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Labor productivity, real wages, and employment: evidence from a panel of OECD economies over 1960-2019

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ABSTRACT

This study empirically investigates the relationship between labor productivity (LP), average real wage (RW), and employment (EMP). The paper's main goal is to provide a test of competing theories of growth and income distribution. Standard theory predicts that real wages should increase following increases in labor productivity. Alternative theories and efficiency wage theories suggest that it is the distribution that causes changes in labor productivity. Theory delivers ambiguous predictions regarding the ultimate effects on employment, which can be either negative if factor substitution prevails or positive if higher wages and higher output per worker generate additional aggregate demand and, therefore, employment. I study a panel of 25 OECD economies over 1960-2019, using several approaches: 1) ECM, DOLS, FMOLS, and ARDL regressions with exogenous and endogenous variables, and 2) a VECM exercise as a robustness check. First, there is a long-run relationship between these variables when LP and RW are considered dependent variables. Second, EMP cannot be explained statistically by LP and RW in the long run: it is weakly exogenous, implying that OECD economies as a group have been, on average labor-constrained in the last six decades. Third, I find a positive two-way causality between LP and RW in both the long and short run, supporting the induced technical change, efficiency wages, and bargaining theories over the neoclassical theory. Fourth, concerning the LP-EMP nexus, in the long run, the results show a negative association, statistically significant for the single-equation estimates from EMP to LP in most specifications. Fifth, there is a positive effect running from EMP to RW in most specifications, statistically significant only in the single-equation. Sixth, both LP positively affects EMP, and RW negatively impacts EMP in the short run.

Keywords: Labor productivity, real wages, employment, OECD

JEL Classification: E12, E24, O47, O50

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1. INTRODUCTION

This paper provides an empirical investigation of the relationship between labor productivity (LP), real wages (RW), and employment (EMP) in a panel of OCED countries. The ultimate goal is to evaluate competing theories of growth and distribution. According to classical political economy -especially the classical-Marxian theory of induced technical change (Foley et al., 2019, Ch. 7)- as well as post-Keynesian economics, changes in RW should cause LP to increase. Rising RW reduces profitability, inducing profit-seeking capitalist firms to invest in labor-saving technical changes to decrease the share of wages in total costs. On the other hand, Neoclassical theory predicts that LP increases should result in increasing RW, given that wages are equal to the marginal product of labor. Accordingly, productivity-enhancing innovations should reverberate into higher wages.

An additional relevant question addressed in this paper is whether increases in RW or LP growth occur at the expenses of EMP or not. With a downward-sloping labor demand curve, the effect of exogenous increases in RW should be negative, at least in the short run. But if LP eventually keeps up with rising RW so that unit labor costs do not change, the effect on employment should vanish in the long run. On the other hand, labor-saving technical change that increases LP may either generate job destruction or job creation in the long run. It is plausible to expect job destruction temporarily, but labor reallocation may offset the initial adverse effects of rising LP on employment.

Therefore, the goal of this paper is to evaluate the relationship between these three economic variables empirically. By using panel time-series methods, this paper looks at both short and long run effects. Specifically, I carry out an empirical analysis in two scenarios: 1) several single-equation approaches where decisions about identification are based on theoretical priors about what are the exogenous and endogenous variables, and 2) a multi-equation approach that assumes an entirely endogenous system.

The data for the OECD economies in the sample -countries at similar stages of development and therefore roughly comparable- appear to support a two-way long-run relationship between RW and LP. As for EMP effects, I find evidence that RW increases negatively affect EMP in the short run, leading to job destruction. Still, in the long run, EMP returns to its trend, signaling that labor reallocation eventually offsets the initial negative impact of rising real wages. In addition, LP positively impacts EMP in the short run, meaning that the output effect due to the additional aggregate demand prevails the factor substitution effect; but eventually, its impact dies out. However, EMP is weakly exogenous in this three-variable system, and other factors mainly explain its long run trajectory, supporting evidence that OECD countries have been labor-constrained -with weakly exogenous employment to population ratio in balanced growth- as a group for the period under analysis.

Among the frameworks that explain RW's influence on LP in the context of the efficiency wages theory, the first one is the shirking model. (Shapiro and Stiglitz, 1984; Copeland, 1989; Cappelli and Chauving, 1991; Brecher, 1992; Barmbay, Sessions, and Treble, 1994; Bulkley and Myles, 1996; Spencer, 2002; Alexopoulos, 2003; D'Orlando, 2004; Ross and Zenou, 2008). This model illustrates how the combination of RW and work requirements offered by firms gives workers a utility level that workers compare to their opportunity costs. Then, based on that comparison, workers will decide to shirk or increase their effort, impacting LP levels. The second type of model that describes the efficiency wages theory is the fairness model. (Akerlof, 1982; Yellen, 1984; Akerlof and Yellen, 1988; Akerlof and Yellen, 1990; Fehr and Kirchsteiger, 1994; Agell and Lundborg, 1995, Fehr, Gachter, and Kirchsteiger, 1996; Agell and Lundborg

2003; Snowdon and Vane, 2005). This model appeals to sociological causes, arguing that RW below the market-clearing wage -'unfair' RW- demotivates workers making them decline their LP, so firms will tend to push wages up to a 'fair' level -or higher- to boost output per worker.

The third framework used to address the efficiency wages theory is the adverse selection model. (Guasch and Weiss, 1980; Weiss, 1980; Greenwald, 1986; Wakita, 1992; Clemenz, 1995; Araujo and Sachsida, 2010). This model considers that employees are heterogeneous in their skill levels and know their capabilities, but firms are imperfectly informed about them. Firms may offer higher wages since firms desire to attract better workers and avoid potential issues due to this asymmetric information. The fourth one is the turnover model. (Phelps, 1968; Stiglitz, 1974; Schlicht, 1978; Salop, 1979; Leonard, 1987; Campbell, 1993; Bentley Macleod and Malcomson, 1995, Toulemonde, 2003; Yang, 2008). In this model, replacing workers carries high costs for firms: time-consuming searching processes, recruitment, training costs, and vacant job costs. Therefore, firms pay higher wages to reduce the workers' motivation to leave the job, reducing labor turnover costs.

In heterodox theories, economists working in the classical-Marxian and post-Keynesian traditions have explored the implications of induced technical change for the relationship between income distribution and labor productivity. The idea of induced technical change originated with Hicks (1932), according to whom firms would have incentives to save on a production factor if their share in the firms' cost increased. Kennedy (1964) formalized this idea and showed that a rising share of wages in a firm's cost would result in a stronger bias toward labor. Recently, induced technical change has witnessed a comeback: Foley (2003), Julius (2005), Tavani (2012, 2013), Zamparelli (2015) are some examples of recent literature in this vein.

The opposite causality from LP to RW has also been explored using different approaches, such as the marginal productivity theory (Clark, 1886; Wicksteed, 1894; Stein, 1958; Mazumdar, 1959; Ostroy, 1984; Booth and Frank, 1999). This theory argues that a firm is willing to pay a worker salary according to what the worker adds to its revenues. Thus, a firm will hire workers up to the point where marginal revenue equals the wage rate. RW determination is also explained in the same vein in a bargaining theory framework (Davidson, 1898; Svejnar, 1986; Cramton and Tracy, 1992; Cahuc, Postel-Vinay, and Robin, 2006). The bargaining theory affirms that the parties' bargaining power determines RW and working conditions to the agreement. In turn, the workers' bargaining strength depends on several factors, such as the worker's productivity, the project's profitability, future economic perspectives, the worker's fallback position, or minimum wage legislation.

With that being said, my conclusion is that the bidirectional causation between RW and LP provides evidence of induced technical change, efficiency wages, and bargaining theories in the OECD economies in the last six decades while rejecting the marginal productivity theory in this set of countries as a group. The positive impact from RW to LP would indicate that rising labor costs have incentivized these economies to incorporate labor-saving technological innovation, which has raised output per unit of employment. An additional explanation is the efficiency wages theory. For its part, the positive effect from LP to RW is required to maintain a constant labor share in balanced growth, therefore matching the Kaldor (1955) stylized facts. It also supports the bargaining theory, which can coexist with the inclusion of induced technical innovations (Tavani, 2012, 2013) and efficiency wages theory.

My empirical results do not appear to back the marginal productivity theory, where unidirectional causality from LP to RW is enough to ensure that the wage share remains constant in the long run. It is an essential result of this paper. Suppose one takes the neoclassical growth model seriously. In that case, labor productivity will grow exogenously to maintain a constant wage share in the long run, and real wages must grow at the same rate. Therefore, the theory predicts unidirectional causality between LP and RW. Viceversa, classical-Marxian induced bias in technical change indicates that increases in a measure of distribution (real wages in this case) should induce firms to adopt more labor-saving technologies, thus increasing labor productivity. However, for the wage share to remain constant in the long run, real wages must grow in line with labor productivity. The empirical results lend support for the induced technical change hypothesis over the neoclassical theory. Importantly, efficiency wages and bargaining theory are compatible with my empirical results.

Concerning the effect of EMP on LP, the empirical evidence shows a tradeoff between the two. Their inverse relationship may exist because the labor demand curve is downward sloping due to diminishing returns, implying that each additional worker hired contributes less and less to the value of the marginal product of labor. Besides that, some authors have pointed to institutional factors. Among these factors, we have those that strengthen employment protection, which increases firing costs, making the firms' decisions more rigid when adjusting their workforce to demand, negatively impacting LP. (Okudaira, Takizawa, and Tsuru, 2013). Likewise, Bjuggren (2018) empirically demonstrates that the more flexible a labor market is, the higher is LP. For its part, Gordon (1995) asserts that any institutional policy or circumstance that pushes wages up will generate a movement along the labor demand curve in the northwest direction, negatively affecting EMP and favoring LP.

Nonetheless, the evidence is ambiguous when the impact from LP to EMP is analyzed. An increase in LP could generate efficiency gains reducing labor demand. (Gali, 1999; Dew-Becker and Gordon, 2008; Aparaschivei, Vasilescu, and Pirciog, 2011). On the other hand, a rise in LP can boost the economy, making it necessary to hire additional labor (Mollick and Cabral, 2009). Still, economic growth could generate a process where job creation overcomes job destruction. (Pivetz, Searson, and Spletzer, 2001). The employment response would depend on the net effect on aggregate demand, supply-side factors -technology, educational levels, capital stock- the temporal horizon, and institutions.

Regarding the effect of RW on EMP, standard economic theory predicts that increasing labor costs would reduce EMP due to factor substitution. If labor becomes more expensive relative to capital, firms will substitute labor for capital. (Baker, Benjamin, and Stanger, 1999; Jung and Lim, 2020). On the other hand, since this substitution effect could occur at a firm or sector level, fired workers can be reallocated to other sectors, so the aggregate EMP does not necessarily decline. Notwithstanding, other theories indicate that if the rise in labor costs does not significantly affect the firms' competitiveness, workers with higher salaries will boost their consumption, positively expanding the aggregate demand affecting EMP.

Other authors explain the impact of RW on EMP from a bargaining power or unionization perspective. For instance, Rama (2001) finds that a minimum wage increase causes a modest EMP decrease overall. However, a mixed effect is present, which depends on the firm's size, where EMP in small firms decreases substantially, and large firms experience an EMP increase. Similarly, Singell and Terborg (2007) also find a mixed effect at the sectoral level. For some industries -e.g., food services- the minimum wage generates a negative EMP effect but a not statistically significant or even positive EMP effect in other industries.

Lastly, higher demand for labor implies an increase in labor prices, assuming all other things are equal. Therefore, economic theory suggests RW tends to rise (dwindle) with a greater (lower) abundance of job opportunities. But it is not only actual variations in EMP that affect wage levels but also the expectations about how stable a job is. Permanent employees, who have greater bargaining power, generally earn higher wage rates than fixed-term employees. (Jimeno and Toharia, 1993; Brown and Sessions, 2005; Amuedo-Dorantes and Serrano-Padial, 2007). Besides that, some models predict that the unemployment rate would not significantly influence wages under certain conditions. For instance, when both the job seeker and the employer are limited to credible threats, implying a paradox in the labor market theory. (Hall and Milgrom, 2008).

Thus, the interrelation between LP, RW, and EMP is complex, and several economic theories explain the causality from each of them to the others based on different theoretical frameworks. (See Table 1). Moreover, their effects could be positive, negative, or ambiguous, depending on the economy, sector, and temporal horizon under analysis. Knowing the responses of these variables to the other ones' changes is a significant input for economic policy decisions in the labor market.

This study contributes to the extant empirical literature by investigating the short and long run effects between LP, RW, and EMP for 25 OECD economies as a group for 1960-2019. For this purpose, I use several panel time-series techniques: error correction model (ECM), dynamic ordinary least squares (DOLS), fully modified ordinary least squares (FMOLS), autoregressive distributed lags (ARDL), and vector error correction model (VECM). I use the ECM, DOLS, FMOLS, and ARDL approaches to test the theories mentioned when I have exogenous and endogenous variables. I use the VECM when all the variables in the system are assumed to be fully endogenous.

The paper is organized as follows. Section 2 provides a literature review of empirical evidence about the LP and RW relationship and between the LP, RW, and EMP nexus. This section covers how several economic theories are supported or rejected when real-world data is applied to different economies and periods using diverse econometric approaches. Section 3 outlines the data and methodology used to estimate the short run and long run effects from each of the variables to the others. Section 4 reports the empirical results. Section 5 summarizes the main findings.

Table 1: Causality among labor productivity, real wages, and employment

Causality	Sign	Theory
LP → EMP	(-)	Efficiency gains lead to a reduction in labor demand
	(+)	Positive output effect on employment
LP → RW	(+)	Bargaining theory Marginal productivity theory
RW → LP	(+)	Induced technical change Shirking model Fairness model Adverse selection model Turnover model
RW → EMP	(-)	Higher labor cost causes labor substitution
EMP → LP	(-)	Less productive workers are fired first Workers increase effort to secure jobs
EMP → RW	(+)	Higher labor demand implies an increase in labor prices

Source: Own elaboration, adapted and extended from Wakeford (2004).

