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# Real Wages and Labor-saving Technical Change: Evidence from a Panel of Manufacturing Industries in Mature and Labor-surplus Economies

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## Working Paper

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# Real wages and labor-saving technical change: evidence from a panel of manufacturing industries in mature and labor-surplus economies.

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**Abstract**

This paper uses panel cointegration and error correction models to unveil the direction of long-run causality between the real product wage and labor productivity at the industry level. I use two datasets of manufacturing industries: the EU-Klems dataset covering 11 industries in 19 developed economies, and the Unido Industrial Statistics Database covering 22 industries in 30 developed and developing economies. In both datasets, I find evidence of cointegration between the two variables, as well as evidence of two-way, long-run Granger causality. These findings are consistent with theories of directed technical change, which claim that a rise in labor costs sparks the adoption of labor-saving innovations. They are also consistent with distributive theories whereby real wages keep apace of labor productivity growth, giving rise to long-run stability in functional distribution.

**Keywords** : Technological Change, Wage Shares, Labor Productivity, Panel Cointegration.

**JEL Classification Codes** : B5, E25, O33.

## Introduction

There is ample documentation of a positive association between aggregate measures of labor productivity and real wages that asserts itself over long time horizons; as a consequence, aggregate factor shares in total income do not exhibit persistent trends (Kaldor, 1961; Gollin, 2002). Several authors have recently combined the notions of directed technical change and distributive conflict to develop a unified account of the evolution of real wages, labor productivity, and factor shares that explains these stylized facts (Foley, 2003; Julius, 2005; Tavani, 2012). This paper empirically examines the main predictions of these and related theories.

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The theory of directed technical change claims that wage pressures arising out of episodes of labor scarcity compel capitalist firms to economize on labor in order to defend profit margins. This notion has roots in both neoclassical and classical economics (see, e.g., Kennedy, 1964; Duménil and Lévy, 1995). Its central claim is that innovations to production do not economize on all factors of production to the same degree. Innovations that are biased towards economizing on labor become more appealing the higher the share of wages in unit costs, so that increases in real product wages can be causally linked to increases in labor productivity.

Theories of distribution emphasize the other side of the relationship. In mature economies, the state of the labor market — in particular, the employment rate — is often posited as a homeostatic mechanism linking increases in labor productivity to increases in real product wages, with the result that functional distribution remains trendless over time (see, e.g., Goodwin, 1967). Others consider functional distribution as conventional: where collective bargaining institutions are in place, organized labor and their political representatives will strive to keep real product wages apace with productivity in order to uphold long-standing distributive norms (Foley and Michl, 1999).

I jointly consider these mechanisms by conducting panel cointegration and error-correction tests, therefore examining the existence and direction of long-run causality between labor productivity and real product wages. I conduct the tests using two datasets of manufacturing industries: the EU-Klems dataset, which includes 11 manufacturing industries in 19 developed economies over the 1970-2007 period (O'Mahony and Timmer, 2009); and a sample of the Industrial Statistics Database of the United Nations Industrial Development Organization (Unido), which includes 22 manufacturing industries in 30 developed and developing countries over the 1981-2008 period[1].

In both datasets, panel cointegration tests support the notion that labor productivity and real product wages have common stochastic trends, implying that the wage share in value added is stationary. In turn, panel error correction models show evidence of two-way, long-run Granger causality between productivity and the real product wage. These findings are congenial both to the theory of directed technical change and to distributive theories linking labor productivity and real wages.

The Unido dataset also allowed me to test a complementary hypothesis: Are these mechanisms also present in developing countries? The existence of surplus labor is likely of strip the rate of

[1]Section 2 discusses the reasons for using a restricted sample of the Unido dataset.

open unemployment of its pivotal role in determining the evolution of real product wages. In fact, the notion of surplus labor has at times been adduced to sever the link between real product wages and labor productivity in the modern activities within developing countries, as embodied in the notion of an infinitely elastic supply of labor to the modern sector (Fei and Ranis, 1964).

Under general conditions, however, the elasticity of labor supply to modern industry and services is finite, as their expansion impinges on labor productivity in traditional repositories of surplus labor, as well as on intersectoral terms of trade (Ros, 2001). As a result, higher real product wages follow in the wake of capital accumulation in these modern sectors. This result poses the question of whether modern firms in developing countries will bias technical change towards labor-saving innovations as they expand — especially since the growing inter-industry division of labor that accompanies development is likely to raise the profitability of adopting more capital-intensive techniques (Young, 1928).

Using the Unido dataset I find preliminary evidence that mechanisms linking labor productivity and real product wages in the long run are also present in the manufacturing sector of developing countries. In particular, I also find two-way, long-run Granger causality between labor productivity and the real product wage — evidence that directed technical change occurs in labor surplus economies as well.

The remainder of this paper is organized as follows. Section 1 motivates my findings in light of the related literature. Section 2 describes my empirical strategy, while sections 3 through 5 discuss the details of implementing it in a panel framework; they also present the results of panel unit root, cointegration, and error correction tests. Section 6 presents alternative methods for estimating the error correction model in order to check the robustness of the results. Finally, section 7 draws the conclusions and implications of the paper, while an Appendix provides further details on data sources and estimation techniques.

## 1 Motivation and Related Literature

The stylized facts of mature economies show that real wages and labor productivity increase at similar rates in the long-run, with the consequence that factor shares do not exhibit persistent trends (Kaldor, 1961)[2]. Standard growth models have reproduced the stationarity of factor shares

[2]The pervasiveness of self-employment in developing countries creates problems of comparability across countries and over time. But recent studies suggest that factor shares are more stable in industries with lower prevalence

in the face of rising labor productivity by assuming that technical change only economizes on labor (i.e.: it is Harrod-neutral), while showing that the rate of capital deepening will converge to the rate of labor-saving technical change (Acemoglu, 2003)[3].

Yet, in order to understand how these facts emerge, it is necessary to explain the direction of technical change as a result of economic decisions. It is also illuminating to entertain explanations for the tendency of real product wages to keep pace with labor productivity without relying on the notion of full employment.

The theory of directed technical change is the cornerstone of the first causal link. At its heart are two notions: first, the notion that technical improvements are unlikely to be neutral in terms of their factor-saving potential; and, second, the notion that the contribution of a factor-saving innovation to reducing total costs is proportional to the share of that factor in total costs.

The classic formulation by Kennedy (1964) embodies these two notions. It models the development and adoption of innovations as a resource-consuming process, so that a trade-off exists between the maximum feasible rates of labor augmentation and capital augmentation. Under these conditions, firms will bias their innovation efforts towards labor-saving innovations in proportion to the wage share in unit costs, in order to obtain the fastest rate of instantaneous cost reduction[4].

Without imposing an exogenous innovation frontier, Duménil and Lévy (1995) find that factor shares determine the mean direction of technical change in a stochastic model. In their model, firms choose whether to adopt (at no cost) a randomly drawn technique depending only on whether it raises their instantaneous profit rates. Their results suggest that the adoption of techniques will be biased towards labor-saving innovations even if the generation of techniques is itself unbiased, as long as wages make up the larger share of total costs.

In the face of directed technical change, a second causal link is needed to explain the observed long-run stationarity of factor shares: that running from higher labor productivity to higher real product wages[5]. For mature economies, many authors have identified the labor market — specif-

of self-employment (such as modern manufacturing), and that aggregate factor shares show stability if part of the income of self-employed entrepreneurs is assigned to labor (Gollin, 2002).

[3]Stable factor shares will also emerge in a competitive economy described by an aggregate production function with a unitary elasticity of substitution between labor and capital. Empirical estimates using firm-level data, however, point to much lower values for this elasticity (see, e.g. Chirinko et al., 2011). Theoretical problems of aggregation also disavow direct empirical predictions on the basis of characteristics attributed to aggregate production functions (Felipe and Fisher, 2003).

[4]For a discussion of the microfoundations of this behavior, see Funk (2002).

[5]I use the term real product wage to refer to the real wage in terms of the output of a productive sector. The empirical investigation in this paper uses industry-level data, and this choice of terminology is useful to avoid confusion with other measures of real wages, such as the consumption real wage (see section 2 below).

ically, fluctuations in the employment rate — as the main homeostatic mechanism preventing short-term fluctuations in factor shares from producing long-term trends. Goodwin (1967) proposed the classic model in which wage growth responds to the buoyancy of the labor market. When combined with a classic, surplus-driven investment behavior, this theory of wage growth gives rise to conservative cycles in the employment rate and functional distribution around constant long-run averages.

Recent contributions have woven Goodwin cycles into models of growth with directed technical change. By combining the two causal links, they yield complete accounts of the time path of real wages, factor shares, and labor and capital productivity (Foley, 2003; Julius, 2005; Tavani, 2012). With surplus-driven investment behavior, these contributions give rise to a steady-state with Harrod-neutral technical change, as well as a constant employment rate and constant factor shares. Although the steady state equilibrium is generally stable, Goodwin cycles still occur in the transitional phase.

