross-section heteroscedasticity (Beck and Katz, 1995). On the other hand, estimated regression 2 employs cross-section weights FGLS to correct for heteroscedasticity across nations, accompanied by period-weights PCSE. This is a coefficient covariance method addressing heteroscedasticity across time.

In this context, regression 1 is robust to correlation and heteroscedasticity across countries, whereas regression 2 is robust to heteroscedasticity across countries and across time. It is worth mentioning that the viability and reliability of efficiency-enhancement procedures, specifically FGLS weights and PCSE, depend on whether the panel data model is short (N>T) or long (T>N), among other factors. For instance, cross-section SUR FGLS, on the one hand, and period SUR PCSE,

[7] While plain GLS assumes that the behavior of the error term is known, “feasible” GLS acknowledges that this is not the case.

on the other, can be useful in correcting period correlation. However, both procedures require that T exceeds N. Given that we are working with a short panel (N>T), neither of these two methodologies can be used to address serial correlation.

Table 2 – *Fixed effects (FE) panel data models*

Dependent variable: Prices level (p_{it})
Method: Panel two-stage least squares
Estimation period: 2020-Q1 to 2022-Q4
Cross-section units: 34
Total panel (balanced) observations: 374
List of instruments: ulc_{it-1}, i_{it-1}, q_{it-1}, dcr_{it-1}, isu_{it-1}, $covid_{it-1}$ and si_{it-1}

	Estimated regression 1	**Estimated regression 2**
FGLS weights	No weights	Cross-section weights
Coefficient covariance method	Cross-section SUR PCSE	Period weights PCSE
ulc_{it}	0.840*** (10.073)	0.894*** (10.811)
i_{it}	0.001 (0.738)	0.001 (0.600)
q_{it}	0.058 (0.771)	0.045 (1.045)
dcr_{it}	−0.152*** (−3.294)	−0.150*** (−8.809)
isu_{it}	0.227*** (3.722)	0.226*** (7.416)
$covid_{it}$	0.0004 (0.084)	−0.002 (−1.297)
si_{it}	−0.080* (−1.846)	−0.081*** (−4.978)
Constant	1.233** (2.127)	0.931** (2.530)
Effects specification	Cross-section fixed dummy variables	Cross-section fixed dummy variables
Adjusted R-squared	0.961	0.951
Prob (F-statistic)	0.0000	0.0000

Notes: asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% significance levels, respectively. The *t*-statistics appear within parentheses. FGLS=feasible generalized least squares, SUR=seemingly unrelated equations, PCSE=panel-corrected standard errors, and Q=quarter.
Source: authors' estimations based on data from the data sources depicted in table A1 and the use of EViews 13.

Before interpreting the evidence, we show that the seven instrumental variables listed in table 2 are valid. The upper (lower) panel of table 3 shows the correlation coefficients between the residuals of regression 1 (regression 2) and the instrumental variables. The *t*-statistics appearing within parentheses clearly indicate that none of the estimated correlation coefficients are statistically significant.

Table 3 – *Correlation coefficients between the models' residuals and the instrumental variables*

Estimated regression 1: 2SLS regression with no FGLS weights and with cross-section SUR PCSE (*t*-statistics in parentheses)						
ulc_{it-1}	i_{it-1}	q_{it-1}	dcr_{it-1}	isu_{it-1}	$covid_{it-1}$	si_{it-1}
–6.27E-09 (–1.21E-07)	–6.70E-10 (–1.29E-08)	6.07E-08 (1.17E-06)	3.71E-09 (7.16E-08)	2.22E-09 (4.28E-08)	–7.24E-09 (–1.40E-07)	–2.19E-09 (–4.23E-08)
Estimated regression 2: 2SLS regression with cross-section FGLS weights and period weights PCSE (*t*-statistics in parentheses)						
ulc_{it-1}	i_{it-1}	q_{it-1}	dcr_{it-1}	isu_{it-1}	$covid_{it-1}$	si_{it-1}
–0.029 (–0.563)	–0.002 (–0.034)	–0.007 (–0.128)	0.043 (0.823)	0.047 (0.915)	0.061 (1.184)	0.030 (0.572)

Notes: none of the estimated correlation coefficients are statistically significant, as shown by the t-statistics within parentheses. 2SLS=two-stage least squares, FGLS=feasible generalized least squares, SUR= seemingly unrelated equations, and PCSE= panel-corrected standard errors.
Source: authors' estimations based on data from the data sources depicted in table A1 and the use of EViews 13.