2. REVIEW OF THE EMPIRICAL LITERATURE

2.1 Labor Productivity and Real Wage

The relationship between LP and RW has been well explored in the economics literature. As mentioned above, the efficiency wage and induced technical change theories support causality from RW to LP, while causality from LP to RW is backed by the marginal productivity and bargaining theories. The empirical evidence has found either unidirectional causation from RW to LP, unidirectional causation from LP to RW, or bidirectional causation depending on the economy analyzed, the period covered, and the econometric specification chosen.

Regarding unidirectional causation from RW to LP, Marquetti (2004), investigating the relationship between these variables for the U.S. economy over the period 1869-1999 using a Granger non-causality test, indicates that RW Granger-cause LP, but LP does not Granger-cause RW. Yildirim (2015) finds unidirectional causality from RW to LP in the short run and long run for the Turkish manufacturing industry from 1988 to 2012, employing cointegration analysis and a Granger non-causality test. Dritsaki (2016) uses the cointegration ARDL framework and Toda and Yamamoto (1995)'s causality test to examine RW and inflation on LP for Bulgaria and Romania over 1991-2014. This author concludes that there is a unidirectional causal relationship going from RW to LP for Romania but a lack of causality among RW and LP for Bulgaria.

Iheanacho (2017) shows a positive and significant long run relationship between RW and LP, where the former is a significant driver of the latter only when inflation, real GDP per capita, and government expenditure, are included controls in an ARDL model for Nigeria over 1981-2012. But Iheanacho does not find the same results when these controls are not included. It is worth noting that, contrary to Dritsaki (2016), Iheanacho (2017) does not test the reverse causality from LP to RW. These findings appear to support non-mainstream theories of distribution-led technical change and growth, where the direction of causality seems to go from changes in income distribution to changes in labor productivity of the same sign.

On the other hand, some authors have found more robust evidence supporting the marginal productivity and the bargaining theories instead of the efficiency wage theory. Ferens (2017), elaborating an ARDL model to estimate the long run effects between LP and RW in the agricultural and manufacturing sectors between 1991 to 2016 for the Polish economy, documents long run causality running from LP to RW in both sectors, but the opposite causality could not be established statistically. Eryilmaz and Bakir (2018) focus their research on the relationship between LP, RW, and inflation in Turkey during 1988-2014. Using a VECM to measure the short and long run impacts among the variables mentioned, the authors do not find support for the efficiency wage theory in Turkey. Still, the wage bargaining theory is more suitable to explain the long run dynamics of this economy during that period.

Other authors have found evidence of bidirectional causality between LP and RW. Strauss and Wohar (2004) study the linkage between LP, RW, and prices for a panel of 459 U.S. manufacturing industries at a four-digit industry-level over 1956-1996. Their evidence suggests a stable long run relationship between LP and RW and between RW and prices for many, but not all industries. The authors observe bidirectional causality between LP and RW in aggregate terms; however, a one-to-one industry relationship between these two variables is firmly rejected.

Kumar, Webber, and Perry (2012) analyze LP, RW, and inflation for the Australian manufacturing sector over 1965-2007. Applying the VECM method and comparing its results with other time series techniques, their study exhibits consistent results on the impact of RW on LP. At the same time, the Granger non-causality test revealed a reciprocal causality running between LP and RW.

De Souza (2017), extending Marquetti (2004) methodology, presents a multi-industry analysis using two disaggregated datasets, including both developing and developed economies, for a panel ECM. De Souza shows evidence of cointegration and two-way, long run Granger causality between LP and RW. Jain (2019), following a VECM for state-level panel data of manufacturing industries in the Indian economy over 2000-2016, observes mutual causality between LP and RW in the long run. However, this author argues that the efficiency wage theory is more appropriate as its long run disequilibrium correcting process is quicker as compared to the marginal productivity theory.

Interestingly, when the relationship between LP and RW is investigated, some authors have found a non-linear effect (Hondroyiannis and Papapetrout, 1997; Gneezy and Rustichini, 2000). Tang (2014) estimates RW and inflation's impact on LP in Malaysia's manufacturing sector using annual data from 1970 to 2007, where a Granger non-causality test within a VECM is used. Tang reports a unilateral causality from RW to LP in both the short and long run, where its effect is non-monotonic and inverted U-shaped.

2.2 Labor Productivity, Real Wage, and Employment (or Unemployment)

An important question unaddressed in the above studies is whether increasing RW and corresponding LP changes imply job creation or job destruction on balance: whether employment rises or falls when workers become more productive. For instance, an increase in LP could have an ambiguous effect on EMP because greater efficiency would reduce labor demand or because a higher output would encourage firms to hire more workers due to a potential demand expansion. Conversely, lower EMP could incentivize workers to increase their effort to secure their jobs. And concerning the RW-EMP nexus, an RW increase raises labor costs causing factor substitution, so a decrease in EMP.

In the same way, an EMP increase would strengthen union bargaining power, leading to growth or maintaining workers' compensation in most cases. Consequently, like in the LP and RW analysis case, in the LP-RW-EMP relationship, several authors have reached different conclusions in the interaction of these three variables, depending on the economy and sector investigated, the period covered, and the econometric approach used.

Regarding the inclusion of EMP, Yusof (2008) explores the long run and dynamic behaviors of the LP-RW-EMP relationship. This author demonstrates the existence of cointegration between these three variables, with LP and EMP appearing to be exogenous. At the same time, RW is the principal variable that adjusts to maintain the long run relationship. Additionally, Yusof (2008) documents that although RW negatively affects EMP in the short run, there is a positive relationship between RW and EMP in the long run. Concerning RW and LP, higher LP leads to higher RW. And for the LP-EMP relationship, there does not appear to be any long run relationship between them.

Bhattacharya *et al.* (2011) examine the long run relationship between LP and EMP and LP and RW for the Indian manufacturing sector. These authors determined that LP-RW and LP-EMP are panels cointegrated for all industries and show unmistakable evidence of increasing EMP and RW boost LP for periods 1973-1974 and 1999-2001. Habanabakize, Meyer, and Oláh (2019) investigate both the short and long run effects of LP, RW, and investment spending on EMP absorption rates in South Africa between 1995Q1 to 2019Q1. These authors show unidirectional positive causation from LP to EMP absorption and unidirectional negative causation from

RW to EMP absorption. Additionally, the authors affirm the existence of a positive relationship between LP, EMP absorption, and investment spending but a negative effect from RW to EMP absorption in the long run.

Other authors have used unemployment (UNM) as a variable interacting with LP and RW. Wakeford (2004), applying an ECM and a Granger non-causality approach, explores the long and short run links of these three variables using quarterly data from 1983 to 2002 for South Africa. Wakeford finds cointegration between LP and RW, but UNM was not connected to the other two variables in the long run. In other words, UNM has little or no effect in terms of restraining RW growth. RW impacts LP negatively in the short run, but LP is not statistically significant in explaining RW variations. However, Wakeford affirms that "not much can be said about unemployment in the short run owing to the construction of the unemployment data series."

Karaalp-Orhan (2017) finds a significant and positive impact from RW and UNM to LP in the long run. The efficiency wage theory is supported since RW has a positive effect on LP. There is a positive association between UNM and LP. Consequently, the author suggests that a rise in RW and UNM rate may induce higher LP by increasing the probability and costs of job loss. Additionally, the causality test indicates unilateral causation from UNM to RW and bidirectional causation between UNM and LP.

Ozturk *et al.* (2019) elaborate on a VECM where RW is the dependent variable, and LP and UNM rate are independent variables in the model for the construction sector in New Zealand between 1983 and 2017. After proving that RW, LP, and UNM rate are cointegrated, the authors document that the variables' short run deviations move towards the long run in about 12 periods. The authors also support that the LP index positively affects RW, while the UNM rate's impact on RW is negative.

In the same way, Ozturk *et al.* (2020) follow the same approach as Ozturk *et al.* (2019) but use LP as a dependent variable and RW and UNM rate as independent variables. The application is for the same sector, country, and period covered in Ozturk *et al.* (2019). In this study, the authors calculate that the cointegrated equilibrium is reached in 1.67 periods. Furthermore, the authors indicate that RW has a positive effect on LP, while the UNM rate on LP is not statistically significant in the long run.

Similar approaches to studying the dynamics among these variables have been considered in other works. For instance, Fedderke and Mariotti (2002) and OECD Employment Outlook (2004) determine that the difference between RW and LP's growth rates is associated negatively with EMP. Junankar and Madsen (2004) conclude that RW and LP's wage gap is correlated positively with higher UNM. Klein (2012), applying a pooled estimation, fixed effects, and a dynamic estimation with unobserved panel effect, finds evidence that the rapid growth of the RW, which outpaced the LP growth in most South African sectors between 2008Q1 to 2011Q2, played an essential role in suppressing employment creation.

3. DATA AND METHODOLOGY

3.1 Description of the variables

This study uses annual data from 1960 to 2019 taken from the Penn World Tables version 10.0. The series used to construct the variables are the following: output-side real GDP at chained PPPs (in mil. 2017US$) (*rgdpo*), the share of labor compensation in GDP at current national prices (*labsh*), number of persons engaged (in millions) (*emp*), and population (in millions) (*pop*). Since the numbers of LP and RW cover a broad range of values and their scales vary considerably across countries, it is convenient to analyze these two variables in logarithms to reduce the wide range to a more manageable size. Then, using these series, I construct the following variables: log labor productivity at constant 2017 purchasing power parity (*LLP*), log average real wage at constant 2017 purchasing power parity (*LRW*), and employment to population ratio (*EPOP*). (See Appendix 1). The dataset is a balanced panel that includes 25 OECD countries[1]. Appendix 2 displays time-series plots for each country.

3.2 Econometric methodology

This paper's empirical strategy determines whether a long run relationship exists among the three variables of interest, LLP, LRW, and EPOP. After demonstrating cointegration, I estimate the speed of adjustment to the long run equilibrium in both the cases where endogenous and exogenous variables compose the system and when all the system variables are endogenous. The former case is analyzed using panels ECM, DOLS, FMOLS, and ARDL approaches, and the latter case is explored using a panel VECM.

These ECM and VECM approaches allow obtaining both short run effects and the system's transition to an equilibrium in the long run, but they have similarities and differences. The panels ECM, DOLS, FMOLS, and ARDL, are single-equation approaches. The panel ECM can be applied when the variables in the system are either $I(0)$ or $I(1)$, not $I(2)$ and this model requires at least a weak exogeneity of the explanatory variables. On the other hand, the panel VECM is a multi-equation approach constructed if there are variables $I(1)$ in the system and cointegration is present. The panel VECM model restricts the long run behavior of endogenous variables to converge to their cointegrating relationships. Like the panel ECM, the panel VECM is a system where each dependent variable is expressed in function of its lags and the other variables' lags.

As mentioned above, these econometric approaches would be appropriate depending on if the variables are $I(0)$ or $I(1)$. Accordingly, before proceeding to the panel cointegration analysis, unit-root tests are performed to know the order of integration of the variables.

4. EMPIRICAL RESULTS

4.1 Panel unit-root tests

I perform several panel unit-root tests with different specifications to know the variables' stationary nature robustly. The tests used are the following: Breitung (Breitung, 2001; Breitung and Das, 2005), Fisher-type test that combines the p-values from panel-specific unit-root tests employing the four methods proposed by Maddala and Wu (1999) and developed by Choi (2001), Harris-Tsavalis (Harris and Tsavalis, 1999), Im-Pesaran-Shin (Im, Pesaran, and Shin, 2003), and Levin-Lin-Chu (Levin, Lin, and Chu, 2002).

Consider a simple panel-data model:

$$y_{it} = \rho_i y_{i,t-1} + z'_{it}\lambda_i + \varepsilon_{it} \qquad (1)$$

[1] Australia, Austria, Belgium, Canada, Chile, Colombia, Denmark, Finland, France, Germany, Iceland, Ireland, Italy, Japan, Luxembourg, New Zealand, Norway, South Korea, Spain, Sweden, Switzerland, The Netherlands, The United Kingdom, The United States, and Turkey.

Where y is the variable to be tested: LLP, LRW, or EPOP, $\mathrm{i} = 1, 2, \ldots N$ are indexes of panels; $\mathrm{t} = 1, 2, \ldots T$ are indexes of time; and ε_{it} is a stationary error term. The vector z'_{it} could represent three cases: 1) the panel-specific means, 2) panel-specific means and a time trend, and 3) z'_{it} could not exist. In the first case, $z'_{it} = 1$ and λ_i are panel-specific means. In the second case, $z'_{it} = (1, t)$ so $z'_{it}\lambda_i$ represents panel-specific means and linear time trends. In the third case, $z'_{it} = 0$. The Breitung, Harris-Tsavalis, and Levin-Lin-Chu tests assume that there is a common unit-root process so that ρ_i is identical across panels: $\rho_i = \rho$ for all *i*. On the other hand, the Fisher-type and Im-Pesaran-Shin tests allow their tests' autoregressive parameters to be panel-specific.

Additionally, these tests have different asymptotic behaviors required for N and T to derive the tests' limiting distributions. Depending on the size of a sample in terms of both N and T, one panel unit-root test would be more appropriate than others. For instance, a panel unit-root test that assumes either fixed N or N tending to infinity slower than T would be more convenient for long panels -small N and large T- cases. Hlouskova and Wagner (2006) and Barbieri (2009) present excellent overviews of the econometrics behind the panel unit-root tests and the statistics' asymptotic properties among the different specifications.

Appendix 3 shows the statistics and their *p*-values in parenthesis for each test and specification of z_{it}. In most cases, the null hypotheses of unit-root presence are not rejected for the levels' variables. But when these variables are expressed in first differences, the null hypotheses are rejected either at 1% or 5% significance. Therefore, I can conclude that LLP, LRW, and EPOP are integrated of order one, or *I*(1).