To ensure convergence to Harrod neutrality, these models rely on the fact that firms always exert additional pressure on the labor market when they engage in capital-saving technical change[6]. As the employment rate rises, so does the wage share, leading firms to promote labor-saving technical change at the expense of capital-saving technical change. A steady state is reached when the wage share is so high as to render capital-saving technical change uneconomical

Three issues pertaining to these models are worth noting. First, Harrod neutrality may be a good approximation of the long-run pattern of technical change of most capitalist economies. But there is evidence of falling capital productivity during several non-fleeting episodes (Foley and Marquetti, 1997; Marquetti, 2003). Examples include the United States during the second half of the 19$^{\text{th}}$ century (Duménil and Lévy, 1995), several advanced economies during the crisis of the so-called golden age of capitalist from the late 1960s through the 1970s (Glyn et al., 1990), and East Asia and Brazil during most of their episodes of industrialization (Young, 1995; Marquetti et al., 2010).

[6]The classical assumptions of differential saving propensities, saving-driven investment, and low elasticity of substitution between capital and labor imply that higher capital productivity leads both to faster capital accumulation and to higher labor absorption per unit of capital. By contrast, labor-saving technical change has contradictory effects on the labor market: on the one hand, for a given rate of accumulation it reduces employment per unit of capital, easing pressure on the labor market. But on the other hand, for a given real wage, it redistributes income towards capitalists, raising the surplus and the rate of accumulation, and thus the rate of employment growth. It is thus possible to solve for a level of both the employment rate and the output-capital ratio that leaves the system stationary with positive rates of labor-saving technical change. For a detailed formalization of these points, see Foley (2003) and Julius (2005).

The classical theory of induced technical change can accommodate Marx-biased patterns, which are characterized by rising labor productivity and falling capital productivity. As shown by Duménil and Lévy (1995), if the wage share in costs is large enough, even techniques that raise labor productivity while lowering capital productivity will be profitably adopted. The viability conditions for this Marx-biased pattern of technical change are further analyzed in deterministic models by Foley and Michl (1999), and Michl (1999). In classical models with a Marx-biased pattern of technical change, several growth paths are possible, although they are generally not steady (Michl, 1999).

Second, in Kennedy's canonical model and its derivatives, the steady-state factor shares are determined by the function describing the direction of technical change (Kennedy, 1964; Julius, 2005). The intuitive reason, again, is that no equilibrium is stationary with positive rates of capital augmentation. Since the rate of capital augmentation is uniquely related to functional income distribution, stationarity in the productivity of capital suffices to determine factor shares.

This property is unappealing for a political-economic understanding of distribution, which regards factor shares as conventional variables, to some degree resulting from the distribution of power across social classes and from social norms governing distribution.

To address this problem, Julius (2005) adopts a wage bargaining rule linking the evolution of real wages to that of labor productivity, thus making the evolution of the wage share in part responsive to worker's level of organization or militancy, as well as other institutional factors not reducible to the state of the labor market. If firms take account of the effect of their technical change decisions on real wages (as is reasonable to assume in a bargaining environment), the model still converges to Harrod-neutrality, but now the equilibrium wage share will depend positively on the bargaining strength of workers.

Finally, these models embody the classical tradition of surplus-driven investment. The literature on directed technical change has devoted less attention to growth regimes constrained by aggregate demand. Naastepad (2006), Rada and Taylor (2006), Rezai (2012), and Sasaki (2013) integrate elements of induced technical change into demand-constrained growth models of the Kacleckian tradition. These papers suggest a number of possible outcomes depending on behavioral relationships and parameter values; but a steady state with constant factor shares and a transitional dynamics described by Goodwin-type cycles are a possibility[7].

[7]Non-Kaleckian models with independent accumulation decisions can also produce distributional cycles. For an example without directed technical change, see Skott (1989).

The theories of distributional cycles and directed technical change above have received empirical support from studies of mature economies. Barbosa-Filho and Taylor (2006) estimate a vector autoregression (VAR) with data for the United States, identifying cycles of capacity utilization and the wage share. They show that these cycles have occurred around a common upward trend for the real wage and labor productivity, resulting in a trendless trajectory for the wage share. Basu et al. (2013) also focus on the US economy. They estimate a three-variable VAR including deviations of the employment rate, the profit share, and nonresidential fixed investment from their trends. The associated impulse-response functions display cyclical fluctuations in these variables consistent with the Goodwin model.

In turn, using cross-country analyses, Sasaki (2008) and Basu (2010) find support for the classical viability condition of Foley and Michl (1999) as an explanation for biases in the pattern of technical change. Finally, using data for the United States covering the 1869-1999 period, Marquetti (2004) estimates an error-correction model and shows that labor productivity responds to autonomous increases of the average real wage in order to maintain a stable, long-run relationship between the real wage and labor productivity.

To summarize, plausible theoretical mechanisms linking the evolution of real product wages and labor productivity have been advanced for mature economies. These mechanisms rely on both the directed technical change hypothesis and on distributive dynamics. Together, they imply that factor shares are mean-reverting in the long run — although the long-run averages can respond to distributive conventions under certain scenarios —, and thus likely to be stationary from a statistical point of view.

A remaining question is whether similar links exist in developing countries. To my knowledge, the frameworks above have not been extended to economies characterized by dualism and surplus labor. Still, it is possible to suggest structural reasons for similar links between real product wages and labor productivity to exist in developing countries.

To be sure, the notion that the rate of open unemployment provides a link between the rate of technical change and real wage growth is less appealing in developing countries. Lewis (1954) posited that the product wage in the modern sector is 'given' in a classical-Marxian sense. Based on the author's canonical formulation of a dual economy growth model, many have modeled the supply of labor to the modern sector as perfectly elastic — divorcing increases in labor productivity therein from increases in real product wages (Fei and Ranis, 1964).

But the notion of a perfectly elastic labor supply to the modern sector does not survive a more general specification. If the average product in the traditional sector increases as workers move to the modern sector, and if traditional output is not a perfect substitute to modern output[8], then all else equal, labor will be available to the modern sector at increasing product wages as capital is accumulated therein. This increase results from endogenous increases in labor productivity in the traditional sector and/or movements of the terms of trade against the modern sector (see, e.g., Sen, 1966; Rao, 1994; Ros, 2001).

These increases in real product wages are likely to induce modern-sector firms to step up the adoption of labor-saving innovations. Their impetus to do so may be reinforced by the growing division of labor across industries which accompanies economic development (Young, 1928; Rosenstein-Rodan, 1943; Murphy et al., 1989). Indeed, a more profuse inter-industry division of labor yields more labor-augmenting capital inputs, and at a lower cost. By the same token, the expansion of output markets raises the profitability expected from their use. Both factors are likely to facilitate the adoption of labor-saving technologies in the face of rising wage costs.

My findings confirm the basic tenets discussed above. First, I find evidence of a long-run relationship between real product wages and labor productivity, and of stationary factor shares. Second, I find evidence of two-way, long-run causality (in the Granger sense) between the two variables. In other words, if real product wages rise above the level implied by the long-run relationship — thus compressing the profit share — firms will step up the adoption of labor-saving innovations, raising labor productivity and helping to restore the long-run functional distribution. Likewise, real product wages will increase if the wage share is compressed below its long-run value. Finally, I find preliminary evidence that these reduced-form relationships also hold in developing countries, although limited data availability should caution against broad generalizations based on this finding (see section 2 below).

## 2 Data and Empirical Strategy

At the sectoral level, the average real product wage and average labor productivity are bound by a national accounting identity. It says that the employee compensation bill has to equal total value

[8]The canonical Lewisian model assumed that both sectors produced the same good, thus implicitly assuming an infinite elasticity of substitution between their outputs (Ros, 2001). Lewis himself implied that the elasticity of labor supply would be finite if the traditional and modern sectors were allowed to differ not only in their modes of production, but also in their outputs, as in the typical duality between agriculture and industry (see Lewis, 1954, pp. 173-176).

added minus the gross operating surplus (as well as taxes minus subsidies on production). This identity can be expressed as

$$\frac{w_i}{p_i} = (1 - \pi_i)\frac{X_i}{L_i} \tag{1}$$

where $w_i/p_i$ is the average employee compensation per worker in terms of the output of sector $i$, $X_i/L_i$ is value added per worker — my measure of labor productivity —, and $\pi_i$ is the share of gross operating surplus (and of subsidies minus taxes on production) in value added. To simplify the exposition, I will use 'wages' to refer to employee compensation[9], and 'profits' to refer to the remaining components of value added. I will therefore refer to $\pi_i$ as the profit share and to $w_i/p_i$ as the real product wage (i.e. the real wage in terms of the output of sector $i$). Unless the context in unambiguous, I refrain from using the term 'real wage', to avoid confusion with other measures of real wages in multi-sector models, such as the purchasing power over a consumption basket.