Table 4 displays two dynamic panel data models, estimated through the AB estimator. To improve efficiency, a white period instrument weighting matrix is also used in both cases. Moreover, to deal with the instrument proliferation problem arising under the AB estimator, we estimate the first model with quarterly data and the second with semi-annual data. In both cases, we report the instrument rank and then implement some important tests.

Shifting from quarterly to semi-annual data has two important advantages. The first is that it makes the number of cross-section units (N) even larger than the number of periods (T), which strengthens the consistency property of the AB estimator (Arellano and Bond, 1991; Baltagi, 2008, p. 150). The second advantage is that the instrument rank goes significantly down, as reported in table 4. This is to deal with the instrument proliferation problem, given that too many instruments can not only result in a biased estimation of the regression parameters but also lower the power of the Sargan-Hansen test (Windmeijer, 2005; Cheng and Bang, 2021). Along these lines, reducing T from 12 to 6 and the instrument count from 34 to 18 presumably mitigates the small sample bias and raises the power of the Sargan-Hansen tests reported in table 5. From the empirical standpoint, table 5 shows that the magnitude of the estimated coefficients certainly changes. However, seven (out of eight) coefficients maintain the same sign and continue to be highly significant. Moreover, the coefficients' signs are consistent with the estimation results obtained by 2SLS (i.e., with regressions 1 and 2).

Next, table 5 presents the outcome of the Sargan-Hansen tests. The probability values for the null hypothesis that the instruments are valid (i.e., uncorrelated with the error term) are 0.201 and 0.182 for regressions 3 and 4, respectively. Furthermore, the outcome of the Sargan-Hansen tests is not compromised by the instrument rank, given that the instrument count does not exceed the number of cross-section units in any of the regressions (Roodman, 2009).

Table 4 – *Dynamic panel data models*

Dependent variable: Prices level (Δp_{it})
Method: Difference GMM (AB estimator)
GMM weights: White period instrument weighting matrix
Coefficient covariance method: Ordinary
GMM iterations: 2-step (update weights once)

	Estimated regression 3	**Estimated regression 4**
Frequency	**Quarterly data**	**Semi-annual data**
Estimation period	2020-Q1 to 2022-Q4	2020-S1 to 2022-S2
Cross-section units	34	34
Total panel (balanced) observations	306	136
Δp_{it-1}	0.928*** (41.785)	0.249** (2.160)
Δulc_{it}	0.129*** (8.894)	0.682*** (7.892)
Δi_{it}	0.001*** (3.488)	0.003*** (4.030)
Δq_{it}	0.135*** (25.072)	–0.132 (–1.097)
Δdcr_{it}	–0.024*** (–10.637)	–0.079*** (–3.207)
Δisu_{it}	0.046*** (16.648)	0.101*** (3.020)
$\Delta covid_{it}$	0.004*** (9.509)	0.006*** (3.176)
Δsi_{it}	–0.018*** (–8.964)	–0.040*** (–5.153)
Instrument rank	34	18

Notes: asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% significance levels, respectively. The *t*-statistics appear within parentheses. Δ=first difference operator, Q=quarterly data, S=semi-annual data, GMM=generalized method of moments, and AB=Arellano-Bond.
Source: authors' estimations based on data from the data sources depicted in table A1 and the use of EViews 13.