4.2 Panel cointegration tests

Before deciding what econometric approach is more appropriate, knowing whether the system's three variables move together is required. If the series are cointegrated, they have a long run relation, even if they temporarily deviate. After concluding that LLP, LRW, and EPOP are all *I*(1), if there is a linear combination of the three *I*(1) variables that is stationary, *I*(0), the series are said to be cointegrated (Engle and Granger, 1987).

4.2.1 Panel cointegration test: Pedroni

Consider a simple panel-data model for the *I*(1) dependent variable y_{it}:

$$y_{it} = x'_{it}\beta_i + z'_{it}\lambda_i + \varepsilon_{it} \qquad (2)$$

Where y is the dependent variable to be tested: LLP, LRW, or EPOP. For each panel, each of the covariates in x_{it} are *I*(1) series and represent the other two variables in the system. $\mathrm{i} = 1, 2, \ldots N$ are indexes of panels, and $\mathrm{t} = 1, 2, \ldots T_i$ are indexes of time. The term z_{it} allows for panel-specific means, panel-specific means and a time trend, or could not exist, same as equation 1; and ε_{it} is the error term.

The Dickey-Fuller *t* statistics in the Pedroni residual panel cointegration test in Table 2 are constructed by fitting equation 2 using ordinary least squares (OLS), obtaining the predicted residuals ε_{it} as follows:

$$\varepsilon_{it} = \rho\varepsilon_{i,t-1} + \nu_{it} \qquad (3)$$

Where ρ is the autoregressive (AR) parameter and ν_{it} is a stationary error term.

The Phillips-Perron *t*-test statistics in the Pedroni's panel cointegration test in Table 2 are also constructed by fitting equation 2 using OLS, obtaining the predicted residuals ε_{it} as follows:

$$\varepsilon_{it} = \rho_i \varepsilon_{i,t-1} + \nu_{it} \qquad (4)$$

Where ρ_i is the panel-specific-AR parameter.

That being said, I conduct Pedroni's Engel-Granger based panel cointegration test allowing for both the same-AR parameters (ρ) as in equation 3 as within-dimension and the panel-specific-AR parameters (ρ_i) as in equation 4 as between-dimension. The within-dimension in Table 2 includes four weighted and four unweighted panel statistics, and the between-dimension consists of three group statistics. Pedroni (1999) and Pedroni (2004) explain these seven tests' derivations and their asymptotic properties in more detail.

Table 2 shows the statistics and *p*-values for Pedroni's tests for each series as a dependent variable and the other two as independent variables. Based on the *p*-values, when LLP is the dependent variable, I reject the null hypothesis of no cointegration in six out of eleven cases, either at 1% or 5% significance. When LRW is the dependent variable, the *p*-values indicate that I can reject the same null hypothesis of no cointegration since most of them -seven out of eleven- are less than 1% or 5%. When EPOP is the dependent variable, the evidence suggests that I cannot reject the null hypothesis of no cointegration for the reason that in only one out of eleven events, the *p*-values are less than 10% significance. I conclude that the variables are cointegrated when LLP and LRW are dependent variables but not when EPOP is the dependent variable.

Table 2: Pedroni's panel cointegration test for LLP, LRW, and EPOP

	Dependent variable					
	LLP		LRW		EPOP	
	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.
Weighted panel statistics						
v-statistic	1.22	0.1118	3.16	0.0008	0.73	0.2321
rho-statistic	-2.53	0.0058	-1.96	0.0252	0.76	0.7765
PP-statistic	-2.87	0.0021	-2.38	0.0087	0.48	0.6839
ADF-statistic	-5.02	0.0001	-4.37	0.0001	-0.63	0.2660
Unweighted panel statistics						
v-statistic	2.18	0.0146	4.04	0.0001	0.09	0.4650
rho-statistic	-0.37	0.3574	-0.83	0.2030	0.91	0.8179
PP-statistic	0.03	0.5120	-0.55	0.2923	0.44	0.6688
ADF-statistic	-0.59	0.2791	-0.62	0.2665	0.38	0.6500
Group statistics						
rho-statistic	-0.73	0.2327	-0.96	0.1681	1.81	0.9649
PP-statistic	-1.68	0.0465	-1.83	0.0339	1.22	0.8881
ADF-statistic	-3.94	0.0001	-3.67	0.0001	-1.38	0.0834

Notes: The null hypothesis is "no cointegration." The weighted and unweighted panel statistics' alternative hypothesis is "cointegration in all panels with common autoregressive coefficients in the residuals.". The group statistics' alternative hypothesis is "cointegration in a subset of panels with panel-specific autoregressive coefficients in the residuals." The deterministic specification includes a constant in the test equation and no deterministic trend. The optimal number of lags is chosen based on the Bayesian information criterion. The Bartlett kernel is selected as a spectral estimation method with a bandwidth set by the Newey-West procedure. Use degree-of-freedom corrected Dickey-Fuller residual variances.

4.2.2 Panel cointegration test: Westerlund

I also perform the Westerlund cointegration test (Westerlund, 2005) as a robustness check. This test assumes panel-specific cointegrating vectors in equation 2, where all panels have individual slope coefficients. This test delivers several statistics based on a model where the AR parameter is either panel-specific-AR or panel-same-AR across the panels. The statistics are obtained by testing the existence of unit-root in the predicted residuals in equation 4. All the statistics test the null hypothesis of no cointegration. The panel-specific-AR specifications' alternative hypothesis is "some panels are cointegrated." The panel-same-AR specifications' alternative hypothesis is "all panels are cointegrated," which restricts $\rho_i = \rho$ in equation 4.

Table 3 confirms that when LLP and LRW are dependent variables, the system cointegrates. On the other hand, when EPOP is the dependent variable, there is no evidence of cointegration since three out of four *p*-values are greater than 5%.

Table 3: Westerlund's panel cointegration test for LLP, LRW, and EPOP

	Dependent variable					
	LLP		LRW		EPOP	
	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.
Demean	-2.34	0.0097	-2.54	0.0056	1.03	0.1523
Some	-3.41	0.0003	-3.65	0.0001	-2.07	0.0191
Trend	-2.47	0.0067	-1.29	0.0994	1.55	0.0611
All panels	-2.67	0.0038	-2.72	0.0033	-1.26	0.1038

Notes: The null hypothesis is "no cointegration." The demeaned, some, and trend panel statistics' alternative hypothesis is "some panels are cointegrated." The all panels' alternative hypothesis is "all panels are cointegrated."

4.2.3 Panel cointegration test: Fisher

Unlike the Pedroni and Westerlund tests, one-way tests, the Fisher panel cointegration test is system-based for the entire panel set. The advantage of this test is that it tells us whether cointegration exists and how many cointegration equations are in the system. Fisher (1932) derives a combined test from the results of individual independent tests. Maddala and Wu (1999), based on Fisher's (1932) output, adjusted the Johansen test (Johansen, 1988; Johansen, 1991) to test the whole panel data by combining tests from individual cross-sections. Fisher panel cointegration computes and reports the *p*-values based on MacKinnon, Haug, and Michelis (1999) using the asymptotic chi-squared distribution for the trace and the maximum eigenvalue tests.

Table 4 provides evidence for the trace and the maximum eigenvalue tests that a long run relationship exists among the three variables. Based on this test's *p*-values, I fail to reject the null hypothesis that there is at most one cointegrating equation in the system, meaning that there is one cointegration equation among these three variables. The lag specification for differenced endogenous variables is chosen based on the Bayesian criterion in Appendix 4. I select the Bayesian information criterion because it is considered more effective for model selection than its competitors, such as the Akaike information criterion. (Koehler and Murphree, 1988; Cavanaugh and Neath, 1999; Medel and Salgado, 2013).

Table 4: Fisher's panel cointegration test for LLP, LRW, and EPOP

Hypothesized No. of CE(s)	Trace test		Maximum eigenvalue test	
	Fisher statistic	Prob.	Fisher statistic	Prob.
None	110.30	0.0001	87.66	0.0008
At most 1	58.85	0.1831	45.25	0.6640
At most 2	79.04	0.0055	79.04	0.0055

Notes: The specification assumes that level data have linear trends, but the cointegrating equations have only intercepts. Probabilities are computed using asymptotic chi-square distribution. Two lags interval in first differences is chosen based on the Bayesian information criterion.

4.3 Panel ECM for labor productivity and real wage

The panel ARDL model contains the lagged value(s) of the dependent variable and the current and lagged values of regressors as explanatory variables. Consider the generalized panel ARDL (p, q) form:

$$y_{it} = \mu_i + \sum_{j=1}^{p} \gamma_{ij}\, y_{i,t-j} + \sum_{j=0}^{q} \beta'_{ij}\, x_{i,t-j} + \varepsilon_{it} \qquad (5)$$

Where y is the dependent variable of the ith cross-section unit: LLP, LRW, or EPOP; x_{it} is a kx1 vector of unit-specific regressors that are allowed to be purely *I*(0) or *I*(1) or cointegrated, which in this case, it is a vector that contains the other two variables different to the dependent variable; μ_i is a unit-specific fixed effect, i $= 1, 2, \dots N$ are indexes of panels, t $= 1, 2, \dots T$ are indexes of time, *p* and *q* are the optimal lags of the dependent and independent(s) variable(s), respectively, and ε_{it} is a $Nx1$ vector of disturbances or errors. Time trends and other fixed regressors could be included.

Since the panel cointegration tests demonstrate a long run relationship among the variables when LLP and LRW are dependent variables, I include an error correction term (ECT) in my generalized equation 5. Therefore, my ECMs for LLP and LRW are the following:

$$\Delta LLP_{it} = \mu_i^{LLP} + \sum_{j=1}^{p-1} \gamma_{ij}^{*}\, \Delta LLP_{i,t-j} + \sum_{j=0}^{q-1} \beta_{i1}^{*}\, \Delta LRW_{i,t-j} + \sum_{j=0}^{q-1} \beta_{i2}^{*}\, \Delta EPOP_{i,t-j} + \xi_i ECT^{LLP} + \varepsilon_{it}^{LLP} \text{ (5a)}$$

$$\Delta LRW_{it} = \mu_i^{LRW} + \sum_{j=1}^{p-1} \gamma_{ij}^{*}\, \Delta LRW_{i,t-j} + \sum_{j=0}^{q-1} \beta_{i1}^{*}\, \Delta LLP_{i,t-j} + \sum_{j=0}^{q-1} \beta_{i2}^{*}\, \Delta EPOP_{i,t-j} + \xi_i ECT^{LRW} + \varepsilon_{it}^{LRW} \text{(5b)}$$

Where for both equations 5a and 5b,

Δ: Operator of first-differences for the short run effects

γ_{ij}^{*} and β_{ij}^{*}: Short run dynamic coefficients

$\gamma_{ij}^{*} = -\sum_{m=j+1}^{p} \gamma_{im}, \quad j = 1, 2, \dots, p-1$

$\beta_{ij}^{*} = -\sum_{m=j+1}^{q} \beta_{im}, \quad j = 1, 2, \dots, q-1$

$\xi_i = -\left(1 - \sum_{j=1}^{p} \gamma_{ij}\right)$: Speed of adjustment parameter with an expected negative sign

$ECT = [y_{i,t-1} - \theta'_i \; x_{it}]$: Error correction term

$\theta_i = \frac{\sum_{j=0}^{q} \beta_{ij}}{1-\sum_{j=1}^{p} \gamma_{ij}}$: Vector of long run coefficients

The literature on dynamic heterogeneous panel estimation identifies several approaches to estimate equations 5a and 5b when both *N* and *T* are large. On the one hand, we have the dynamic fixed effects (DFE) estimator, which could be used when the time-series data for each group are pooled, and only the intercepts are allowed to differ across panels. This specification requires the strong assumption that the slope coefficients and error variances are identical, meaning that all panel responses are the same in the long run and short run. If the slope coefficients exhibit heterogeneity across panels, this estimator would generate inconsistent and misleading results. Another problem with the DFE estimator is the potential simultaneity bias due to the endogeneity between the residuals and lagged explanatory variables, especially for small samples.

On the other hand, we have the mean group (MG) estimator proposed by Pesaran and Smith (1995). Contrary to the DFE, the MG estimator allows the intercepts, slope coefficients, and error variances to differ across panels. This specification estimates separate regressions for each group and calculates a simple arithmetic average of the coefficients. This estimator produces consistent estimates of the parameters' average under the assumption that both the intercepts and the slopes vary across panels, allowing heterogeneity in short- and long run relationships.

In the middle, we have the pooled mean group (PMG) estimator proposed by Pesaran, Shin, and Smith (1999). This estimator combines pooling and averaging of coefficients allowing the intercepts, short run coefficients, and error variances to differ across panels like the MG estimator but constrains the long run coefficients to be the same across panels like the DFE estimator.

Before evaluating what ECM specification is more appropriate when the LLP and LRW are the dependent variables, selecting the optimal lag orders for both cases is required. Finding the optimal lag order of the dependent and independent variables is essential for the performance of the ECM estimates of θ_i. If the lag orders are underestimated, it will result in inconsistent estimates, while if the lag orders are overestimated, it will lead to a loss of efficiency. Appendix 5 shows that when LLP and LRW are the dependent variables, and the other two are the independent ones in each case, based on the Bayesian information criterion, the ECM(1,1,1) is the model that fits better equations 5a and 5b.

Knowing that the optimal lag order is one lag for each variable in the system, I perform the Hausman test to find what specification -DFE, MG, or PMG- is more appropriate for the ECMs. Based on the Hausman test in Appendix 6, I cannot reject the null hypothesis that the PMG estimator is more efficient than MG and DFE when LLP and LRW are dependent variables. The first columns of Tables 5A and 5B present the ECMs for LLP and LRW as dependent variables, respectively, using the PMG specification. The MG and DFE are used as a robustness check in the second and third columns.