I computed empirical measures of the product wage, labor productivity, and the wage share using primary series from the EU-Klems dataset (O'Mahony and Timmer, 2009), and the Industrial Statistics Database of the United Nations Industrial Development Organization (Unido). The EU-Klems dataset covers 11 manufacturing industries in 19 developed economies over the 1970-2007 period. The included series of the Unido dataset cover 22 manufacturing industries in 30 developed and developing countries over the 1981-2008 period. Both datasets use the 2-digit Isic classification (third revision), although the Eu-Klems database often aggregates the series across groups of two or more industries. Section A.1 in the Appendix provides a detailed description of both datasets and of the construction of each series.

Both datasets are unbalanced, especially the Unido dataset. To mitigate potential inference distortions associated with short panels, I excluded series with less than 15 consecutive observations. I also excluded the so-called 'transition' economies of Eastern Europe, which during a substantial part of the sample period were under socialist economic regimes. These two operations reduced the number of usable countries from the initially large pool of the Unido dataset.

[9] As is well-known, the concept of employee compensation used in national accounting differs from the common view of what constitutes labor income. For example, it includes incomes, such as bonuses for top-level directors, that are better thought of as being paid out of profits. Perhaps more importantly, it tends to ignore the income of the self-employed, regarding it as entrepreneurial income. This last feature appears to account for a large share of the variation in aggregate factor shares between developed and developing countries (Gollin, 2002). Arguably, however, the use of employee compensation may make more sense in a test of the induced technical change hypothesis, as it is unclear why labor incomes inputed to self-employed entrepreneurs would trigger labor-saving innovations in the same way as labor incomes of employed workers do.

Regarding the classification of countries by level of development, I adopted the following criterion: if a country achieved a PPP-adjusted real per capita income of at least half of the level of the United States for most of the sample period (computed from the Penn World Tables 8.0), the country was classified as developed. I chose this criterion since a few countries can be said to have transitioned into developed status in recent decades, such as the East Asian economies. The results were qualitatively insensitive to reasonable variations on this criterion (for a list of countries in each group, see section A.1 in the Appendix).

After these adjustments, the average length of the EU-Klems series was 37.3 years, for a total of 209 groups (combinations of country and industry). The average length of their Unido counterparts is 19.9 years, for a total of 411 groups[10]. The small number of countries classified as developing (17 countries, for a total of 194 groups) should caution against broad generalizations about their differences and similarities with developed countries based on my findings.

The empirical strategy in this paper is closest to that of Marquetti (2004). I first test for the existence of a long-run relationship between the product wage and labor productivity that is consistent with a stationary wage share; I then examine the direction of long-run causality between the two variables by means of an error correction model.

My procedure begins by determining the order of integration of each variable. To this end, I use a unit root test that can accommodate unbalanced panels (Im et al., 2003). The test is based on pooling individual Dickey-Fuller t-statistics across groups. I conclude that the real product wage and labor productivity are integrated of order one, and that the wage share is stationary in all groups (see section 3).

After concluding that the real product wage and labor productivity are unit-root processes, I examine whether they share a common stochastic trend — implying that the two variables are bound by a long-run equilibrium relationship which gives rise to a stationary wage share. The accounting identity in (1) implies a trivial relation between the real product wage, labor productivity, and the wage share which is consistent with many data-generating processes. By itself, it does not imply that the wage share is stationary. Such stationarity, in the face of trending series of real product wages and labor productivity, is rather evidence of the action of economic mechanisms, such as those reviewed in section 1 above. The finding of cointegration is thus evidence in favor of these mechanisms.

[10]Not all included countries had series of the minimum length for all industries.

I examine the cointegration hypothesis by means of a test proposed by Pedroni (1999, 2004). The test extends the residual-based procedure of Engle and Granger (1987) to panel data, and it unambiguously suggests that the real wage and labor productivity are cointegrated (see section 4).

Finally, I examine the direction of long-run Granger causality between the two variables using an error correction model. Short-run disturbances to the equilibrium relationship between the real product wage and labor productivity will cause factor shares to depart from their estimated long-run values. The tests for the existence and the direction of long-run Granger causality examine how either variable adjusts to restore equilibrium, bearing on the validity of the economic mechanisms reviewed above.

The error correction model requires unbiased estimates of deviations from the long-run equilibrium. To obtain them, I estimate the panel cointegration vector using the fully modified ordinary least squares (FMOLS) method (Pedroni, 2001). I find that both variables shoulder the burden of reestablishing the long-run relationship in both datasets, with no evidence of substantive differences between developed and developing countries in this respect (see section 5). These findings are robust to alternative estimation methods and model specifications (see section 6).

The next sections describe these procedures and their results in more detail.

# 3 Testing For Unit Roots

## 3.1 Conceptual Issues

In order to estimate an error correction model, it is necessary to determine the order of integration of each variable. Previous studies using long, aggregate time series for the United Kingdom and the Unites States found that labor productivity and the real product wage have each one unit root, while the wage share is stationary (Alogoskoufis and Smith, 1991; Marquetti, 2004). Such long time series, however, are unavailable in the EU-Klems and Unido datasets, and as a result I employ a unit root test designed for panel data in order to obtain power gains.

The test follows the procedure in Im, Pesaran, and Shin (2003), which can accommodate unbalanced panels. The IPS test pools t-statistics obtained from individual augmented Dickey-Fuller regressions, like (2) below.

$$\Delta y_{j,t} = a_{0,j} + \gamma_j y_{j,t-1} + \sum_{i=1}^{p} \beta_{j,i} \Delta y_{j,t-i} + \epsilon_{j,t} \tag{2}$$

where $y$ denotes the tested variable, $\Delta$ denotes first differences, and $j = 1, ..., N$ indexes the groups, which in both datasets are unique combinations of country and industry. The IPS procedure tests whether $\gamma_j$ is less than zero for some $j$'s, implying that the variable is stationary in at least a subset of panels. By contrast, if the null hypothesis that $\gamma = 0$ is maintained the test concludes that the series has a unit root in all panels[11].

Implementing the IPS test requires attention to three issues. The first is how to address potential autocorrelation and cross-sectional dependence in the sequence of residuals $\{\epsilon_{j,t}\}$. To address the problem of autocorrelation, I followed a standard parametric correction and included lagged differences in the individual Dickey-Fuller equations.

The problem of cross-sectional dependence is potentially more pervasive — macroeconomic or institutional shocks in a country are likely to be felt in many of its industries. To address this obvious source of cross-sectional dependence, I draw on Levin et al. (2002) and, for each variable and time period, subtract the country-wide mean from each observation. This procedure removes sources of contemporaneous correlation in the error term across industries within the same country[12].

The second issue is deciding whether the model above should include a linear trend. Since the IPS test lacks a procedure to formally test the significance of deterministic terms under the null hypothesis, we need to visually inspect the series and use economic intuition in order to judge whether the baseline specification should include a trend.

The top panels in figures A.1 and A.2 in the Appendix plot (in logarithmic scale) the product wage, labor productivity, and the wage share for the aggregate manufacturing sector in each country. As expected, the dominant pattern is of upward trends in wages and productivity. This visual pattern could be consistent with either a trend-stationary process or a random walk with a drift. If we were estimating equation (2) with these untransformed variables, it would be sensible to include a trend in the baseline specification — thus, if the null hypothesis of a unit root were rejected, we would adopt the alternative that those series have a deterministic trend.

[11] The heterogeneous alternative hypothesis results from the fact that individual test statistics are averaged across panels. Unfortunately, if the null is rejected the test cannot determine the number of panels for which the null does not hold, or their identity.

[12] Of course, other, more complex patterns of cross-sectional dependence may not be fully addressed by demeaning.

Once country-specific annual means are removed, however, the generalized visual trends in the real product wage and labor productivity disappear, as shown in the bottom panels of figures A.1 and A.2 in the Appendix (which show the same plots for individual industries after transformation). The reason is that the transformed variables should be interpreted as deviations from the contemporaneous country mean. Although individual series might exhibit persistent upward trajectories, generalized trends in the same direction are ruled out by construction. It is thus sensible to adopt a baseline model with panel-specific means under the alternative hypothesis, but without linear trends. Although in the Appendix I report the test results for the model with a trend as a robustness check, the description in this section focuses on the model without a trend.