Table 5 – *Sargan-Hansen test*

Null hypothesis: the instruments are uncorrelated with the error term

Estimated regression 3		**Estimated regression 4**	
Difference GMM with quarterly data		**Difference GMM with semi-annual data**	
J-statistic	Probability value	*J*-statistic	Probability value
31.756	0.201	13.807	0.182

Note: GMM=generalized method of moments.
Source: authors' estimations based on data from the data sources depicted in table A1 and the use of EViews 13.

The Arellano-Bond (AB) tests for serial correlation appear in table 6. Such tests are applied to equation (6), whose variables are in first differences. In this context, if the combined error term in equation (5), u_{it}, is identically independently distributed, then Δu_{it} in equation (6) should exhibit: 1) negative first-order autocorrelation; and 2) no second-order autocorrelation (Arellano and Bond, 1991). In the case of regression 3, the probability values for the specified null hypotheses suggest that there is first-order autocorrelation and no second-order autocorrelation, just as expected. In regression 4, we failed to establish first-order autocorrelation at the 10% significance level, but there is no second-order autocorrelation, as expected. What is more, we have that: 1) the estimated coefficients of the two regressions are mostly consistent in terms of signs and statistical significance; 2) the white period instrument weighting matrix used in the estimation process is robust to serial correlation; and 3) when the number of cross-section units is larger than the number of periods and the instruments used are valid, the AB estimator is consistent, free of endogeneity issues, and basically needs no information about residual behavior (Arellano and Bond, 1991; Baltagi, 2008, p. 150).

Table 6 – *Arellano-Bond (AB) test for serial correlation*

	Estimated regression 3		**Estimated regression 4**	
	Difference GMM with quarterly data		**Difference GMM with semi-annual data**	
Null hypothesis	**m-statistic**	**Prob. value**	**m-statistic**	**Prob. value**
No first-order autocorrelation	−2.365	0.018	−1.384	0.167
No second-order autocorrelation	−0.838	0.402	−0.832	0.405

Note: GMM=generalized method of moments.
Source: authors' estimations based on data from the data sources depicted in table A1 and the use of EViews 13.

To interpret the empirical evidence, we first address those findings that are fully consistent across econometric procedures and remedial measures. Under the 2SLS methodology (regressions 1 and 2) and the difference GMM (regressions 3 and 4), we find that:

1) The estimated coefficient of ULC, either in levels or first differences, is positive and statistically significant at the 1% significance level. Therefore, ULC have been a key source of inflation in OECD nations. This is in line with Cherkasky's (2022) evidence that nominal wages are a source of inflation in Latin America. However, Cherkasky employs nominal wages as a proxy for ULC, thereby ignoring the critical role played by labor productivity. It is also worth mentioning that our evidence underscores the relevance of the employment retention programs implemented during the pandemic (Akbulaev et al., 2020; Makin and Layton, 2021; Céspedes et al., 2020), given that the loss of qualified workers tends to raise ULC and, consequently, prices. This phenomenon occurs during the recovery phase because those workers cannot be easily recruited again (Céspedes et al., 2020).
2) The estimated parameter of income support is also positive and statistically significant at the 1% level, so this variable (mainly fiscal transfers) represents a source of demand-pull inflation during the reference period. This finding aligns with the conclusion presented by

Jordà et al. (2022), de Soyres et al. (2022), and Kliesen and Wheelock (2023), who assert that inflation in the US and other nations was primarily driven by expansionary fiscal policies amidst the various production restraints generated by social distancing measures and the pandemic itself.

3) Debt/contract relief has a negative estimated coefficient, achieving statistical significance at the 1% level in every regression. Therefore, the alleviation of financial distress brings down supply-side inflationary pressures, which is in line with the Gibson paradox as explained by Barth and Ramey (2001). As previously mentioned, these authors regard interest rates as a component of unit production costs, especially for firms heavily reliant on working capital financing. Furthermore, our finding contradicts Abdelkafi et al. (2023), who argue that debt/contract relief initiatives lead to inflation.
4) The stringency index has a negative estimated parameter, which is statistically significant at the 10% level in regression 1 and at the 1% level in the other three regressions. Consequently, the net effect of closure and containment measures on prices was negative during the 2020-2022 period.