Based on Table 5A, I can conclude a long run causality running from LRW and EPOP jointly to LLP since the error correction terms (ECT) are statistically significant at 1%. In the PMG specification, the system is getting back to equilibrium at a speed of 5.7% annually when LLP is the dependent variable, and the independent variables are LRW and EPOP. Concerning the long run individual effects, a 1% increase in RW leads to a 1.08% increase in LP in the long run. This result supports the efficiency wages theory or alternative theories of distribution-led growth where a rise in RW induces higher worker productivity by raising job loss costs. For its part, a one percentage point increase in EPOP negatively affects LP by a 0.02% decrease in the long run. For the short run impacts, RW has a positive effect on LP. A 1% increase in RW leads to a 0.83% increase in LP in the short run, while the EPOP's influence on LP is minimal and not statistically significant.

An analogous description of the results can be done in Table 5B for LRW as a dependent variable. Its output tells us that there exists a long run causality running from LLP and EPOP jointly to LRW. In the PMG specification, the system is getting back to equilibrium at a speed of 8.4% annually when LRW is the dependent variable. Additionally, LLP's long run elasticity equal to 0.84% backs the performance-based pay and the bargaining theories. Similarly, a one percentual point increase in EPOP also has a positive and statistically significant effect on RW in the long run, but its magnitude is so tiny, 0.01%. About the short run dynamics, a 1% increase in LP causes a 0.74% increase in RW, while the short run effect from EPOP to LRW is not statistically significant.

4.4 Panel DOLS and panel FMOLS

As a robustness check, I also run dynamic ordinary least squares (DOLS) and fully modified ordinary least squares (FMOLS) estimations, which are methods to examine only long run parameters. Both DOLS and FMOLS are performed using pooled, pooled weighted, and grouped specifications. While the first and second specifications consider the 'within dimension' of the panel, the third one is based on the 'between dimension.'

4.4.1 Panel DOLS

Pooled, pooled weighted, and grouped specifications of panel DOLS are extensions of the Saikkonen (1992) and Stock and Watson (1993) DOLS time-series estimator to panel data form. Panel DOLS specifications augment the cointegrating regression with lags and leads of the short run terms. Thus, serial correlation and asymptotic endogeneity are corrected, making the cointegrating equation's error term orthogonal to stochastic regressor innovations. Consider the augmented panel cointegrating regression form:

$$y_{it} = X'_{it}\beta + \sum_{j=-q_i}^{f_i} \Delta X'_{it+j}\,\phi_i + \varepsilon_{it} \quad (6)$$

Where,

y_{it}: Dependent variable, either LLP or LRW, purged of the individual deterministic trends
X_{it}: Vector of the two independent variables different from the dependent variable, purged of the individual deterministic trends
β: Vector of long run coefficients, the coefficients of interest
ϕ_i: Vector of short run dynamic coefficients
q: Lags of the differenced regressors, ΔX_{it+j}
f: Leads of the differenced regressors, ΔX_{it+j}
ε_{it}: Vector of disturbances or errors

Let A_{it} be regressors constructed by interacting the ΔX_{it+j} terms with cross-section dummy variables, and let $H'_{it} = \; X'_{it}, A'_{it} \; '$.

Pooled DOLS (Kao and Chiang, 2001) uses ordinary least squares to estimate the parameters of interest of equation 6, where its estimators can be expressed in the following form:

$$\begin{bmatrix} \beta_{D\_pooled} \\ \alpha_{D\_pooled} \end{bmatrix} = \left[\sum_{i=1}^{N} \sum_{t=1}^{T} H_{it} H'_{it} \right]^{-1} \left[\sum_{i=1}^{N} \sum_{t=1}^{T} H_{it} y'_{it} \right]$$

Pooled weighted DOLS (Mark and Sul, 1999; Mark and Sul, 2003), for its part, allows for heterogeneity in the individual long run residual variances, ω_i, obtained after running preliminary DOLS estimation. Its estimators are in the following form:

$$\begin{bmatrix} \beta_{D\_pooled\_w} \\ \alpha_{D\_pooled\_w} \end{bmatrix} = \left[\sum_{i=1}^{N} \omega_i^{-1} \sum_{t=1}^{T} H_{it} H'_{it} \right]^{-1} \left[\sum_{i=1}^{N} \omega_i^{-1} \sum_{t=1}^{T} H_{it} y'_{it} \right]$$

Grouped DOLS (Pedroni, 2001b) estimates the parameters by taking the average over the individual cross-section DOLS estimates, where its estimators are obtained in the following form:

$$\begin{bmatrix} \beta_{D\_grouped} \\ \alpha_{D\_grouped} \end{bmatrix} = \frac{1}{N} \sum_{i=1}^{N} \left\{ \left[\sum_{t=1}^{T} H_{it} H'_{it} \right]^{-1} \left[\sum_{t=1}^{T} H_{it} y'_{it} \right] \right\}$$

Columns fourth, fifth, and sixth in Tables 5A and 5B show the pooled DOLS, pooled weighted DOLS, and grouped DOLS regressions when LLP and LRW are dependent variables, respectively. Coefficients of the effects from LRW to LLP and LLP to LRW are similar in magnitude to those found in the ECM, where all signs are positive and statistically significant at a 1% level. In Table 5A, EPOP negatively impacts LLP in two out of three specifications -pooled and pooled weighted- where the coefficients are statistically significant, confirming what is found in the ECM. In Table 5B, an EPOP ratio has a positive and statistically significant effect at a 1% level on LRW in the same two out of three specifications, supporting what is found in the ECM.

4.4.2 Panel FMOLS

Like the panel DOLS, panel FMOLS also has the same three specifications: pooled, pooled weighted, and grouped, but in the FMOLS case, these specifications are extensions of the Phillips and Hansen (1990) FMOLS time-series estimator to panel data form, where these authors present an FMOLS asymptotically unbiased estimator that eliminates problems caused by the long run correlation between stochastic regressor innovations and the cointegrating equation.

Consider the panel cointegrating equation form:

$$\begin{aligned} y_{it} &= X'_{it}\beta + D'_{1,it}\psi_i + \varepsilon_{1,it} \qquad (7) \\ X_{it} &= \theta'_1 D_{1,it} + \theta'_2 D_{2,it} + v_{2,it} \\ \Delta v_{2,it} &= \varepsilon_{2,it} \end{aligned}$$

Where,

y_{it}: Dependent variable, either LLP or LRW
X_{it}: Vector of the two independent variables different from the dependent variable
β: Vector of long run coefficients, the coefficients of interest

$D_{1,it}$: Deterministic trend regressors in both the regressor equation and cointegrating equation
$D_{2,it}$: Deterministic regressors included in the regressor equation but excluded in the cointegrating equation
ε_{it}: Vector of disturbances or errors

If the deterministic trend terms in the panel cointegrating equation consist only of cross-section dummy variables, equation 7 becomes:

$$y_{it} = X'_{it}\beta + \psi_i + \varepsilon_{1,it} \qquad \text{(7')}$$

And,

$$\Delta X_{it} = \varepsilon_{2,it}$$

Let Λ the one-sided long run covariance matrix, and Ω the long run covariance matrix, where:

$$\Lambda_i = \sum_{j=0}^{\infty} E(\varepsilon_{it}\ \varepsilon'_{it-j}) = \begin{bmatrix} \lambda_{11i} & \lambda_{12i} \\ \lambda_{21i} & \lambda_{22i} \end{bmatrix}$$
$$\Omega_i = \sum_{j=-\infty}^{\infty} E(\varepsilon_{it}\ \varepsilon'_{it-j}) = \begin{bmatrix} \omega_{11i} & \omega_{12i} \\ \omega_{21i} & \Omega_{22i} \end{bmatrix}$$

The modified dependent variable, y_{it}, and the serial correlation correction term, λ_{it}, are expressed as follows:

$$y^+_{it} = y_{it} - \omega_{12i}\ \Omega^{-1}_{22i}\ \varepsilon_2$$
$$\lambda_{12i} = \lambda_{12} - \omega_{12i}\ \Omega^{-1}_{22i}\ \widetilde{\Lambda}_{22i}$$

Pooled FMOLS (Phillips and Moon, 1999) estimator sums across cross-sections separately in the numerator and denominator. This estimator can be expressed in the following form:

$$\beta_{F\_pooled} = \left[\sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}X'_{it}\right]^{-1} \sum_{i=1}^{N}\sum_{t=1}^{T}\left[X_{it}\ y^+_{it} - \lambda'_{12i}\right]$$

Pooled weighted FMOLS (Kao and Chiang, 2001; Pedroni, 2001a) is an estimator for heterogeneous cointegrated panels. This estimator is calculated by allowing the long run variances to differ across cross-sections, and it can be obtained from the following expression:

$$\beta_{F\_pooled\_w} = \left[\sum_{i=1}^{N}\sum_{t=1}^{T} X^*_{it}X^{*\prime}_{it}\right]^{-1} \sum_{i=1}^{N}\sum_{t=1}^{T}[X^*_{it}\ y^*_{it} - \lambda^{*\prime}_{12i}]$$

Where,

$X^*_{it} = \Omega^{-1/2}_{22i} X_{it}$

$y^*_{it} = \omega^{-1/2}_{12i}\, y^{++}_{it}$

$\lambda^*_{12i} = \omega^{-1/2}_{12i}\ \lambda_{12i}\ \Omega^{-1/2}_{22i}$

$y^{++}_{it} = y_{it} - \omega_{12i}\ \Omega^{-1}_{22i}\ \varepsilon_2 - \omega^{1/2}_{12i}\left[\omega^{1/2}_{12i}\ X'_{it} - \ \omega_{12i}\ X_{it}\ '\right]\beta_0$

β_0: Preliminary estimate of the long run coefficient

Grouped FMOLS (Pedroni, 2001a; Pedroni, 2001b) estimator averages the individual cross-sections. Its estimator is the following:

$$\beta_{F\_grouped} = \frac{1}{N}\sum_{i=1}^{N}\left\{\left[\sum_{t=1}^{T} X_{it}X_{it}'\right]^{-1}\sum_{t=1}^{T}\left[X_{it}\ y_{it} - \boldsymbol{\lambda}_{\mathbf{12}\boldsymbol{i}}'\right]\right\}$$

Columns seventh, eighth, and ninth in Tables 5A and 5B show the pooled FMOLS, pooled weighted FMOLS and grouped FMOLS regressions when LLP and LRW are dependent variables, respectively. Like the ECM and DOLS cases, coefficients of the effects from LRW to LLP and LLP to LRW are all positive and statistically significant at a 1% level. In Table 5A, EPOP negatively impacts LLP in the pooled and pooled weighted specifications. At the same time, in Table 5B, an EPOP ratio has a positive and statistically significant effect at a 1% level on LRW in the same two specifications. Contrary to expected, the grouped FMOLS specifications are the only ones that show an opposite and statistically significant effect from EPOP to LLP and EPOP to LRW in Tables 5A and 5B, respectively, compared to all the others in the ECM, DOLS, and FMOLS specifications.

Table 5A: ECM, DOLS, and FMOLS models for LLP as the dependent variable

	ECM			DOLS			FMOLS		
	PMG	MG	DFE	Pooled	Pooled W.	Grouped	Pooled	Pooled W.	Grouped
Long-run									
LRW	1.0798***	1.1382***	1.1074***	1.0895***	1.0702***	1.0359***	1.0893***	1.0854***	1.0346***
	(0.0097)	(0.0688)	(0.0381)	(0.0047)	(0.0076)	(0.0482)	(0.0058)	(0.0001)	(0.0031)
EPOP	-0.0177***	-0.0333	-0.0051	-0.0085***	-0.0048***	0.0043	-0.0091***	-0.0030***	0.0045***
	(0.0021)	(0.0282)	(0.0037)	(0.0011)	(0.0017)	(0.0139)	(0.0013)	(0.0002)	(0.0008)
ECT	-0.0569***	-0.1829***	-0.0398***						
	(0.0158)	(0.0380)	(0.0100)						
Short-run									
Δ LRW $_{t-1}$	0.8270***	0.7014***	0.8781***						
	(0.0309)	(0.0374)	(0.0170)						
Δ EPOP $_{t-1}$	0.0007	0.0021*	-0.0017**						
	(0.0012)	(0.0012)	(0.0007)						
Constant	0.0320***	0.0963*	-0.0103						
	(0.0074)	(0.0552)	(0.0137)						

Notes: For the ECM specifications, the optimal number of lags is chosen based on the Bayesian information criterion, and a constant is included as a fixed regressor. For all the DOLS specifications, the optimal lags and leads are chosen based on the Bayesian information criterion. The lag specification for the long run variance is based on the Bayesian information criterion. The Bartlett kernel is selected as a spectral estimation method with a bandwidth set by the Newey-West automatic procedure, and degrees-of-freedom adjustment is used. The coefficient covariance matrix for the pooled DOLS is calculated assuming homogeneous variances. The individual covariances for the grouped DOLS are calculated using a rescaled OLS method. For all the FMOLS specifications, the Bartlett kernel is selected as a spectral estimation method with a bandwidth set by the Newey-West automatic procedure, and degrees-of-freedom adjustment is used to calculate their long run variances. The coefficient covariance matrix for the pooled FMOLS is calculated assuming homogeneous variances. Standard errors in parentheses. * *p*-value < 0.10, ** *p*-value < 0.05, *** *p*-value < 0.01.