The final issue is the test's size and power, that is, the incidence of incorrect and correct rejections of the null hypothesis — a well-known shortcoming of unit root tests. When lagged differences are included in the estimated equations, the IPS procedure computes a transformed statistic ($\bar{W}_t$) based on the average t-statistics of the individual Dickey-Fuller tests. The $\bar{W}_t$ statistic converges in distribution to a standard normal. Simulations in Im, Pesaran, and Shin (2003) indicated that if a linear trend is absent, the test based on $\bar{W}_t$ has good size and power when the number of time periods is around 20, as long as the number of panels is sufficiently large (around 50)[13].

### 3.2 Results

Tables A.2 and A.3 in the Appendix summarize the test results using the EU-Klems and Unido datasets. In accordance with the previous findings of Alogoskoufis and Smith (1991) and Marquetti (2004), I find general support for the hypothesis that the real product wage and labor productivity have each one unit root, while the wage share is stationary.

On two instances, however, the results were ambiguous. First, the test rejected the null hypothesis that the wage share has a unit root in all groups using the EU-Klems database, but only when a small number of lagged differences were included in the test (see columns 1 and 2 of Table A.2). When the specification included deeper lags (columns 3 and 4), the test failed to reject the null.

The latter finding is difficult to justify theoretically, since it may imply that the wage share — when reckoned in levels as opposed to deviations from country means — is a trending variable.

[13] When a linear trend is estimated, however, maintaining power requires a higher number of time periods.

When calculated according to national accounting methods, however, the norm is for the wage share to be bounded between zero and one. Exceptions may occur (such as when the gross operating surplus is negative), but they not systematic.

To reduce the test's ambiguity regarding the wage share, I used a panel unit root test developed by Choi (2001) as a robustness check. This alternative test rests on the notion of meta analysis, combining the conclusions which would have been drawn from tests conducted at the individual level. The procedure begins by conducting individual Phillips-Perron tests in each panel. Like the augmented Dickey-Fuller framework above, the Phillips-Perron framework corrects for serial correlation in the residuals, but does so non-parametrically. The p-values associated with the individual test statistics are then combined into two summary statistics. The $Z$ statistic follows a standard normal distribution under the null of unit root, while the $L$ statistic follows a Student $t$ distribution with the number of degrees of freedom determined by the number of panels in the dataset — see Choi (2001) for details about their construction. The Choi test adopts the same null and alternative hypotheses as the IPS test.

As indicated by Table A.2 in the Appendix, the meta analysis test unambiguously rejects the null hypothesis of a unit root, and this is the conclusion that I will uphold for the remainder of the paper.

The other ambiguous result concerns labor productivity in the Unido dataset. The test rejected the null hypothesis that labor productivity has a unit root when a panel-specific number lagged differences — determined according to the Bayesian information criterion (Bic) — were included in the test (column 1 in Table A.3). But the test failed to reject the null when the specification included deeper lags (columns 2 through 4). The use of the Bic criterion yielded a choice of zero lags for most panels — the average number of lags was 0.11 —, raising a concern with potential autocorrelation in the residuals; I thus adopt the conclusion of the specifications with deeper lags.

## 4 Testing for Cointegration

After concluding that the real wage and labor productivity are unit-root processes, it's time to examine whether they share a common stochastic trend by employing Pedroni's panel cointegration test (Pedroni, 1999, 2004). The test is an extension of the Engle-Granger residual-based cointegration test to a panel data framework. It was specifically designed for heterogeneous panels, allowing a unique long-run relationship between the product wage and labor productivity in each industry and country.

The procedure begins by estimating a long-run equation for each group, as in (3) below.

$$ln(PW)_{j,t} = a_{0j} + \beta_j ln(LP)_{j,t} + \epsilon_{tj} \tag{3}$$

where $PW$ stands for the real product wage and $LP$ denotes labor productivity. Following the Engle-Granger methodology, the procedure tests whether the residuals of the equation above are stationary. By applying logs to the accounting identity in equation (1), one can readily see that stationarity in the residuals above implies stationarity in factor shares. The finding of cointegration is thus evidence of the economic mechanisms reviewed in section 1.

Pedroni (1999, 2004) proposes several statistics to test for cointegration in a panel framework. They are based on standard unit root tests for single time series, but they differ in the way in which the individual residual series are combined across groups. The statistics of the first type (termed group statistics) require that individual test statistics be computed and then averaged across groups, resulting in group means statistics similar in spirit to the IPS test above. They are obtained under the null hypothesis that the all individual residuals have a unit root — i.e.: no cointegration —, and they lead to an alternative hypothesis that the residuals for a subset of groups are stationary, with panel-specific autoregressive coefficients. In other words, if the null is rejected, we conclude that there is cointegration in a subset of groups.

The statistics of the second type (termed panel statistics) pool the residuals along the 'within' dimension of the data, that is, by averaging the components of the test statistics across groups before computing the final statistics. Now the alternative hypothesis is that there is cointegration in all groups, with common autoregressive coefficients in the residual series.

The statistics also differ on the basis of the original unit root test that they extend. Two of them, the group-ADF and panel-ADF statistics, adopt a parametric correction for autocorrelation in the residuals, thus being extensions of the augmented Dickey-Fuller test. The remainder adopt non-parametric corrections. The group-PP and panel-PP statistics extend the Phillips-Perron t-statistic (based on the t-statistic of an autoregressive regression of the residuals), while the group-$\rho$ and panel-$\rho$ statistics extend the Phillips-Perron $\rho$-statistic (based on the difference between the actual autoregressive coefficient and its value under the null hypothesis). Finally, the panel-$\upsilon$

statistic extends the variance-ratio test used by Phillips and Ouliaris (1990). All the tests are single-tailed, with the null of no cointegration being rejected for high positive values of the panel-$v$-statistic and for low negative values of the remaining statistics.

As in the case of the unit root tests described in section 3, I used country-demeaned data when estimating the long-run relation between the product wage and labor productivity, in order to mitigate the problem of cross-sectional dependence. As we can see in Table 1, there is ample evidence against the null of no cointegration, among both the panel and the group test statistics. This conclusion holds for the Eu-Klems dataset (columns 1 and 2) and for the full sample of the Unido dataset (columns 3 and 4). It also holds for the samples developed and developing countries (columns 5 and 6).

This conclusion implies that real product wages and labor productivity are bound by a long-run equilibrium relationship, sharing common stochastic trends. By implication, factor shares are stationary. This finding confirms the stylized facts of economic growth described above, and it can be interpreted in light of the economic mechanisms — such as directed technical change and the homeostatic properties of labor markets — which have been adduced to explain these facts.

# 5 Testing for Long-Run Granger Causality

Having found evidence of a long-run relationship between the product wage and labor productivity, I turn to the problem of assessing whether deviations from this relationship elicit compensatory adjustments in either variable. To this end, I estimate a panel error-correction model (ECM), as in (4) below.

$$
\begin{aligned}
\Delta ln(PW)_{j,t} =& a_{PW,j} + \alpha_{PW}(e_{j,t-1}) + \sum_{i=1}^{p} \phi(i)_{11} \Delta ln(PW)_{j,t-i} + \\
&+ \sum_{i=1}^{p} \phi(i)_{12} \Delta ln(LP)_{j,t-i} + \epsilon_{PW,j,t} \\
\Delta ln(LP)_{j,t} =& a_{LP,j} + \alpha_{LP}(e_{j,t-1}) + \sum_{i=1}^{q} \phi(i)_{21} \Delta ln(PW)_{j,t-i} + \\
&+ \sum_{i=1}^{q} \phi(i)_{22} \Delta ln(LP)_{j,t-i} + \epsilon_{LP,j,t}
\end{aligned}
\tag{4}
$$

where $e_{j,t-1}$ are the estimated residuals obtained from the the long-run equilibrium equation (eq. 3) lagged one period.

The test about the direction of long-run causality between the two variables focuses on the adjustment coefficients $\alpha_{PW}$ and $\alpha_{LP}$. The $\alpha_{LP}$ coefficient indicates the direction and speed of adjustment of labor productivity to deviations from the long-run equilibrium occurred in the previous year. Given the specification of (3), a positive $\alpha_{LP}$ indicates that an autonomous increase in the real product wage elicits a subsequent increase in labor productivity to help reestablish the long run equilibrium. This adjustment mechanism, if found to exist, is congenial to the theory of directed technical change. After all, it indicates that labor productivity in manufacturing rises endogenously as a response to an expansion of the wage share above its long-run value.

Likewise, $\alpha_{PW}$ indicates the direction and speed of adjustment of the real product wage. Now a negative $\alpha_{PW}$ would indicate that the real product wage declines if the wage share rises above its long-run value, helping to restore equilibrium. The theories of distributive conflict and structural change discussed in the introduction illuminate this adjustment.