Now, under the AB estimator (i.e., in regressions 3 and 4), we additionally observe the following:

1) Interest rates (Δi_{it}) bear a positive relationship with prices (Δp_{it}), and this result holds at the 1% significance level in regressions 3 and 4. Therefore, higher financial costs can be inflationary when financial distress is widespread. This finding is consistent with the evidence provided by Hayat et al. (2021) in the specific case of Pakistan. Moreover, it aligns with the Gibson paradox, as explained by Barth and Ramey (2001), and sheds light on why debt/contract relief policies (i.e., transitory measures to reduce the financial strain on debtors) are deflationary.
2) The net impact of the new COVID-19 cases smoothed per million is inflationary and this evidence holds at the 1% significance level.
3) The estimated coefficient of the lagged dependent variable (Δp_{it-1}) is positive and statistically significant at the 1% level, indicating that there is an inflationary inertia. Furthermore, with the inclusion of the lagged dependent variable, the impact of the other regressors is conditioned by the inflationary momentum.

The coefficient of the real effective exchange rate is statistically significant (at the 1% level) in regression 3 but not in regression 4. Therefore, the evidence in favor of the pass-through effect from currency depreciation to inflation is relatively weak.

4. Conclusions and policy implications

This paper evaluates the key sources of inflation in 34 OECD nations during the COVID-19 pandemic. To that end, we rely on an amplified price equation estimated through 2SLS and difference GMM. One key finding is that ULC are a major source of price instability. As is well known, ULC are directly related to wages and inversely related to labor productivity. In this perspective, closure and containment measures, and the propagation of the virus itself, generated a negative labor supply shock (Hevia and Newmeyer, 2020) and thus higher ULC. Moreover, massive layoffs forced many people to migrate from one industry to another, bringing down labor productivity insofar as the new jobs required different skills (Céspedes et al., 2020; Akbulaev et al., 2020). Labor productivity also fell because unemployment eroded labor force qualifications (Barišić and Kovač, 2022). Therefore, an effective anti-inflationary strategy during and after a pandemic should include a wide range of training programs, not only to raise labor productivity and reduce ULC but also to assist the unemployed in meeting employers' demands. The need to invest more in training and education is greater in the less advanced economies. Moreover, opening new paths for legal immigration to wealthy nations could increase labor supply and lower ULC.

Income support measures are a source of demand-pull inflation in all regressions, presumably because they include massive cash transfers to vulnerable population groups. This finding is consistent with the view that, although countercyclical fiscal policies were useful to safeguard production capacities and bring down job losses, they were inflationary to a certain degree. Akbulaev et al. (2020) indicate that countercyclical policies were inflationary because they were not properly synchronized with the slow-paced normalization of GSC once social distancing policies were relaxed, whereas Niedźwiedzińska (2021) argues that fiscal and monetary responses were remarkable in magnitude and speed of implementation. Therefore, an important lesson for future health crises is that supply-side policy packages should align with the scale and velocity of fiscal and monetary expansion.

The evidence that debt/contract relief policies are deflationary is also consistent across all regressions. The implication is that government interventions aimed at lessening financial turmoil among small-business owners can effectively work on the supply side to reduce bankruptcies and stabilize prices. Another finding that holds across every regression is that closure and containment measures induced a deflationary effect, mainly because they led to lower sales and revenues in a wide spectrum of business operations (Meyer et al., 2022). Therefore, the demand-side effect of social distancing prevailed over the inflationary supply-side effect, namely the disruption of GSC.

Under the AB estimator, regardless of whether we use quarterly or semi-annual data, the coefficient of the interest rate is positive and statistically significant. Higher interest rates can exacerbate inflation under certain conditions. During the pandemic, many industries were facing lower sales, production bottlenecks, and delivery problems. Therefore, many companies were struggling to pay wages, taxes, debts, and rents (Antonescu, 2020; Makin and Layton, 2021). So, in the presence of financial distress, elevated interest rates can contribute to cost-push inflation (Barth and Ramey, 2001; Céspedes et al., 2020; Cherkasky, 2022; Cucciniello et al., 2022). This is in line with the finding that debt/contract relief is deflationary and calls for supply-side incentives such as extending preferential credit to capital-constraint enterprises, especially to micro, small, and medium-sized enterprises.