Table 5B: ECM, DOLS, and FMOLS models for LRW as the dependent variable

	ECM			DOLS			FMOLS		
	PMG	MG	DFE	Pooled	Pooled W.	Grouped	Pooled	Pooled W.	Grouped
Long-run									
LLP	0.8354***	0.8056***	0.7894***	0.9086***	0.9313***	0.9632***	0.9098***	0.9146***	0.9641***
	(0.0125)	(0.0388)	(0.0326)	(0.0038)	(0.0062)	(0.0141)	(0.0049)	(0.0001)	(0.0030)
EPOP	0.0097***	0.0118***	0.0063**	0.0101***	0.0052***	-0.0034	0.0102***	0.0015***	-0.0037***
	(0.0015)	(0.0040)	(0.0026)	(0.0009)	(0.0014)	(0.0042)	(0.0012)	(0.0003)	(0.0008)
ECT	-0.0840***	-0.2030***	-0.0553***						
	(0.0156)	(0.0319)	(0.0101)						
Short-run									
Δ LLP $_{t-1}$	0.7384***	0.6273***	0.7631***						
	(0.0370)	(0.0411)	(0.0156)						
Δ EPOP $_{t-1}$	0.0003	-0.0012	0.0023***						
	(0.0009)	(0.0010)	(0.0007)						
Constant	0.7008***	0.0273	0.0843***						
	(0.0122)	(0.0607)	(0.0126)						

Notes: For the ECM specifications, the optimal number of lags is chosen based on the Bayesian information criterion, and a constant is included as a fixed regressor. For all the DOLS specifications, the optimal lags and leads are chosen based on the Bayesian information criterion. The lag specification for the long run variance is based on the Bayesian information criterion. The Bartlett kernel is selected as a spectral estimation method with a bandwidth set by the Newey-West automatic procedure, and degrees-of-freedom adjustment is used. The coefficient covariance matrix for the pooled DOLS is calculated assuming homogeneous variances. The individual covariances for the grouped DOLS are calculated using a rescaled OLS method. For all the FMOLS specifications, the Bartlett kernel is selected as a spectral estimation method with a bandwidth set by the Newey-West automatic procedure, and degrees-of-freedom adjustment is used to calculate their long run variances. The coefficient covariance matrix for the pooled FMOLS is calculated assuming homogeneous variances. Standard errors in parentheses. * *p*-value < 0.10, ** *p*-value < 0.05, *** *p*-value < 0.01.

4.5 Panel ARDL for employment-to-population ratio

Since there is no cointegration when EPOP is the dependent variable, I only specify the short run ARDL model. My reparametrized panel ARDL (p, q) from equation 5 for this case is the following:

$$\Delta EPOP_{it} = \mu_I^{EPOP} + \sum_{j=1}^{p-1} \gamma_{ij}^* \, \Delta EPOP_{i,t-j} + \sum_{j=0}^{q-1} \beta_{i1}^* \, \Delta LLP_{i,t-j} + \sum_{j=0}^{q-1} \beta_{i2}^* \, \Delta LRW_{i,t-j} + \varepsilon_{it}^{EPOP} \quad \text{(5c)}$$

Appendix 7 shows that the optimal lag length for equation 5c is three lags. Therefore, equation 5c is ran using three lags for each independent variable, as indicated in Appendix 8. However, it seems like the independent variable $\Delta EPOP_{t-3}$ might be redundant because it is not statistically significant (*p*-value = 0.5017, not shown), and its coefficient in absolute terms is minimal. Hence, I perform a redundant variable test to this variable, which results are presented in Appendix 9. Based on the *F* and the Likelihood ratio statistics, I cannot reject the null hypothesis that the variable ΔEPR_{t-3} is insignificant.

Table 6 exhibits the short run ARDL regression when EPOP is the dependent variable after dropping its third lag in the set of independent variables. I can conclude that an increase in LLP positively impacts EPOP, meaning that greater efficiency in the short run triggers economic activity, giving room for more jobs in the short run. On the other hand, an increase in LRW negatively affects EPOP, probably due to factor substitution caused by higher labor costs in the short run. Appendix 10 shows the Wald tests for the joint significance of the lags of LLP and LRW. These tests confirm that LLP lags and LRW lags are jointly significant to explain the model's short run dynamics.

Table 6: Short run ARDL model for ΔEPOP as the dependent variable and ΔLLP and ΔLRW as independent variables

Variable	Coefficient
Δ EPOP $_{t-1}$	0.5264*** (0.0268)
Δ EPOP $_{t-2}$	-0.0705** (0.0270)
Δ LLP $_{t-1}$	3.9125*** (0.8494)
Δ LLP $_{t-2}$	1.9168** (0.8491)
Δ LLP $_{t-3}$	1.4863* (0.8511)
Δ LRW $_{t-1}$	-2.3652*** (0.9061)
Δ LRW $_{t-2}$	-3.0793*** (0.8959)
Δ LRW $_{t-3}$	-1.8503** (0.8981)
Constant	0.0736*** (0.0223)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors in parenthesis

4.6 Panel vector error correction model (VECM)

As a robustness check of the results found for the panels ECM, DOLS, FMOLS, and ARDL, I assume an entirely endogenous system in this section, which is not true. The endogenous three-equations system to be estimated is the following:

$$\Delta LLP_{it} = \mu_i^{LLP} + \sum_{j=1}^{p-1} \gamma_{i1}^* \, \Delta LLP_{i,t-j} + \sum_{j=0}^{q-1} \beta_{i1}^* \, \Delta LRW_{i,t-j} + \sum_{j=0}^{q-1} \beta_{i2}^* \, \Delta EPOP_{i,t-j} + \xi_i ECT^{LLP} + \varepsilon_{itt}^{LLP} \quad (5a)$$

$$\Delta LRW_{it} = \mu_i^{LRW} + \sum_{j=1}^{p-1} \gamma_{i1}^* \, \Delta LRW_{i,t-j} + \sum_{j=0}^{q-1} \beta_{i1}^* \, \Delta LLP_{i,t-j} + \sum_{j=0}^{q-1} \beta_{i2}^* \, \Delta EPOP_{i,t-j} + \xi_i ECT^{LRW} + \varepsilon_{itt}^{LRW} \quad (5b)$$

$$\Delta EPOP_{it} = \mu_i^{EPOP} + \sum_{j=1}^{p-1} \gamma_{i1}^* \, \Delta EPOP_{i,t-j} + \sum_{j=0}^{q-1} \beta_{i1}^* \, \Delta LLP_{i,t-j} + \sum_{j=0}^{q-1} \beta_{i2}^* \, \Delta LRW_{i,t-j} + \xi_i ECT^{EPOP} + \varepsilon_{itt}^{EPOP} \quad (5c')$$

If the previous analysis results are robust, I would expect the speed of adjustment parameters when LLP and LRW are the dependent variables to be statistically significant. On the other hand, since there is no cointegration when EPOP is the dependent variable, I constraint the $ECT^{EPOP} = 0$ in the equation 5c'. Appendix 11 shows the LR test for binding restriction, where the null hypothesis $ECT^{EPOP} = 0$ is not rejected. It confirms that EPOP is weakly exogenous, meaning that this variable does not adapt to the long run deviations, and LLP and LRW are making the adjustment.

The optimal lag length for a panel VECM should be the optimal lag order for a panel VAR minus one. However, as shown in Appendix 4, there is no consensus about the panel VAR's optimal lag length among the information criteria. Since I must choose a sufficient number of lags to avoid serial correlation in the residuals, I performed several VEC residual serial correlation Lagrange Multiplier tests starting from one lag and increasing them until five lags. At lag five, I could not reject the null hypothesis of "no serial correlation at lag h" and the null hypothesis of "no serial correlation at lags 1 to h at 5% significance." Consequently, I choose five lags for this three-variables model. Appendix 12 presents the VEC residual serial correlation LM tests for five lags in the panel VECM. Additionally, Appendix 13 shows the VEC residual Portmanteau test for autocorrelation as a robustness check, concluding no serial correlation in the VECM with five lags.

Appendix 14 displays the panel VECM results. The error correction terms for LLP and LRW as dependent variables are statistically significant at 1% significance. Still, their adjustment speeds are 1.1% and 0.5%, respectively, lower than those in the ECM.

Regarding the short run effects, the Wald tests shown in Appendix 15 tell us whether each independent variable's five lags are jointly significant to explain the dependent variable. The Wald test about the short run effect from LRW to LLP is statistically significant at 1% significance. This finding is consistent with what was found for the ECM, where LRW shows a positive and statistically significant impact on LLP in the short run. For the short run impact from EPOP to LLP, the Wald test reveals that the EPOP's five lags are jointly significant to explain LLP's negative effect at 5% significance.

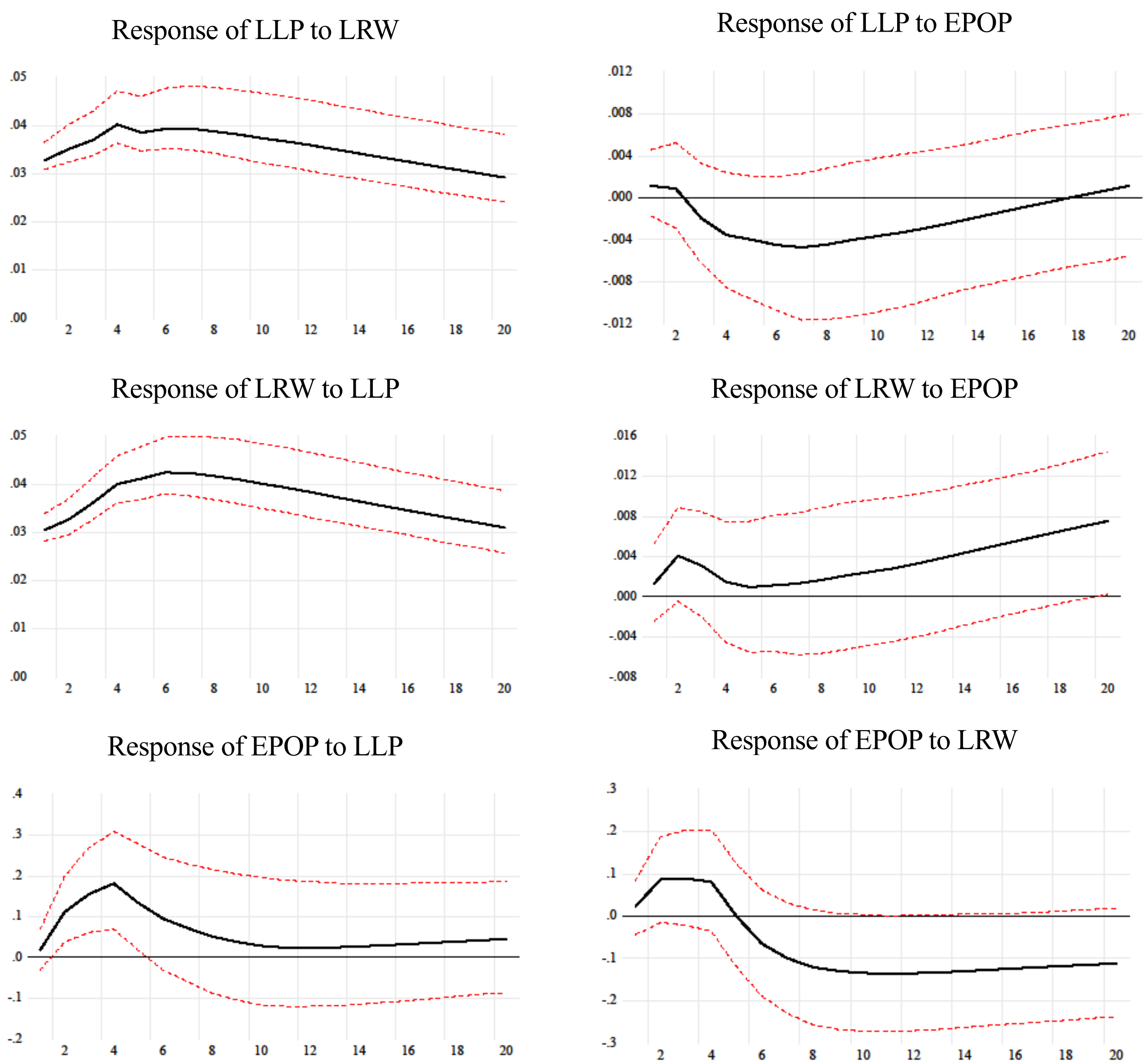
Like the ECM, in the panel VECM, the short run effect from LLP to LRW is also positive and statistically significant at 1% significance. On the other hand, the short run impact from EPOP to LRW is statistically significant, different from the ECM case, where its effect is not statistically significant in the PMG and MG specifications. For its part, like the short run ARDL model, the panel VECM indicates that an LLP increase has a positive effect on EPOP, and LRW increase impacts negatively on EPOP in the short run, both statistically significant at 1% significance.

To evaluate the stability of the panel VECM, I need to obtain the roots of the characteristic polynomial. For a k-variables model with r cointegrating equations, the companion matrix will have $k - r$ unit eigenvalues. If the system's stability holds, the remaining eigenvalues' moduli must be less than one. In this case, since $k = 3$ and $r = 1$ as found in Fisher's cointegration test, this system must have at most two imposed unit-roots, and the rest of the eigenvalues must be inside the unit circle. Appendix 16 confirms the system's stability.

Figure 1 presents the responses of each variable to the impulses of the other two. I use the generalized impulses specification to construct an orthogonal set of innovations that do not depend on the VEC ordering (Pesaran and Shin, 1998). The impulse-response functions (IRFs) confirm what I find in most single-equation specifications: ECM, DOLS, and FMOLS. There is a two-way causality between LLP and LRW, and these effects are positive and permanent in the long run. EPOP negatively affects LLP and positively affects LRW. Still, their impacts seem much smaller in magnitude, but contrary to the single-equation approach, they are not statistically significant.

Regarding LLP and LRW on EPOP, while the former is positive, the latter is negative, consistent with the ARDL model results. However, it seems like only LLP has a significant impact on EPOP in the medium-run. Since the variables under study modeled in the VECM are *I(1)*, they are not mean-reverting; therefore, it is expected that some shocks would not die out over time. Additionally, notice that the scale of the vertical axis of responses of EPOP is different because this variable is expressed in percentual points while LLP and LRW are in logarithm.

Figure 1: Impulse-responses to generalized one standard deviation innovations, 95% confidence interval using Hall's percentile bootstrap with 1000 bootstrap repetitions



4.7 Robustness check: labor productivity per hour worked and real wage per hour worked

Alternative ways to measure LP and RW are labor productivity per hour worked (LPH) and average real wage per hour worked (RWH), respectively. Appendix 17 shows how these two variables are constructed using PWT 10.0. Since several countries in the panel do not have data for average annual hours worked by persons engaged in the 60s, I replicate the previous regressions using the same 25 OECD economies in 1970-2019 using LPH, RWH, and EPOP.