Adjustment coefficients of the right sign ensure that the cointegration equation is a stable long-run equilibrium. But stability can also occur if one of the adjustment coefficients is zero. In that case, only one variable shoulders the burden of restoring equilibrium. For example, if $\alpha_{LP} = 0$ then deviations from the long-run relationship would be entirely corrected by the product wage. A test for the sign and significance of $\alpha_{PW}$ and $\alpha_{LP}$ therefore sheds light on the theoretical predictions discussed above — and on whether their strength depends on the level of development of the economies under examination.

I restrict my testing procedure to long-run effects. Failure to reject the null hypothesis that $\alpha_{LP} = 0$, for example, does not imply that shocks to the product wage cannot affect labor productivity; but it implies that those effects, if they exist, are confined to the short-run. These short-run effects (such as changes in resource utilization over business cycles) are captured by the $\phi(i)$ coefficients on the lagged differences in (4)[14].

## 5.1 Estimation Issues

### 5.1.1 Correcting for Endogeneity Bias in the Residuals

In order to estimate the error-correction model in equation (4), it is necessary to obtain estimates of the residuals from the long-run relationship in equation (3). Estimating a panel version of the (3)

[14] Testing the significance of $\alpha_{PW,LP}$ jointly with the $\phi(i)$ coefficients is the standard way of examining Granger causality; but this test is not very informative for my purposes, since I am interested in the long-run predictions of the theories under examination.

by OLS produces consistent estimates, but the biases in small samples can be substantial, since the cointegration relation does not rule out the endogeneity of the regressor (Kao and Chiang, 2001). In addition, OLS estimates also have second-order bias, which is not eliminated asymptotically; while this bias is small in single equation estimates of cointegration vectors, it can grow large in panels where the number of groups far exceeds the number of time periods (Pedroni, 2001).

Several alternative estimators have recently been proposed to address these problems. Intuitively, these estimators use the information that the right-hand side variables have unit roots to control for innovations which would otherwise be absorbed into the error term.

The baseline estimates of the cointegration equation in this paper use the group-mean fully modified ordinary least squares estimator (FMOLS) proposed by Pedroni (2001). The idea behind the FMOLS estimator is to use non-parametric estimates of the covariance matrix to purge the product wage series of its correlation with unobserved shocks to labor productivity. For more details about the construction of the FMOLS estimator, see section A.2 in the Appendix.

Besides correcting for the endogeneity problem, the group-mean FMOLS estimator has key advantages which stem from the fact that it pools information across the 'between' dimension of the panel. First, it allows for heterogeneity across groups both in the long-run coefficient and in the dynamics of short-run disturbances. When the long-run coefficient is indeed heterogeneous across groups, the group-mean estimator provides a consistent point estimate of the sample mean of the cointegration vector. Second, simulations show that it has excellent bias-reduction properties even in very small samples, and that it outperforms pooled alternatives regarding inference in small samples (Pedroni, 2001).

### 5.1.2 Estimating the Pooled Error Correction Model

The estimation of the error correction model is subject to another source of bias: that which emerges when the regressions in (4) are estimated in order to allow both for group-specific fixed effects and lags of the dependent variable. Doing so creates a mechanical correlation between the lagged dependent variables and the error term which can be severe in short panels (Nickell, 1981).

To address this problem, I estimate the equations in (4) by means of a system GMM procedure in the spirit of Arellano and Bond (1991), and Arellano and Bover (1995). The procedure begins by applying first differences to the variables in order to eliminate the group-specific fixed effects. It then uses lags of the untransformed variables as instruments for the transformed variables.

Since these lags are predetermined with respect to the error term in the transformed equation, this strategy effectively removes the mechanical correlation [15].

## 5.2 Results

Table 2 summarizes the results for the EU-Klems dataset. Columns (1)-(3) show estimates of the $\alpha_{PW}$ coefficient in equation (4), for systems with two up to four lagged differences (i.e.: $p, q = 2, 3, 4$)[16]. The null hypothesis that the real product wage is exogenous to deviations from the long-run equilibrium is rejected in all specifications. The estimated error-correction coefficients are negative, implying that the real product wage increases if the wage share falls below the value implied by long-run equilibrium.

In turn, columns (4)-(6) show estimates of the $\alpha_{LP}$ coefficient in equation 4. Now the null hypothesis is that shocks to the product wage have no long-run effects on labor productivity. Again, the null hypothesis is rejected in all specifications. As expected, the estimated error-correction coefficients are positive, implying that a positive shock to the real product wage induces an increase in labor productivity in order to restore the long-run relationship.

These findings are confirmed by the Unido dataset, as evidenced by Table 4. Columns (1) and (2) show the estimates of $\alpha_{PW}$ and $\alpha_{LP}$ for the whole sample, finding two-way causality in the manner just described.

In turn, the specifications in columns (3)-(8) test whether the adjustment coefficients differ between developed and developing countries. This hypothesis is examined by testing the significance of an interaction term between $\alpha_{PW,LP}$ and a dummy variable indicating whether an observation belongs to a developing country. Columns (3-5) show that, like the main effects, the coefficients on $\alpha_{PW}$ in the interaction terms are negative. But they are imprecisely estimated and thus deemed statistically insignificant at conventional levels. Columns (6)-(8) lead to a similar conclusion: the coefficients on the interaction terms have the same signs as the main effects, but the large standard errors render them statistically insignificant, with the possible exception of the specification in column (6).

[15] The system GMM approach also estimates equations with the untransformed variables, now using lags of the transformed variables as instruments. These instruments are by construction purged of correlation with the unobserved fixed effects; it is also assumed that they are uncorrelated with other components of the contemporaneous error term. Estimating a stacked system of transformed and untransformed variables is preferred on efficiency grounds.

[16] The magnitude and significance of the estimated coefficients were insensitive to the choice of lags, as were the conclusions of the Arellano-Bond test for second-order autocorrelation in the residuals.

These baseline estimates show no clear evidence of statistically significant quantitative differences between developing and developed countries regarding the response of either variable to autonomous shocks. Moreover, the main and the interaction effects have the same sign, further suggesting that the responses are qualitatively similar — i.e. in both groups, the variables respond in the same direction. In this sample of developing countries, neither labor productivity nor the real product wage can be considered exogenous to deviations from the long-run relationship.

## 6 Robustness Checks

In this section, I test the robustness of the results above to an alternative method of estimating the cointegration vector, as well as to relaxing the assumption that developed and developing countries share the same average long-run relationship between real product wages and labor productivity.

The alternative method for estimating the cointegration vector is based on Kao and Chiang (2001). It has two differences with respect to the group-mean FMOLS method used in the baseline estimates. First, it employs a parametric correction to finite sample bias. The correction consists of adding lags and leads of the first difference of the right-hand side variable of the cointegrating vector, thus applying the dynamic ordinary least squares estimator (DOLS) to a panel framework. Intuitively, this correction parametrically controls for innovations in the labor productivity series which would otherwise be absorbed into the error term. Second, unlike the group-mean FMOLS estimator, it pools information across the within dimension of the panel (for more details, see section A.2 in the Appendix).

Columns (1)-(4) show the baseline error-correction models estimated with the residuals obtained by DOLS. Columns (1) and (2) show the adjustment coefficients of the model estimated with the EU-Klems dataset, resulting in only minor changes in the magnitude of the coefficients with respect to the baseline estimates.

With respect to the Unido dataset, the models in columns (3) and (4) show more noticeable changes in the magnitude of the coefficients — developing countries now display statistically significant differences in the response of both variables to disequilibrium[17]. Still, this robustness check upholds the same qualitative conclusions of the baseline models: in both groups of countries there is two-way causality between labor productivity and product wages in the manner predicted by the literature on induced technical change and stationary factor shares.

[17] These findings are robust to the choice of lagged differences in the error correction model.

Finally, in columns (5)-(8) I relax the assumption that the two groups of countries share the same cointegration vector. I estimate group-specific cointegration vectors using group-mean FMOLS, followed by group-specific error correction models. Again, this exercise does not change the qualitative conclusions above. But noticeable quantitative effects appear for the case of developed countries, which display faster adjustment of labor productivity to disequilibrium, and slower adjustment of the product wage.

# 7 Conclusion

Classical and institutional economists have long claimed that intercapitalist competition compels firms to adopt new techniques of production in search of above-average profits[18]. This fundamental impetus is reinforced during the process of economic development, as new techniques become profitable due to growing inter-industry division of labor and expanding markets.

The theories of directed technical change and distribution reviewed in this paper provide a persuasive account for why technical change under these conditions tends to be biased towards labor-saving innovations, with labor productivity and real wages exhibiting common long-run trends. Using data for manufacturing industries and panel cointegration techniques, this paper estimated this long-run relationship and tested the direction of long-run causality between the two variables.

My empirical findings confirm the hypothesis that shifts in functional distribution towards labor triggers labor-saving technical change. It also shows that higher real product wages follow in the wake of increases in labor productivity, giving rise to stationary factor shares.