The number of new COVID-19 cases smoothed per million puts an upward pressure on prices, considering that this variable serves as a proxy for the quantity of workers requiring isolation periods due to illness. As this quantity peaked, supply-side disruptions became more critical, and cost-push inflation intensified. Lastly, the evidence also suggests that inertial inflation coexists with supply- and demand-side inflation. The highly significant impact of lagged price changes on current price changes reflects an inflationary momentum which, once again, highlights the need to supplement conventional contractionary policies with innovative supply-side incentives.

Appendix

Table A1 – *Measurement units and data sources of the selected variables*

Variable	Measurement unit	Source of information
Consumer prices (P_{it})	Index with a base period equal to 100	OECD database
Unit labor costs (ULC_{it})	Index with a base period equal to 100	OECD database
Policy-related interest rate (R_{it})	Nominal rate	Bank for International Settlements (BIS) and International Monetary Fund (IMF)
Real effective exchange rate (Q_{it})	Index based on consumer prices	BIS and IMF
Debt/contract relief for households index (DCR_{it})	Ordinal indicator taking on 3 possible values: 0, 1 and 2	Oxford COVID-19 Government Response Tracker (OxCGRT)
Income support index (ISU_{it})	Ordinal indicator taking on 3 possible values: 0, 1 and 2	OxCGRT
New COVID-19 cases ($COVID_{it}$)	New cases smoothed per million	OxCGRT
Stringency index (SI_{it})	A normalized index ranging from 0 to 100	OxCGRT

References

Abdelkafi I., Loukil S. and Romdhane Y. (2023), “Economic uncertainty during COVID-19 pandemic in Latin America and Asia”, *Journal of the Knowledge Economy*, 14 (2), pp. 1582-1601-. Available online.

Akbulaev N., Mammadov I. and Aliyev V. (2020), “Economic impact of COVID-19”, *SYLWAN*, 164 (5), pp. 113-126. Available online.

Agur I. (2022), “Government finance by central banks and inflation expectations at the onset of the COVID pandemic”, *Applied Economics Letters*, 31 (2), pp. 107-112. Available online.

Antonescu D. (2020), “Supporting small and medium size enterprises through the COVID-19 crises in Romania”, *Central European Journal of Geography and Sustainable Development*, 2 (1), pp. 38-57. Available online.

Apergis E. and Apergis N. (2021), “Inflation expectations, volatility and COVID-19: evidence from the US inflation swap rates”, *Applied Economics Letters*, 28 (15), pp. 1327-1331. Available online.

Arellano M. and Bond S. (1991), “Some test of specification for panel data: Monte Carlo evidence and an application to employment equations”, *The Review of Economic Studies*, 58 (2), pp. 277-297. Available online.

Baltagi B. (2008), *Econometric analysis of panel data*, Chichester, West Sussex (UK): John Wiley & Sons Ltd.

Barišić P. and Kovač T. (2022), “The effectiveness of the fiscal policy response to COVID-19 through the lens of short and long run labor market effects of COVID-19 measures”, *Public Sector Economics*, 46 (1), pp. 43-81. Available online.

Barlow P., van Schalkwyk M., McKee M., Labonté R. and Stuckler D. (2021), “COVID-19 and the collapse of global trade: building an effective public health response”, *The Lancet Planetary Health*, 5 (2), pp. 102-107. Available online.

Barth M.J. and Ramey V.A. (2001), “The cost channel of monetary transmission”, *NBER Macroeconomics Annual 2001*, 16, pp. 199-256. Available online.

Beck N. and Katz J.N. (1995), “What to do (and not to do) with time-series cross-section data”, *The American Political Science Review*, 89 (3), pp. 634-647. Available online.