These three variables are non-stationary in levels but stationary in the first differences, as shown in Appendix 18. Pedroni's cointegration test shows evidence of cointegration when LPH is the dependent variable. It is because, in seven out of eleven cases, the null hypothesis of no cointegration is rejected either at 1%, 5%, or 10% significance level. This test also demonstrates that cointegration exists when RWH is the dependent variable. In six out of eleven cases, the same null hypothesis is rejected either at 1% or 5%

significance level for this variable. And like the EPOP's case for 1960-2019, for 1970-2019 again, there is no evidence of cointegration when EPOP is the dependent variable. (See Appendix 19). Westerlund's cointegration test is also run as a robustness check. (See Appendix 20). Like in the LLP and LRW cases, the optimal lag length for their ECMs when they are the dependent variables, using the Bayesian information criterion, is ECM(1,1,1). (See Appendix 21).

Tables 7A and 7B show the ECMs for LPH and RWH, respectively. Like Tables 5A and 5B, the ECM, DOLS, and FMOLS models are displayed with different specifications. Like the LLP and LRW cases, in most cases, LPH and RWH have a positive and statistically significant impact on each other. Still, their magnitudes differ since these variables are different by construction. For instance, in the PMG specification of the ECM, from Table 7A, I can say that there exists a long run causality running from RWH and EPOP jointly to LPH since the error correction term (ECT) is statistically significant at 1%. In the PMG specification, the system is getting back to equilibrium at a speed of 10.4% annually when LPH is the dependent variable, and the independent variables are RWH and EPOP.

In the same PMG specification in Table 7A, a one dollar per hour worked increase in real wages leads to a 1.9 dollars rise in output per hour worked in the long run, on average, and *ceteris paribus*. Concerning the effect of EPOP on LPH in the long run, this table presents evidence of an adverse impact from EPOP to LPH in the PMG specification: one percentual point increase in the employment-to-population ratio decreases LPH by 0.12 dollars in the long run. In any case, Table 7A shows that it is always negative in the other specifications when it is statistically significant at 1% or 10% level. In Table 7B, EPOP positively impacts RWH in all nine specifications, where eight of them are statistically significant at a 1% level.

Table 7A: ECM, DOLS, and FMOLS models for LPH as the dependent variable

	ECM			DOLS			FMOLS		
	PMG	MG	DFE	Pooled	Pooled W.	Grouped	Pooled	Pooled W.	Grouped
Long-run									
LRW	1.8968***	1.9698***	1.1278	1.7468***	1.7168***	1.9578***	1.6804***	1.6836***	1.9710***
	(0.0285)	(0.1306)	(0.8002)	(0.0291)	(0.0266)	(0.0929)	(0.0403)	(0.0015)	(0.0200)
EPOP	-0.1245***	-0.8620**	0.9929	-0.0288*	-0.0219	-0.1090*	0.0026	-0.0007	-0.1147***
	(0.0256)	(0.3718)	(1.1887)	(0.0168)	(0.0154)	(0.0559)	(0.0229)	(0.0007)	(0.0112)
ECT	-0.1035***	-0.2207***	0.0127						
	(0.0328)	(0.0370)	(0.0115)						
Short-run									
Δ LRW $_{t-1}$	1.2894***	1.1101***	1.7461***						
	(0.0857)	(0.0754)	(0.0453)						
Δ EPOP $_{t-1}$	0.0472	0.1501**	-0.0970*						
	(0.0547)	(0.0579)	(0.0517)						
Constant	0.3160**	3.1052***	0.4947						
	(0.1536)	(1.0551)	(0.4369)						

Notes: For the ECM specifications, the optimal number of lags is chosen based on the Bayesian information criterion, and a constant is included as a fixed regressor. For all the DOLS specifications, the optimal lags and leads are chosen based on the Bayesian information criterion. The lag specification for the long run variance is based on the Bayesian information criterion. The Bartlett kernel is selected as a spectral estimation method with a bandwidth set by the Newey-West automatic procedure, and degrees-of-freedom adjustment is used. The coefficient covariance matrix for the pooled DOLS is calculated assuming homogeneous variances. The individual covariances for the grouped DOLS are calculated using a rescaled OLS method. For all the FMOLS specifications, the Bartlett kernel is selected as a spectral estimation method with a bandwidth set by the Newey-West automatic procedure, and degrees-of-freedom adjustment is used to calculate their long run variances. The coefficient covariance matrix for the pooled FMOLS is calculated assuming homogeneous variances. Standard errors in parentheses. * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01.

Table 7B: ECM, DOLS, and FMOLS models for RWH as the dependent variable

	ECM			DOLS			FMOLS		
	PMG	MG	DFE	Pooled	Pooled W.	Grouped	Pooled	Pooled W.	Grouped
Long-run									
LLP	0.4771***	0.4802***	0.2294	0.5332***	0.5456***	0.5122***	0.5360***	0.5472***	0.5103***
	(0.0076)	(0.0225)	(0.2372)	(0.0078)	(0.0078)	(0.0075)	(0.0125)	(0.0015)	(0.0040)
EPOP	0.1142***	0.3709***	1.0387	0.0555***	0.0434***	0.0623***	0.0567***	0.0471***	0.0627***
	(0.0134)	(0.0977)	(0.8813)	(0.0077)	(0.0076)	(0.0076)	(0.0121)	(0.0007)	(0.0039)
ECT	-0.1230***	-0.2410***	-0.0125						
	(0.0300)	(0.0312)	(0.0099)						
Short-run									
Δ LLP $_{t-1}$	0.3795***	0.3188***	0.3410***						
	(0.0314)	(0.0291)	(0.0100)						
Δ EPOP $_{t-1}$	-0.0005	-0.0709**	0.0640***						
	(0.0285)	(0.0331)	(0.0230)						
Constant	-0.1009	-2.1198***	-0.2599						
	(0.1135)	(0.5373)	(0.1946)						

Notes: For the ECM specifications, the optimal number of lags is chosen based on the Bayesian information criterion, and a constant is included as a fixed regressor. For all the DOLS specifications, the optimal lags and leads are chosen based on the Bayesian information criterion. The lag specification for the long run variance is based on the Bayesian information criterion. The Bartlett kernel is selected as a spectral estimation method with a bandwidth set by the Newey-West automatic procedure, and degrees-of-freedom adjustment is used. The coefficient covariance matrix for the pooled DOLS is calculated assuming homogeneous variances. The individual covariances for the grouped DOLS are calculated using a rescaled OLS method. For all the FMOLS specifications, the Bartlett kernel is selected as a spectral estimation method with a bandwidth set by the Newey-West automatic procedure, and degrees-of-freedom adjustment is used to calculate their long run variances. The coefficient covariance matrix for the pooled FMOLS is calculated assuming homogeneous variances. Standard errors in parentheses. * p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01.

With respect to the short run effects from LPH and RWH on EPOP, I run a panel ARDL, where three lags are the optimal lag length for this model based on three out of five information criteria. (See Appendix 22). Table 8 shows that, like the EPOP-LLP-LRW case, while LPH has a positive effect on EPOP in the short run, an RWH increase adversely impacts EPOP. The Wald test presented in Appendix 23 shows that the three lags of each independent variable cause EPOP jointly. Finally, a panel VECM could not be performed for the LPH-RWH-EPOP case because serial autocorrelation of residuals is present for all possible lags in the model.

Table 8: Short run ARDL model for ΔEPOP as the dependent variable and ΔLPH and ΔRWH as independent variables

Variable	Coefficient
Δ EPOP $_{t-1}$	0.5357***
	(0.0297)
Δ EPOP $_{t-2}$	-0.0629*
	(0.0337)
Δ EPOP $_{t-3}$	-0.0403
	(0.0297)
Δ LPH $_{t-1}$	0.0586***
	(0.0146)
Δ LPH $_{t-2}$	0.0254*
	(0.0148)
Δ LPH $_{t-3}$	0.0226
	(0.0148)
Δ RWH $_{t-1}$	-0.1104***
	(0.0327)
Δ RWH $_{t-2}$	-0.0834**
	(0.0328)
Δ RWH $_{t-3}$	-0.0263
	(0.0332)
Constant	0.1040***
	(0.0246)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors in parenthesis

5 CONCLUDING REMARKS

This paper contributes to the literature about the interaction between LP, RW, and EPOP in the OECD countries, using two approaches: 1) with exogenous and endogenous terms and 2) restricting the system to only endogenous variables as a robustness check. The results found validate several economic theories depending on the intertemporal horizon.

One of my empirical findings is that EPOP is weakly exogenous in this 3-dimensional system, meaning that this variable does not adapt to the long run deviations, and the adjustment is borne out by LP and RW. Regarding the relationship between LP and RW, the results show bidirectional causality between them, supporting the induced technical change, efficiency wages, and bargaining theories over the marginal productivity for the OECD countries considered in my sample as a group and including employment the third variable in this system. The impact of this double causality is in both the short and long run, being the long run effects are a little more substantial in magnitude.

This study also finds a small and negative long run causality running from EPOP to LP only for the single-equation specifications. There would be several explanations for this inverse relationship, but among these reasons are the positive association between the dismissal of the less productive workers and increases in LP, and the incentive that workers could have to increase their effort level when EPOP is declining in the economy overall. About the impact from EPOP to RW, I find a small and positive relationship in most of the nine single-equation specifications in the long run, but not in the multi-equation approach.

For its part, the single-equation models and the multi-equation specification are consistent in finding a positive short run causality from LP to EPOP, and negative short run causation from RW to EPOP is statistically significant only in the single-equation models. The findings mentioned above on the causality among LP, RW, and EPOP are robust to the two measures of LP and RW: per worker and hour worked.

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APPENDIX

Appendix 1: Construction of the logarithm of labor productivity at constant 2017 purchasing power parity (*LLP*), the logarithm of average real wage at constant 2017 purchasing power parity (*LRW*), and employment-to-population ratio (*EPOP*).

- The logarithm of labor productivity at constant 2017 purchasing power parity (LLP)

$$LP = \frac{rgdpo}{emp}$$

$$LLP = ln\ LP$$

- The logarithm of average real wage at constant 2017 purchasing power parity (LRW)

$$RW = \frac{rgdpo \quad labsh}{emp}$$

$$LRW = ln\ RW$$

- Employment to population ratio (EPOP)

$$EPOP = 100\left(\frac{emp}{pop}\right)$$

Where,

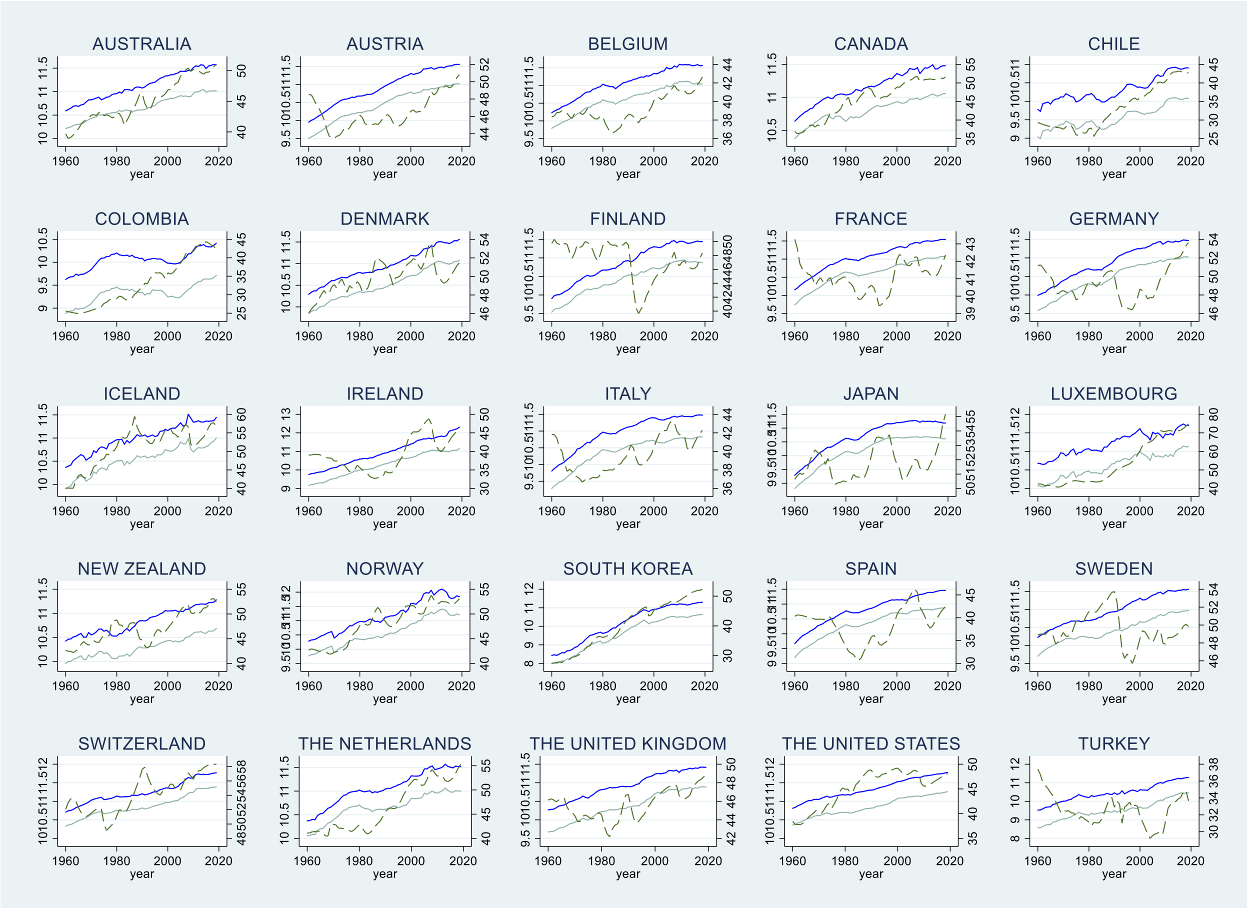
rgdpo: Output-side real GDP at chained PPPs (in mil. 2017US$). Output-side real GDP allows a comparison of productive capacity across countries and over time.

labsh: Share of labor compensation in GDP at current national prices. Reports the share represented by labor income in GDP in terms of the prices in that period (i.e., current prices).

emp: Number of persons engaged (in millions). "Per person engaged" in PWT includes all persons aged 15 years and over, who during the reference week performed work, even just for one hour a week, or were not at work but had a job or business from which they were temporarily absent. It includes self-employed persons.

pop: Population (in millions). Reports population data by country from the World Bank and United Nations sources.