Developing and developed countries in the sample showed no qualitative differences in the adjustment of the two variables do departures from this long-run relationship, as reckoned by error correction models. Of course, the underlying causal mechanisms may differ between the two groups, especially the explanation for increases in real product wages (see section 1).

My findings have implications that extend beyond the theories reviewed in this paper. First, they suggest that protracted policies of real wage restraint may stifle productivity growth[19]. Second, the evidence on developing countries lends support to nuanced dual economy models without

[18]See, e.g., Marx (1976), p. 433.

[19]For a stimulating discussion of this possibility with regard to the Dutch experience in recent decades, see Naastepad (2006).

a perfectly elastic supply of labor to the modern sector. Finally, the finding of two-way causality between labor productivity and real wages suggests that directed technical change is an important causal mechanism behind the so-called Kaldor-Verdoorn relation — the empirical observation that output and labor productivity growth are correlated. An integration of the two mechanisms merits further research.

## References


Acemoglu, D. (2003). Labor- and capital-augmenting technical change. *Journal of the European Economic Association 1*(1), 1–37.

Alogoskoufis, G. and R. Smith (1991). On error correction models: specification, interpretation, estimation. *Journal of Economic Surveys 5*(1), 97–128.

Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The Review of Economic Studies 58*(2), 277–297.

Arellano, M. and O. Bover (1995). Another look at the instrumental variable estimation of error-components models. *Journal of econometrics 68*(1), 29–51.

Barbosa-Filho, N. H. and L. Taylor (2006). Distributive and demand cycles in the US economy — a structuralist Goodwin model. *Metroeconomica 57*(3), 389–411.

Basu, D. (2010). Marx-biased technical change and the neoclassical view of income distribution. *Metroeconomica 61*(4), 593–620.

Basu, D., Y. Chen, and J.-S. Oh (2013). Class struggle and economic fluctuations: VAR analysis of the post-war US economy. *International Review of Applied Economics 27*(5), 575–596.

Chirinko, R. S., S. M. Fazzari, and A. P. Meyer (2011). A new approach to estimating production function parameters: the elusive capital–labor substitution elasticity. *Journal of Business & Economic Statistics 29*(4), 587–594.

Choi, I. (2001). Unit root tests for panel data. *Journal of International Money and Finance 20*(2), 249–272.

Duménil, G. and D. Lévy (1995). A stochastic model of technical change: an application to the US economy (1869–1989). *Metroeconomica 46*(3), 213–245.

Engle, R. F. and C. W. J. Granger (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica: Journal of the Econometric Society 55*(2), 251–276.

Fei, J. C. and G. Ranis (1964). *Development of the Labor Surplus Economy.* Homewood, IL: Irwin.

Felipe, J. and F. M. Fisher (2003). Aggregation in production functions: what applied economists should know. *Metroeconomica 54*(2-3), 208–262.

Foley, D. and A. A. Marquetti (1997). Economic growth from a classical perspective. In J. Teixeira (Ed.), *Growth, Distribution and Structural Change: Contemporaneous Analysis*. Brasilia: University of Brasilia Press.

Foley, D. K. (2003). Endogenous technical change with externalities in a classical growth model. *Journal of Economic Behavior & Organization 52*(2), 167–189.

Foley, D. K. and T. R. Michl (1999). *Growth and distribution*. Cambridge, MA: Harvard University Press.

Funk, P. (2002). Induced innovation revisited. *Economica 69*(273), 155–171.

Glyn, A., A. Hughes, A. Lipietz, and A. Singh (1990). The rise and fall of the golden age. In S. Marglin and J. Schor (Eds.), *The Golden Age of Capitalism: Reinterpreting the Postwar Experience*. Oxford: Clarendon Press.

Gollin, D. (2002). Getting income shares right. *Journal of Political Economy 110*(2), 458–474.

Goodwin, R. M. (1967). A growth cycle. In C. H. Feinstein (Ed.), *Socialism, Capitalism and Economic Growth*, pp. 54–58. Cambridge: Cambridge University Press.

Im, K. S., M. H. Pesaran, and Y. Shin (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics 115*(1), 53–74.

Julius, A. J. (2005). Steady-state growth and distribution with an endogenous direction of technical change. *Metroeconomica 56*(1), 101–125.

Kaldor, N. (1961). Capital accumulation and economic growth. In F. A. Lutz and D. Hague (Eds.), *The Theory of Capital*, pp. 177–222. New York: St. Martin's Press.

Kao, C. and M.-H. Chiang (2001). On the estimation and inference of a cointegrated regression in panel data. *Advances in Econometrics 15*, 179–222.

Kennedy, C. (1964). Induced bias in innovation and the theory of distribution. *The Economic Journal 74*(295), 541–547.

Levin, A., C.-F. Lin, and C.-S. James Chu (2002). Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics 108*(1), 1–24.

Lewis, W. A. (1954). Economic development with unlimited supplies of labour. *The Manchester School 22*(2), 139–191.

Marquetti, A. (2004). Do rising real wages increase the rate of labor-saving technical change?: Some econometric evidence. *Metroeconomica 55*(4), 432–441.

Marquetti, A., E. Maldonado Filho, and V. Lautert (2010). The profit rate in Brazil, 1953-2003. *Review of Radical Political Economics 42*(4), 485–504.

Marquetti, A. A. (2003). Analyzing historical and regional patterns of technical change from a classical-Marxian perspective. *Journal of Economic Behavior & Organization 52*(2), 191–200.

Marx, K. (1976). *Capital: A critique of Political Economy*, Volume I. Penguin Classics.

Michl, T. R. (1999). Biased technical change and the aggregate production function. *International Review of Applied Economics 13*(2), 193–206.

Murphy, K. M., A. Shleifer, and R. W. Vishny (1989). Industrialization and the big push. *The Journal of Political Economy 97*(5), 1003–1026.

Naastepad, C. W. M. (2006). Technology, demand and distribution: a cumulative growth model with an application to the dutch productivity growth slowdown. *Cambridge Journal of Economics 30*(3), 403–434.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the Econometric Society 49*(6), 1417–1426.

O'Mahony, M. and M. P. Timmer (2009). Output, input and productivity measures at the industry level: The EU KLEMS database. *The Economic Journal 119*(538), 374–403.

Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bulletin of Economics and Statistics 61*(S1), 653–670.

Pedroni, P. (2001). Fully modified OLS for heterogeneous cointegrated panels. *Advances in Econometrics 15*, 93–130.

Pedroni, P. (2004). Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Econometric Theory 20*(03), 597–625.

Phillips, P. C. and S. Ouliaris (1990). Asymptotic properties of residual based tests for cointegration. *Econometrica: Journal of the Econometric Society 58*(1), 165–193.

Rada, C. and L. Taylor (2006). Empty sources of growth accounting, and empirical replacements a la Kaldor and Goodwin with some beef. *Structural Change and Economic Dynamics 17*(4), 486–500.

Rao, J. M. (1994). Agrarian structure, labour supplies and the terms of trade. In A. Dutt (Ed.), *New Directions in Analytical Political Economy*, pp. 247–270. Aldershot: Edward Elgar.

Rezai, A. (2012). Goodwin cycles, distributional conflict and productivity growth. *Metroeconomica 63*(1), 29–39.

Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics 71*(1), 135–158.

Ros, J. (2001). *Development theory and the economics of growth.* Ann Arbor, MI: Univ of Michigan Press.

Rosenstein-Rodan, P. N. (1943). Problems of industrialisation of Eastern and South-Eastern Europe. *The Economic Journal 53*(210/211), 202–211.

Sasaki, H. (2008). Classical biased technical change approach and its relevance to reality. *International Review of Applied Economics 22*(1), 77–91.

Sasaki, H. (2013). Cyclical growth in a Goodwin–Kalecki–Marx model. *Journal of Economics 108*(2), 145–171.

Sen, A. K. (1966). Peasants and dualism with or without surplus labor. *The Journal of Political Economy 74*(5), 425–450.

Skott, P. (1989). Effective demand, class struggle and cyclical growth. *International Economic Review 30*(1), 231–47.

Tavani, D. (2012). Wage bargaining and induced technical change in a linear economy: Model and application to the US (1963–2003). *Structural Change and Economic Dynamics 23*(2), 117–126.

United Nations (2008). *Country Practices for the Collection and Calculation of the Index of Industrial Production.* New York: United Nations, Department of Economic and Social Affairs, Statistics Division.

Young, A. (1995). The tyranny of numbers: confronting the statistical realities of the East Asian growth experience. *The Quarterly Journal of Economics 110*(3), 641–680.

Young, A. A. (1928). Increasing returns and economic progress. *The Economic Journal 38*(152), 527–542.