Céspedes L., Chang R. and Velasco A. (2020), “Macroeconomic policy responses to a pandemic”, in Djankov S. and Panizza U. (eds.), *COVID-19 in Developing Economies* (pp. 175-186), London: Center for Economic Policy Research. Available online.

Cheng N. and Bang Y. (2021), "A comment on the practice of the Arellano-Bond/Blundell-Bond generalized method of moments estimator in IS research", *Communications of the Association for Information Systems*, 48 (1), pp. 423-442. Available online.

Cherkasky M. (2022), "Inflación global en el bienio 2021-2022 y su impacto en América Latina", *Serie Estudios y Perspectivas-Officina de la CEPAL en la Argentina*, no. 55, Buenos Aires: CEPAL. Available online.

Christensen J., Gamble J. and Zhu S. (2020), "Coronavirus and the Risk of Deflation", *FRBSF Economic Letter,* 2020-11, May 11, pp. 1-5. Available online.

Clarida R., Duygan-Bump B. and Scotti C. (2021), "The COVID-19 crisis and the Federal Reserve's policy response", *Finance and Economics Discussion Series*, n. 2021-035, Washington (DC): Board of Governors of the Federal Reserve System. Available online.

Cucciniello M.C., Deleidi M. and Levrero E.S. (2022), "The cost channel of monetary policy: The case of the United States in the period 1959-2018", *Structural Change and Economic Dynamics*, 61, pp. 409-433. Available online.

de Soyres F., Santacreu A. and Young H. (2022), "Fiscal policy and excess inflation during Covid-19: A cross-country view", *FED Notes*, July 15, Washington (DC): Board of Governors of the Federal Reserve System. Available online.

Devereux M., Güçeri İ, Simmler M. and Tam E. (2020), "Discretionary fiscal responses to the COVID-19 pandemic", *Oxford Review of Economic Policy*, 36 (S1), pp. S225-S241. Available online.

Economic Commission for Latin America and the Caribbean (2020), "Latin America and the Caribbean and the COVID-19 pandemic: Economic and social effects". Available online.

Erdoğan S., Yildirim D.Ç. and Gedikli A. (2020), "Dynamics and determinants of inflation during the COVID-19 pandemic period in European countries: A spatial panel data analysis", *Duzce Medical Journal*, 22 (S1) (special issue), pp. 61-67. Available online.

Gharehgozli O. and Lee S. (2022), "Money supply and inflation after COVID-19", *Economies*, 10 (5), pp. 1-14. Available online.

Gibson A.H. (1923), "The future course of high-class investment values", *Banker's Magazine*, 115, pp. 15-34.

Gordon R. and Stock J. (1998), "Foundations of the Goldilocks economy: Supply shocks and the time-varying NAIRU", *Brookings Papers on Economic Activity*, 2, pp. 297-346. Available online.

Greene W. (2008), *Econometric Analysis*, 6th ed., Upper Saddle River (NJ): Pearson-Prentice Hall.

Hale T., Angrist N., Goldszmidt R., Kira B., Petherick A., Phillips T., Webster S., Cameron-Blake E., Hallas L., Majumdar S. and Tatlow H. (2021), "A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker)", *Nature Human Behaviour*, 5 (4), pp. 529-538. Available online.

Hayat M., Ghulam H., Batool M., Naeem M., Ejaz A., Spulbar C. and Birau R. (2021), "Investigating the causal linkages among inflation, interest rate, and economic growth in Pakistan under the influence of COVID-19 pandemic: A wavelet transformation approach", *Journal of Risk and Financial Management*, 14 (6), art. 277. Available online.

Hevia C. and Neumeyer A. (2020), "A conceptual framework for analyzing the economic impact of COVID-19 and its policy implications", *UNDP LAC COVID-19 Policy Documents Series*, no. 1, New York: United Nation Development Programme – Latin America and the Caribbean. Available online.

Jordà Ò., Liu C., Nechio F. and Rivera-Reyes F. (2022), "Why Is US Inflation Higher than in Other Countries*?*", *FRBSF Economic Letter*, 2022-07, 28 March, San Francisco (CA): Federal Reserve Bank of San Francisco. Available online.