Appendix 2: The logarithm of labor productivity at constant 2017 purchasing power parity (blue line), the logarithm of average real wage at constant 2017 purchasing power parity (light green line), and the employment-to-population ratio (dashed line) for the 25 countries in the sample. The employment-to-population ratio series are on the right axis.



Appendix 3: Panel unit-root tests for LLP, LRW, and EPOP in levels and first differences

Panel unit-root test	Specification	LLP	LRW	EPOP	ΔLLP	ΔLRW	ΔEPOP
Breitung	$z'_{it} = 1$	16.42	15.8	6.24	-13.20***	-11.51***	-14.34***
	$z'_{it} = 0$	21.24	20.65	6.42	-17.72***	-17.20***	-17.46***
	$z'_{it} = (1, t)$	7.20	7.37	4.02	-19.28***	-17.37***	-13.45***
Fisher	Inv. χ^2, ADF	20.05	37.42	33.54	67.60**	91.43***	83.81***
	Inv. normal, ADF	3.29	2.4	2.33	-2.55***	-4.17***	-3.89***
	Inv. logit t, ADF	3.42***	2.64	2.36	-2.43***	-4.11***	-3.70***
	Modified inv. χ^2, ADF	-2.2	-1.26	-1.65	1.76**	4.14***	3.38***
Harris-Tsavalis	$z'_{it} = 1$	0.98	0.98	0.99	0.12***	0.14***	0.45***
	$z'_{it} = 0$	1.00	1.00	1.00	0.39***	0.39***	0.49***
	$z'_{it} = (1, t)$	0.93	0.93	0.93	0.17***	0.18***	0.47***
Im-Pesaran-Shin	$z'_{it} = 1$	-2.74***	-2.79***	1.19	-27.04***	-23.71***	-18.41***
	$z'_{it} = (1, t)$	1.79	1.45	-2.62***	-27.88***	-25.28***	-16.93***
Levin-Lin-Chu	z'it = 0, unadjusted t	25.86	19.95	4.58	-20.23***	-19.26***	-22.00***
	z'it = 0, adjusted t	25.57	19.72	4.52	-20.00***	-19.05***	-21.77***
	$z'_{it} = (1, t)$	-0.72	-1.79**	-5.48***	-29.27***	-25.92***	-18.07***

Notes: *** p-value < 0.01, ** p-value < 0.05. Operator Δ before the name of the variables denotes that the variable is expressed in first-differences. The null hypothesis for the Breitung, Harris-Tsavalis, and Levin-Lin-Chu tests is that panels contain unit-roots, and their alternative hypothesis is that panels are stationary. The null hypothesis for the Fisher-type tests is that all panels contain unit-roots, and their alternative hypothesis is that at least one panel is stationary. The null hypothesis for the Im-Pesaran-Shin test is that all panels contain unit-roots, and their alternative hypothesis is that some panels are stationary. I choose the optimal lags for the Im-Pesaran-Shin, and the Levin-Lin-Chu tests based on the Bayesian information criterion.

Appendix 4: VAR lag order selection criteria for endogenous variables LLP, LRW, and EPOP

Lag	LogL	LR	FPE	AIC	BIC	HQ
0	-4268.34	NA	1.43E-01	6.57	6.58	6.58
1	4292.78	17069.57	2.77E-07	-6.59	-6.54	-6.57
2	4523.07	458.10	1.97E-07	-6.93	-6.84	-6.89
3	4557.72	68.77	1.89E-07	-6.97	-6.85*	-6.92*
4	4568.01	20.36	1.89E-07	-6.97	-6.81	-6.91
5	4592.13	47.65	1.85E-07*	-6.99*	-6.80	-6.92
6	4597.39	10.36	1.86E-07	-6.99	-6.76	-6.90
7	4607.23	19.34*	1.86E-07	-6.99	-6.72	-6.89
8	4613.33	11.97	1.86E-07	-6.98	-6.68	-6.87

Notes: *Indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at a 5% level). FPE: Final predictor error. AIC: Akaike information criterion. BIC: Bayesian information criterion. HQ: Hannan-Quinn information criterion. Endogenous variables: LLP, LRW, and EPOP.

Appendix 5: Model selection criterion for the ECM models for LLP and LRW as dependent variables

Dependent variable: LLP		Dependent variable: LRW	
BIC	Specification	BIC	Specification
-5.1284	**(1, 1, 1)**	**-5.2259**	**(1, 1, 1)**
-5.0328	(1, 2, 2)	-5.1662	(2, 1, 1)
-5.0238	(2, 1, 1)	-5.0654	(1, 2, 2)
-4.9554	(2, 2, 2)	-5.0624	(3, 1, 1)
-4.9292	(3, 1, 1)	-5.0247	(2, 2, 2)
-4.8549	(3, 2, 2)	-4.9486	(4, 1, 1)
-4.8285	(1, 3, 3)	-4.9207	(3, 2, 2)
-4.8184	(4, 1, 1)	-4.8616	(1, 3, 3)
-4.7531	(2, 3, 3)	-4.8590	(5, 1, 1)
-4.7493	(4, 2, 2)	-4.8179	(4, 2, 2)
-4.7411	(5, 1, 1)	-4.7952	(2, 3, 3)
-4.6630	(5, 2, 2)	-4.7337	(5, 2, 2)
-4.6495	(3, 3, 3)	-4.7008	(3, 3, 3)
-4.6026	(1, 4, 4)	-4.6456	(1, 4, 4)
-4.5429	(4, 3, 3)	-4.6056	(2, 4, 4)
-4.5363	(2, 4, 4)	-4.5932	(4, 3, 3)
-4.4546	(5, 3, 3)	-4.5137	(5, 3, 3)
-4.4325	(3, 4, 4)	-4.4789	(3, 4, 4)
-4.4127	(1, 5, 5)	-4.4566	(1, 5, 5)
-4.3558	(4, 4, 4)	-4.4286	(4, 4, 4)
-4.3519	(2, 5, 5)	-4.3692	(2, 5, 5)
-4.2622	(5, 4, 4)	-4.3367	(5, 4, 4)
-4.2463	(3, 5, 5)	-4.2880	(3, 5, 5)
-4.1630	(4, 5, 5)	-4.1998	(4, 5, 5)
-4.0697	(5, 5, 5)	-4.0927	(5, 5, 5)

Note: BIC: Bayesian information criterion.

Appendix 6: Hausman tests

	Dependent variable: LLP		Dependent variable: LRW	
	PMG vs. MG	PMG vs. DFE	PMG vs. MG	PMG vs. DFE
$\chi^2_{df=2}$	0.82	0.01	0.80	0.02
Prob. $> \chi^2$	0.6644	0.9935	0.6705	0.9919

<u>Hausman test between PMG and MG</u>
Null hypothesis: Difference in coefficients is not systematic. PMG is more efficient than MG.
Alternative hypothesis: The null hypothesis is not true.

<u>Hausman test between PMG and DFE</u>
Null hypothesis: Difference in coefficients is not systematic. PMG is more efficient than DFE.
Alternative hypothesis: The null hypothesis is not true.

Appendix 7: Autoregressive lag order selection criteria for the ARDL model with EPOP as a dependent variable and LLP and LRW as independent variables

Lag	LogL	LR	FPE	AIC	BIC	HQ
0	-4344.74	NA	32.6588	6.3240	6.3354	6.3283
1	-1468.33	5736.09	0.4984	2.1416	2.1568	2.1473
2	-1276.61	382.06	0.3777	1.8642	1.8832	1.8713
3	-1269.97	13.21*	0.3746*	1.8560*	1.8788*	1.8645*
4	-1269.19	1.56	0.3747	1.8563	1.8829	1.8662
5	-1269.18	0.01	0.3753	1.8577	1.8881	1.8691

Notes: * Indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at a 5% level). FPE: Final prediction error. AIC: Akaike information criterion. BIC: Bayesian information criterion. HQ: Hannan-Quinn information criterion. Endogenous variable: EPOP. Exogenous variables: constant, LLP, and LRW.

Appendix 8: Short run ARLD model with ΔEPOP as the dependent variable and three lags for each independent variable

Variable	Coefficient
Δ EPOP $_{t-1}$	0.5252*** (0.0269)
Δ EPOP $_{t-2}$	-0.0610** (0.0305)
Δ EPOP $_{t-3}$	-0.0182 (0.0270)
Δ LLP $_{t-1}$	3.9186*** (0.8496)
Δ LLP $_{t-2}$	1.8318** (0.8587)
Δ LLP $_{t-3}$	1.4271* (0.8558)
Δ LRW $_{t-1}$	-2.3926*** (0.9072)
Δ LRW $_{t-2}$	-2.9923*** (0.9054)
Δ LRW $_{t-3}$	-1.7899** (0.9027)
Constant	0.0754*** (0.0225)

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors in parenthesis

Appendix 9: Redundant variable test for $\Delta EPOP_{t-3}$

	Value	df	Prob.
t - statistic	0.67	1390	0.5017
F - statistic	0.45	(1, 1390)	0.5017
Likelihood ratio	0.45	1	0.5000

F - test summary:	Sum of Sq.	df	Mean Squares
Test SSR	0.16	1	0.1635
Restricted SSR	503.46	1391	0.3619
Unrestricted SSR	503.30	1390	0.3621

LR test summary	Value
Restricted LogL	-1270.61
Unrestricted LogL	-1270.38

Note: Null hypothesis: $\Delta EPOP_{t-3}$= 0

Appendix 10: Wald tests for the short run ARDL model for LLP, LRW, and EPOP

Null hypothesis: $\Delta LLP_{t-1} = \Delta LLP_{t-2} = \Delta LLP_{t-3} = 0$

Test Statistic	Value	df	Prob.
F - statistic	10.7769	(3, 1391)	0.0001
Chi - square	32.3308	3	0.0001

Null hypothesis: $\Delta LRW_{t-1} = \Delta LRW_{t-2} = \Delta LRW_{t-3} = 0$

Test Statistic	Value	df	Prob.
F - statistic	9.3277	(3, 1391)	0.0001
Chi - square	27.9831	3	0.0001

Appendix 11: LR test for binding restriction in the VECM

Null hypothesis: $ECT^{EPOP} = 0$

Test Statistic	Value	df	Prob.
Chi - square	0.8438	1	0.3583

Appendix 12: VECM residual serial correlation LM tests

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.3998	9	0.8832	0.4887	(9, 3232.2)	0.8832
2	16.4024	9	0.0589	1.8251	(9, 3232.2)	0.0589
3	7.0309	9	0.6339	0.7812	(9, 3232.2)	0.6339
4	16.5175	9	0.0568	1.8380	(9, 3232.2)	0.0568
5	4.7928	9	0.8520	0.5324	(9, 3232.2)	0.8520

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.3998	9	0.8832	0.4887	(9, 3232.2)	0.8832
2	20.5481	18	0.3028	1.1423	(18, 3748.2)	0.3028
3	29.8735	27	0.3199	1.1071	(27, 3861.6)	0.3199
4	44.1189	36	0.1659	1.2271	(36, 3897.9)	0.1659
5	46.1669	45	0.4238	1.0263	(45, 3910.3)	0.4238

* Edgeworth expansion corrected likelihood ratio statistic.

Appendix 13: VECM residual Portmanteau tests for autocorrelations

Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	df
1	0.04	-	0.04	-	-
2	0.56	-	0.56	-	-
3	0.87	-	0.87	-	-
4	1.85	-	1.85	-	-
5	2.67	-	2.68	-	-
6	18.09	0.2028	18.16	0.1994	14
7	26.21	0.2909	26.33	0.2855	23
8	34.35	0.3556	34.52	0.3482	32

Notes: Null hypothesis is “No residual autocorrelations up to lag h.” *Test is valid only for lags larger than the VEC lag order.

Appendix 14: Panel VECM for ΔLLP, ΔLRW, and ΔEPOP as dependent variables

ΔLLP		ΔLRW		ΔEPOP	
Long-run					
LRW	0.4601**	LLP	2.1881***	LLP	-
	(0.2046)		(0.4558)		-
EPOP	-0.0340**	EPOP	-0.0742**	LRW	-
	(0.0147)		(0.0302)		-
ECT	-0.0113***	ECT	-0.0053***	ECT	0.0000
	(0.0017)		(0.0007)		(0.0000)
Short-run					
ΔLRW_{t-1}	-0.0569	ΔLLP_{t-1}	0.0045	ΔLLP_{t-1}	3.8805***
	(0.0580)		(0.0503)		(0.8538)
ΔLRW_{t-2}	0.1232**	ΔLLP_{t-2}	0.0679	ΔLLP_{t-2}	1.8838**
	(0.0585)		(0.0511)		(0.8676)
ΔLRW_{t-3}	0.0565	ΔLLP_{t-3}	0.0786	ΔLLP_{t-3}	1.3437
	(0.0596)		(0.0522)		(0.8860)
ΔLRW_{t-4}	-0.1739***	ΔLLP_{t-4}	0.1232**	ΔLLP_{t-4}	1.3342
	(0.0597)		(0.0525)		(0.8917)
ΔLRW_{t-5}	-0.0866	ΔLLP_{t-5}	0.1162**	ΔLLP_{t-5}	0.8417
	(0.0632)		(0.0564)		(0.9576)
$\Delta EPOP_{t-1}$	-0.0010	$\Delta EPOP_{t-1}$	0.0040**	ΔLRW_{t-1}	-2.0954**
	(0.0017)		(0.0016)		(0.9179)
$\Delta EPOP_{t-2}$	-0.0045**	$\Delta EPOP_{t-2}$	-0.0049***	ΔLRW_{t-2}	-2.7031***
	(0.0020)		(0.0019)		(0.9246)
$\Delta EPOP_{t-3}$	-0.0010	$\Delta EPOP_{t-3}$	-0.0017	ΔLRW_{t-3}	-1.2699
	(0.0020)		(0.0019)		(0.9423)
$\Delta EPOP_{t-4}$	-0.0002	$\Delta EPOP_{t-4}$	0.0005	ΔLRW_{t-4}	-3.4080***
	(0.0019)		(0.0018)		(0.9438)
$\Delta EPOP_{t-5}$	0.0005	$\Delta EPOP_{t-5}$	0.0012	ΔLRW_{t-5}	-0.9219
	(0.0017)		(0.0016)		(0.9991)
Constant	0.0169***	Constant	0.0129***	Constant	0.0987***
	(0.0016)		(0.0015)		(0.0257)

Notes: *** *p*-value < 0.01, ** *p*-value < 0.05. Standard errors in parentheses.