Table 1: Pedroni (1999, 2004) Panel Cointegration Tests

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Unweighted Panel Statistics** | | | | | | |
| $\nu$-statistic | 6.48*** | 6.48*** | 5.71*** | 5.71*** | 7.36*** | 3.16*** |
| $\rho$-statistic | -6.57*** | -6.57*** | -18.47*** | -18.47*** | -10.87*** | -13.42*** |
| PP-statistic | -5.9*** | -5.9*** | -23.86*** | -23.86*** | -12.21*** | -17.77*** |
| ADF-statistic | -7.18*** | -1.51* | -25.11*** | -5.68*** | -12.45*** | -18.734*** |
| **Weighted Panel Statistics** | | | | | | |
| $\nu$-statistic | 3.71*** | 3.71*** | 0.66 | 0.66 | 2.21*** | -1.04 |
| $\rho$-statistic | -9.92*** | -9.92*** | -18.83*** | -18.83*** | -12.59*** | -13.95*** |
| PP-statistic | -9.17*** | -9.17*** | -25.45*** | -25.45*** | -16.25*** | -19.53*** |
| ADF-statistic | -9.94*** | -2.55*** | -27.32*** | -7.61*** | -17.80*** | -20.57*** |
| **Group Statistics** | | | | | | |
| $\rho$-statistic | -6.23*** | -6.23*** | -8.22*** | -8.22*** | -4.64*** | -7.05*** |
| PP-statistic | -7.34*** | -7.34*** | -23.63*** | -23.63*** | -14.56*** | -18.99*** |
| ADF-statistic | -9.18*** | -2.13** | -25.90*** | -8.50*** | -16.91*** | -19.80*** |
| Dataset | Eu-Klems | Eu-Klems | Unido | Unido | Unido (developed) | Unido (developing) |
| Individual intercept | Y | Y | Y | Y | Y | Y |
| Individual trend | N | N | N | N | N | N |
| ADF lags | Bic | 2 | Bic | 2 | Bic | Bic |
| Groups | 209 | 209 | 410 | 410 | 216 | 194 |
| Observations | 7942 | 7942 | 9907 | 9907 | 5185 | 4699 |

*Note:* The alternative hypothesis associated with the panel statistics is of cointegration in all panels with common autoregressive coefficients in the residuals. The alternative hypothesis associated with the group statistics is of cointegration in a subset of panels with panel-specific autoregressive coefficients in the residuals. 'ADF lags' denote the number of lags specified in the augmented Dickey-Fuller regressions used to calculate the ADF-statistics. 'Bic' indicates that a panel-specific number of lags was chosen according to the Bayesian Information Criterion. The Bartlett kernel with a bandwidth chosen by the Newey-West procedure was used to estimate the long-run variance when calculating the statistics derived from the Phillips-Perron and Phillips-Ouliaris tests. For the calculation of the weighted statistics, the individual terms were weighted by their corresponding long-run variances. The long-run relation between the product wage and labor productivity was estimated using country-demeaned data.

Table 2: EU-Klems: Tests for Long-Run Granger Causality

| | (1) Product Wage | (2) Product Wage | (3) Product Wage | (4) Labor Prod. | (5) Labor Prod. | (6) Labor Prod. |
|---|---|---|---|---|---|---|
| Residual$_{t-1}$ | -0.096*** | -0.095** | -0.085** | 0.055** | 0.060** | 0.051** |
| | (0.035) | (0.038) | (0.033) | (0.026) | (0.027) | (0.022) |
| Country-year FE | Y | Y | Y | Y | Y | Y |
| ECM lags | 2 | 3 | 4 | 2 | 3 | 4 |
| Lags of GMM Instruments | 2 | 2 | 2 | 2 | 2 | 2 |
| Num. of GMM Instruments | 141 | 175 | 207 | 141 | 175 | 207 |
| AR(2) test (p-value) | 0.942 | 0.598 | 0.817 | 0.944 | 0.936 | 0.979 |
| Hansen test (p-value) | 0.128 | 0.262 | 0.356 | 0.163 | 0.272 | 0.379 |
| Groups | 209 | 209 | 209 | 209 | 209 | 209 |
| Avg. Obs. per Group | 34.368 | 33.368 | 32.368 | 34.368 | 33.368 | 32.368 |

*** p<0.01, ** p<0.05, * p<0.1

*Notes*: Column titles indicate the dependent variable, specified as in equation (4). Standard errors robust to arbitrary forms of correlation within groups are in parentheses. All specifications were estimated using the system GMM procedure of Arellano and Bover (1995). 'ECM lags' indicate the number of lagged differences included in the specification of equation (4). 'Lags of GMM Instruments' indicate the number of lagged levels used as instruments for the transformed lagged dependent variable (and the number of lagged differences used as instruments for the equation in levels). All specifications used country-demeaned data.

Table 3: Unido: Tests for Long-Run Granger Causality

| | (1) Product Wage | (2) Labor Prod. | (3) Product Wage | (4) Product Wage | (5) Product Wage | (6) Labor Prod. | (7) Labor Prod. | (8) Labor Prod. |
|---|---|---|---|---|---|---|---|---|
| $\text{Residual}_{t-1}$ | -0.139*** | 0.218*** | -0.073*** | -0.078*** | -0.085*** | 0.144*** | 0.150*** | 0.169*** |
| | (0.036) | (0.045) | (0.027) | (0.028) | (0.028) | (0.042) | (0.044) | (0.050) |
| $\text{Residual}_{t-1} \times$ (developing country dummy) | | | -0.066 | -0.093 | -0.075 | 0.143* | 0.098 | 0.118 |
| | | | (0.051) | (0.059) | (0.058) | (0.085) | (0.076) | (0.090) |
| Country-year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| ECM lags | 2 | 2 | 1 | 2 | 3 | 1 | 2 | 3 |
| Num. of GMM Instruments | 11 | 11 | 10 | 13 | 16 | 10 | 13 | 16 |
| Lags of GMM Instruments | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 |
| AR(2) test (p-value) | 0.233 | 0.689 | 0.449 | 0.218 | 0.604 | 0.696 | 0.712 | 0.648 |
| Hansen test (p-value) | 0.424 | 0.369 | 0.097 | 0.416 | 0.383 | 0.642 | 0.379 | 0.631 |
| Groups | 410 | 410 | 410 | 410 | 410 | 410 | 410 | 410 |
| Avg. Obs. per Group | 16.871 | 16.866 | 17.871 | 16.871 | 15.871 | 17.866 | 16.866 | 15.866 |

*** p<0.01, ** p<0.05, * p<0.1

*Notes*: Column titles indicate the dependent variable, specified as in equation (4). Standard errors robust to arbitrary forms of correlation within groups are in parentheses. All specifications were estimated using the system GMM procedure of Arellano and Bover (1995). 'ECM lags' indicate the number of lagged differences included in the specification of equation (4). 'Lags of GMM Instruments' indicate the number of lagged levels used as instruments for the transformed lagged dependent variable (and the number of lagged differences used as instruments for the equation in levels). The specifications in this table used a 'collapsed' instrument matrix, in order to contain instrument proliferation and improve the reliability of the Hansen overidentification test (Roodman, 2009). The coefficient estimates were insensitive to using a sparse instrument matrix. All specifications used country-demeaned data.

Table 4: Tests for Long-Run Granger Causality: Robustness Checks

| | | | | | Developed Countries | | Developing Countries | |
|---|---|---|---|---|---|---|---|---|
| | (1) Product Wage | (2) Labor Prod. | (3) Product Wage | (4) Labor Prod. | (5) Product Wage | (6) Labor Prod. | (7) Product Wage | (8) Labor Prod. |
| Residual$_{t-1}$ | -0.125*** | 0.044*** | -0.238*** | 0.131** | -0.043** | 0.206*** | -0.201** | 0.276*** |
| | (0.016) | (0.013) | (0.031) | (0.055) | (0.022) | (0.055) | (0.078) | (0.092) |
| Residual$_{t-1}\times$ (developing country dummy) | | | -0.087* | 0.242*** | | | | |
| | | | (0.046) | (0.082) | | | | |
| Dataset | EU-Klems | EU-Klems | Unido | Unido | Unido | Unido | Unido | Unido |
| Coint. Vector Estimator | DOLS | DOLS | DOLS | DOLS | FMOLS | FMOLS | FMOLS | FMOLS |
| Country-year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| ECM lags | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| Lags of GMM Instruments | 2 | 2 | 4 | 4 | 4 | 4 | 4 | 4 |
| Num. of GMM Instruments | 175 | 175 | 16 | 16 | 14 | 14 | 14 | 14 |
| AR(2) test (p-value) | 0.544 | 0.889 | 0.446 | 0.536 | 0.346 | 0.424 | 0.574 | 0.929 |
| Hansen test (p-value) | 0.310 | 0.264 | 0.457 | 0.567 | 0.143 | 0.696 | 0.410 | 0.727 |
| Groups | 209 | 209 | 411 | 411 | 238 | 238 | 194 | 194 |
| Avg. Obs. per Group | 33.368 | 33.368 | 15.869 | 15.864 | 15.055 | 15.055 | 15.072 | 15.062 |

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

*Notes*: Column titles indicate the dependent variable, specified as in equation (4). Standard errors robust to arbitrary forms of correlation within groups are in parentheses. All specifications were estimated using the system GMM procedure of Arellano and Bover (1995). 'ECM lags' indicate the number of lagged differences included in the specification of equation (4). 'Lags of GMM Instruments' indicate the number of lagged levels used as instruments for the transformed lagged dependent variable (and the number of lagged differences used as instruments for the equation in levels). The specifications in columns (3)-(8) used a 'collapsed' instrument matrix, in order to contain instrument proliferation and improve the reliability of the Hansen overidentification test (Roodman, 2009). The coefficient estimates were insensitive to using a sparse instrument matrix. DOLS indicates the use of pooled dynamic least squares for estimating the cointegration vector. The DOLS specifications included one forward and three lagged differences of the log of labor productivity. FMOLS indicates the use of group-mean fully modified ordinary least squares. All specifications used country-demeaned data.