Keynes J.M. (1930), *A Treatise on Money*, London: Macmillan.

Kliesen K.L. and Wheelock D.C. (2023), "The COVID-19 Pandemic and Inflation: Lessons from major US Wars", *Federal Reserve Bank of St. Louis Review*, 105 (4), pp. 1-27. Available online.

Kmenta J. (1986), *Elements of Econometrics*, Ann Arbor (MI): University of Michigan Press.

Maital S. and Barzani E. (2020), "The global economic impact of COVID-19: A summary of research", *Samuel Neaman Institute for National Policy Research*, March. Available online.

Makin A. and Layton A. (2021), "The global fiscal response to COVID-19: Risks and repercussions", *Economic Analysis and Policy*, 69 (C), pp. 340-349. Available online.

Meyer B., Prescott B. and Sheng X. (2022), "The impact of the COVID-19 pandemic on business expectations", *International Journal of Forecasting*, 38 (2), pp. 529-544. Available online.

Niedźwiedzińska J. (2021), "Initial monetary policy response to the COVID-19 pandemic in inflation targeting economies", *Gospodarka Narodowa, The Polish Journal of Economics*, 308 (4), pp. 125-165. Available online.

Oxford COVID-19 Government Response Tracker Coding Interpretation Guide (2022). Available online (date of access: 20 November 2022).

Rizvi S.A.R., Sharma S.S. and Juhro S.M. (2023), "Demystifying COVID-19 policy actions: The case of inflation control in ASEAN", *Pacific-Basin Finance Journal*, 83, pp. 1-9. Available online.

Roodman D. (2009), "A Note on the Theme of Too Many Instruments", *Oxford Bulletin of Economics and Statistics*, 71 (1), pp. 135-158. Available online.

Santacreu A.M. and LaBelle J. (2022), "Global supply chain disruptions and inflation during the COVID-19 pandemic", *Federal Reserve Bank of St. Louis Review*, 104 (2), pp. 1-14. Available online.

Sargent T.J. (1973), "Interest rates and prices in the long run: A study of the Gibson Paradox", *Journal of Money, Credit and Banking*, 5 (1), pp. 385-449. Available online.

Shapiro A.H. (2020), "Monitoring the Inflationary Effects of COVID-19", *FRBSF Economic Letter*, 2020-24, 24 August, San Francisco (CA): Federal Reserve Bank of San Francisco. Available online.

Shiller R.J. and Siegel J.J. (1977), "The Gibson paradox and historical movements in real interest rates", *Journal of Political Economy*, 85 (5), pp. 891-907. Available online.

Susskind D. and Vines D. (2020), "The economics of the COVID-19 pandemic: an assessment", *Oxford Review of Economic Policy*, 36 (1), pp. S1-S13. Available online.

Tauber K. and Van Zandweghe W. (2021), "Why has durable goods spending been so strong during the COVID-19 pandemic?", *Economic Commentary*, 16, Cleveland (OH): Federal Reserve Bank of Cleveland. Available online.

Thirlwall A.P. (1974), *Inflation, Saving and Growth in Developing Economies*, London and Basingstoke UK: Macmillan.

Tooke T. (1838), *A History of Prices, and of the State of the Circulation, from 1793 to 1837*, London (UK): Longman, Orme, Brown, Green, and Longman's.

Victor V., Karakunnel J., Loganathan S. and Meyer D. (2021), "From a recession to the COVID-19 pandemic: Inflation-unemployment comparison between the UK and India", *Economies*, 9 (2), pp. 1-19. Available online.

Windmeijer F. (2005), "A finite sample correction for the variance of linear efficient two-step GMM estimators", *Journal of Econometrics*, 126 (1), pp. 25-51. Available online.

Yeh S.-S. (2021), "Tourism recovery strategy against COVID-19 pandemic", *Tourism Recreation Research*, 46 (2), pp. 188-194. Available online.