Appendix 15: Wald tests for the short run effects in the panel VECM

Null hypothesis	Dependent variable	$\chi^2_{df = 5}$	Prob.
$\Delta LRW_{t-1} = \Delta LRW_{t-2} = \Delta LRW_{t-3} = \Delta LRW_{t-4} = \Delta LRW_{t-5} = 0$	ΔLLP	19.0447	0.0019
$\Delta EPOP_{t-1} = \Delta EPOP_{t-2} = \Delta EPOP_{t-3} = \Delta EPOP_{t-4} = \Delta EPOP_{t-5} = 0$	ΔLLP	13.6959	0.0177
$\Delta LLP_{t-1} = \Delta LLP_{t-2} = \Delta LLP_{t-3} = \Delta LLP_{t-4} = \Delta LLP_{t-5} = 0$	ΔLRW	15.4008	0.0088
$\Delta EPOP_{t-1} = \Delta EPOP_{t-2} = \Delta EPOP_{t-3} = \Delta EPOP_{t-4} = \Delta EPOP_{t-5} = 0$	ΔLRW	14.6453	0.0120
$\Delta LLP_{t-1} = \Delta LLP_{t-2} = \Delta LLP_{t-3} = \Delta LLP_{t-4} = \Delta LLP_{t-5} = 0$	ΔEPOP	32.9368	0.0001
$\Delta LRW_{t-1} = \Delta LRW_{t-2} = \Delta LRW_{t-3} = \Delta LRW_{t-4} = \Delta LRW_{t-5} = 0$	ΔEPOP	33.8622	0.0001

Appendix 16: Roots of the characteristic polynomial

Root	Modulus
1.0000	1.0000
1.0000	1.0000
0.9737	0.9737
0.7086	0.7086
0.6125 - 0.2501 *i*	0.6616
0.6125 + 0.2501 *i*	0.6616
0.1825 + 0.6001 *i*	0.6273
0.1825 - 0.6001 *i*	0.6273
0.3705 - 0.4880 *i*	0.6127
0.3705 + 0.4880 *i*	0.6127
-0.4436 + 0.3754 *i*	0.5812
-0.4436 - 0.3754 *i*	0.5812
-0.1228 - 0.5543 *i*	0.5677
-0.1228 + 0.5543 *i*	0.5677
-0.5062	0.5062
-0.3303 - 0.3183 *i*	0.4587
-0.3303 + 0.3184 *i*	0.4587
0.0217	0.0217

Notes: VECM imposes two unit-roots.
Endogenous variables: LLP, LRW, and EPOP.

Appendix 17: Construction of the labor productivity per hour worked at constant 2017 purchasing power parity (*LPH*), and average real wage per hour worked at constant 2017 purchasing power parity (*RWH*)

- Labor productivity per hour worked at constant 2017 purchasing power parity (LPH)

$$LPH = \left(\frac{rgdpo}{emp}\right) avh^{-1} = \left(\frac{rgdpo}{emp}\right)\left(\frac{h}{emp}\right)^{-1} = \frac{rgdpo}{h}$$

- Average real wage per hour worked at constant 2017 purchasing power parity (RWH)

$$RWH = \left[\frac{rgdpo \quad labsh}{emp}\right] avh^{-1} = \left[\frac{rgdpo \quad labsh}{emp}\right]\left(\frac{h}{emp}\right)^{-1} = \frac{rgdpo \quad labsh}{h}$$

Where,

rgdpo: Output-side real GDP at chained PPPs (in mil. 2017US$). Output-side real GDP allows a comparison of productive capacity across countries and over time.

labsh: Share of labor compensation in GDP at current national prices. Reports the share represented by labor income in GDP in terms of the prices in that period (i.e., current prices).

emp: Number of persons engaged (in millions). "Per person engaged" in PWT includes all persons aged 15 years and over, who during the reference week performed work, even just for one hour a week, or were not at work but had a job or business from which they were temporarily absent. It includes self-employed persons.

avh: Average annual hours worked by persons engaged.

h: Average annual hours worked

Appendix 18: Panel unit-root tests for LPH, RWH, and EPOP in levels and first differences

Panel unit-root test	Specification	LPH	RWH	EPOP	ΔLPH	ΔRWH	ΔEPOP
Breitung	$z'_{it} = 1$	16.52	16.03	6.63	-13.72***	-13.08***	-13.64***
	$z'_{it} = 0$	18.43	17.94	7.56	-16.18***	-15.98***	-15.48***
	$z'_{it} = (1, t)$	3.82	3.82	2.20	-16.74***	-15.32***	-12.81***
Fisher	Inv. χ^2, ADF	4.81	3.50	33.36	56.70	69.92**	74.82**
	Inv. normal, ADF	7.85	9.12	2.52	-1.02	-2.54***	-3.30***
	Inv. logit t, ADF	8.24	9.84	2.50	-1.02	-2.44***	-3.10***
	Modified inv. χ^2, ADF	-4.52	-4.65	-1.66	0.67	1.99**	2.48***
Harris-Tsavalis	$z'_{it} = 1$	1.00	1.00	0.99	0.11***	0.13***	0.45***
	$z'_{it} = 0$	1.02	1.02	1.00	0.40***	0.40***	0.50***
	$z'_{it} = (1, t)$	0.92	0.90	0.91	0.17***	0.18***	0.47***
Im-Pesaran-Shin	$z'_{it} = 1$	8.73	8.48	0.93	-23.88***	-22.80***	-16.57***
	$z'_{it} = (1, t)$	0.62	-0.10	-3.53***	-23.58***	-22.20***	-14.47***
Levin-Lin-Chu	z'it = 0, unadjusted t	21.57	18.80	5.50	-18.24***	-18.86***	-19.66***
	z'it = 0, adjusted t	21.24	18.52	5.42	-17.98***	-18.58***	-19.37***
	$z'_{it} = (1, t)$	-0.38	-1.93**	-5.03***	-23.69***	-22.92***	-15.12***

Notes: The table shows the statistics and their *p*-values in parenthesis for each panel unit-root test and specification. The null hypothesis for the Breitung, Harris-Tsavalis, and Levin-Lin-Chu tests is that panels contain unit-roots, and their alternative hypothesis is that panels are stationary. The null hypothesis for the Fisher-type tests is that all panels contain unit-roots, and their alternative hypothesis is that at least one panel is stationary. The null hypothesis for the Im-Pesaran-Shin test is that all panels contain unit-roots, and their alternative hypothesis is that some panels are stationary. I choose the optimal lags for the Im-Pesaran-Shin, and the Levin-Lin-Chu tests based on the Bayesian information criterion. Operator Δ before the name of the variables denotes that the variable is expressed in first-differences.

Appendix 19: Pedroni's panel cointegration test for LPH, RWH, and EPOP

	Dependent variable					
	LPH		RWH		EPOP	
	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.
Weighted panel statistics						
v-statistic	1.93	0.0267	2.42	0.0077	0.33	0.3715
rho-statistic	-1.07	0.1414	-1.22	0.1115	1.31	0.9050
PP-statistic	-1.56	0.0598	-2.07	0.0192	0.72	0.7644
ADF-statistic	-3.59	0.0002	-3.90	0.0001	-1.44	0.0753
Unweighted panel statistics						
v-statistic	2.33	0.0098	2.49	0.0064	0.09	0.4632
rho-statistic	1.95	0.9745	-0.52	0.2680	0.93	0.8238
PP-statistic	3.46	0.9997	-0.45	0.3262	0.22	0.5854
ADF-statistic	-1.46	0.0728	-2.12	0.0170	-1.45	0.0739
Group statistics						
rho-statistic	0.34	0.6325	0.16	0.5621	2.47	0.9932
PP-statistic	-1.75	0.0402	-1.21	0.1138	1.41	0.9201
ADF-statistic	-2.98	0.0014	-2.69	0.0036	-2.50	0.0063

Notes: The null hypothesis is "no cointegration." The weighted and unweighted panel statistics' alternative hypothesis is "cointegration in all panels with common autoregressive coefficients in the residuals.". The group statistics' alternative hypothesis is "cointegration in a subset of panels with panel-specific autoregressive coefficients in the residuals." The deterministic specification includes a constant in the test equation and no deterministic trend. The optimal number of lags is chosen based on the Bayesian information criterion. The Bartlett kernel is selected as a spectral estimation method with a bandwidth set by the Newey-West procedure. Use degree-of-freedom corrected Dickey-Fuller residual variances.

Appendix 20: Westerlund's panel cointegration test for LPH, RWH, and EPOP

	Dependent variable					
	LPH		RWH		EPOP	
	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.
Demean	-0.31	0.3771	-1.11	0.1337	0.48	0.3172
Some	-3.28	0.0005	-3.45	0.0003	-1.83	0.0335
Trend	-1.00	0.1575	-1.70	0.0447	1.26	0.1043
All panels	-2.53	0.0057	-2.27	0.0115	-0.87	0.1922

Notes: The null hypothesis is "no cointegration." The demeaned, some, and trend panel statistics' alternative hypothesis is "some panels are cointegrated." The all panels' alternative hypothesis is "all panels are cointegrated."

Appendix 21: Model selection criterion for the ECMs for LPH and RWH as dependent variables

Dependent variable: LPH		Dependent variable: RWH	
BIC	Specification	BIC	Specification
2.6041	**(1, 1, 1)**	**1.3367**	**(1, 1, 1)**
2.7164	(2, 1, 1)	1.4124	(2, 1, 1)
2.7213	(1, 2, 2)	1.4838	(1, 2, 2)
2.8184	(2, 2, 2)	1.5316	(3, 1, 1)
2.8218	(3, 1, 1)	1.5812	(2, 2, 2)
2.9170	(3, 2, 2)	1.6556	(4, 1, 1)
2.9489	(4, 1, 1)	1.6888	(3, 2, 2)
2.9605	(1, 3, 3)	1.7386	(1, 3, 3)
3.0324	(5, 1, 1)	1.7424	(5, 1, 1)
3.0332	(4, 2, 2)	1.8089	(4, 2, 2)
3.0496	(2, 3, 3)	1.8262	(2, 3, 3)
3.1173	(5, 2, 2)	1.8959	(5, 2, 2)
3.1778	(3, 3, 3)	1.9536	(3, 3, 3)
3.2203	(1, 4, 4)	1.9926	(1, 4, 4)
3.2966	(4, 3, 3)	2.0702	(2, 4, 4)
3.2998	(2, 4, 4)	2.0721	(4, 3, 3)
3.3732	(5, 3, 3)	2.1562	(5, 3, 3)
3.4116	(1, 5, 5)	2.1921	(3, 4, 4)
3.4303	(3, 4, 4)	2.2060	(1, 5, 5)
3.4870	(2, 5, 5)	2.2768	(4, 4, 4)
3.5148	(4, 4, 4)	2.2841	(2, 5, 5)
3.5780	(5, 4, 4)	2.3659	(5, 4, 4)
3.6178	(3, 5, 5)	2.4182	(3, 5, 5)
3.7063	(4, 5, 5)	2.5029	(4, 5, 5)
3.7922	(5, 5, 5)	2.6059	(5, 5, 5)

Note: BIC: Bayesian information criterion.

Appendix 22: Autoregressive lag order selection criteria for the ARDL model with EPOP as a dependent variable and LPH and RWH as independent variables

Lag	LogL	LR	FPE	AIC	BIC	HQ
0	-3604.40	NA	35.7046	6.4132	6.4266	6.4182
1	-1252.36	4687.35	0.5464	2.2335	2.2514	2.2403
2	-1092.34	318.62	0.4119	1.9508	1.9732	1.9593
3	-1086.14	12.34*	0.4081	1.9416	1.9684*	1.9517*
4	-1084.71	2.84	0.4078*	1.9408*	1.9721	1.9526
5	-1084.50	0.42	0.4083	1.9422	1.9780	1.9557

Notes: * Indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at a 5% level). FPE: Final prediction error. AIC: Akaike information criterion. BIC: Bayesian information criterion. HQ: Hannan-Quinn information criterion. Endogenous variable: EPOP. Exogenous variables: constant, LPH, and RWH.

Appendix 23: Wald tests for the short run ARDL model for LPH, RWH, and EPOP

Null hypothesis: $\Delta LPH_{t-1} = \Delta LPH_{t-2} = \Delta LPH_{t-3} = 0$

Test Statistic	Value	df	Prob.
F - statistic	7.7376	(3, 1140)	0.0001
Chi - square	23.2127	3	0.0001

Null hypothesis: $\Delta RWH_{t-1} = \Delta RWH_{t-2} = \Delta RWH_{t-3} = 0$

Test Statistic	Value	df	Prob.
F - statistic	7.0784	(3, 1140)	0.0001
Chi - square	21.2351	3	0.0001