# A Appendix

## A.1 Data Series

The series used in this paper were calculated for each industry and country as follows. Using the Eu-Klems dataset, the real product wage was calculated as the ratio of compensation of employees (COMP) to the price index of value added (VA_P), divided by total hours worked (H_EMPE); the wage share was calculated as the ratio of compensation of employees to value added; and labor productivity was calculated as the ratio of value added to the price index of value added, divided by total hours worked.

Using the Unido dataset, a series of real value added was inferred from the index of number of industrial production (51). The aim of this index is to reflect the evolution of the volume of value added. In most countries, however, the volume of output is used as a proxy (United Nations, 2008). The series of real value added was calculated as the product of value added at current prices (20) and the index number of industrial production (51), divided by 100; a price deflator was calculated as the ratio of value added at current prices and the calculated real value added series; the real product wage was then calculated as the ratio of wages and salaries (5) to the price deflator, divided by employment (4); the wage share was calculated as the ratio of wages and salaries to value added at current prices; labor productivity was calculated as the ratio of real value added to employment.

As described in section 2, only series with at least 15 consecutive observations were included. Regarding the classification of countries by level of development, I adopted the following criterion: if a country achieved a PPP-adjusted real per capita income of at least half of the level of the United States for most of the sample period (computed from the Penn World Tables 8.0), the country was classified as developed. I chose this criterion since a few countries can be said to have transitioned into developed status in recent decades, such as the East Asian economies. The results were qualitatively insensitive to reasonable variations on this criterion.

The countries included in the Eu-Klems dataset are Austria, Australia, Belgium, Denmark, Spain, Finland, France, Germany, Greece, Ireland, Italy, Japan, South Korea, Luxembourg, Netherlands, Portugal, Sweden, United Kingdom, and the United States. The countries included in the Unido dataset, and classified as *developed* are Canada, Hong Kong, Finland, Ireland, Israel, Italy, Japan, Norway, Singapore, Spain, Sweden, United Kingdom, and the United States. The countries included in the Unido dataset, and classified as *developing* are Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, Egypt, Ethiopia, India, Iran , Jordan, Malawi, Mexico, South Korea, Sri Lanka, Turkey, and Uruguay.

### A.2 Methods for Estimating the Cointegration Vector

The estimators of the cointegration vector (equation 3) in this paper attempt to control for innovations in labor productivity which would otherwise be absorbed into the error term, causing the identification assumption to fail. To illustrate the problem, consider the following representation of the cointegration relationship between the product wage and labor productivity (for more details, see Pedroni, 2001):

$$\begin{aligned} ln(PW)_{j,t} &= a_{0j} + \beta_j ln(LP)_{j,t} + \epsilon_{j,t} \\ \Delta ln(LP)_{j,t} &= \mu_{j,t} \end{aligned} \tag{5}$$

where the first equation is the panel-specific, long-run relation between the two variables as expressed in (3). The second equation draws on the notion that labor productivity has a unit root, assuming that it follows an autoregressive process whose innovations are given by the disturbance $\mu_{j,t}$.

The problem is that innovations to labor productivity ($\mu_{j,t}$) are correlated with innovations to the product wage ($\epsilon_{j,t}$) — because of common omitted covariates, for example —, causing the identification assumption behind the estimation of (3) by OLS to fail.

#### A.2.1 Group-Mean Fully Modified OLS

To see how the group-mean FMOLS method addresses the problem, define the composite error term $\xi_{j,t} = (\epsilon_{j,t}, \mu_{j,t})$ as a vector comprised of the two innovation terms. Then, for each group in the dataset, it is possible to define a long-run covariance matrix as

$$\Omega_j = \lim_{T \to +\infty} E\left[\frac{1}{T}\left(\sum_{t=1}^{T} \xi_{j,t}\right)\left(\sum_{t=1}^{T} \xi_{j,t}\right)\right] \tag{6}$$

so that:

$$\Omega_j = \begin{bmatrix} \Omega_{11,j} & \Omega'_{21,j} \\ \Omega_{21,j} & \Omega_{22,j} \end{bmatrix} \tag{7}$$

where $\Omega_{11,j}$ is the long-run variance of $\epsilon_{j,t}$, $\Omega_{22,j}$ is the long-run variance of $\mu_{j,t}$, and $\Omega_{21,j}$ is the (non-zero) long-run covariance between $\mu_{j,t}$ and $\epsilon_{j,t}$. The matrix $\Omega_j$ can be decomposed as $\Omega_j = \Omega_j^0 + \Gamma_j + \Gamma'_j$, where $\Omega_j^0$ is a matrix of contemporaneous covariances and $\Gamma_j$ is a weighted sum of autocovariances.

Given the notation above, the group-mean panel FMOLS estimator is given by

$$\begin{aligned} \hat{\beta}_{FMOLS} =& \frac{1}{N}\sum_{j=1}^{N}\left\{\sum_{t=1}^{T}\left[ln(LP)_{j,t} - \overline{ln(LP)}_j\right]^2\right\}^{-1} \\ & \times \left\{\sum_{t=1}^{T}\left[ln(LP)_{j,t} - \overline{ln(LP)}_j\right] ln(PW)^*_{j,t} - T\hat{\sigma}_j\right\} \end{aligned} \tag{8}$$

where

$$\begin{aligned} ln(PW)^*_{j,t} &= \left[ln(PW)_{j,t} - \overline{ln(PW)}_t\right] - \frac{\hat{\Omega}_{21,j}}{\hat{\Omega}_{22,j}}\delta ln(LP)_{j,t} \\ \hat{\sigma}_j &= \hat{\Gamma}_{21,j} + \hat{\Omega}^0_{21,j} - \frac{\hat{\Omega}_{21,j}}{\hat{\Omega}_{22,j}}(\hat{\Gamma}_{22,j} + \hat{\Omega}^0_{22,j}) \end{aligned} \tag{9}$$

The carets denote estimates of the underlying parameters. In order to obtain estimates of the long-run covariance matrix on the basis of which the other estimates magnitudes are obtained, the procedure requires the use of a non-parametric kernel estimator that is robust to heteroskedasticity and autocorrelation. For this paper, I used the Bartlett kernel with order chosen by the Newey-West procedure.

As we can see, the group-mean FMOLS estimator corrects for the correlation in the residuals across the two series; it does so by utilizing the estimated values of the covariance between $\mu_{j,t}$ and $\epsilon_{j,t}$. Notice that if this covariance is zero, the group-mean FMOLS estimator reduces to a standard group-mean OLS estimator.

The correction above can be extended to estimates of the standard error of $\beta_{GM-FMOLS}$, so that hypothesis testing regarding the cointegration vector can be conducted on the basis of individual t-statistics. Since such testing is not the aim of this paper, the reader is referred to Pedroni (2001) for a thorough discussion.

### A.2.2 Dynamic OLS

The dynamic ordinary least squares (DOLS) used in section 6 includes lags and leads of labor productivity to equation (3) to parametrically control for innovations in the labor productivity series which would otherwise be absorbed into the error term. The point estimates are obtained by running a regression of the form

$$ln(PW)_{j,t} = a_{0j} + \beta_j ln(LP)_{j,t} + \sum_{i=-q_1}^{q_2} c_{i,j} \Delta ln(LP)_{j,t+i} + v_{tj} \tag{10}$$

where $q_1$ and $q_2$ indicate the number of lagged and forward differences. The DOLS method used in this paper also differs form the group-mean FMOLS in that it pools information across the 'within' dimension of the panel, as can be inferred from the equation above.

Table A.1: Data Series and Manufacturing Industries

| **Unido** | | **Eu-Klems** | |
|---|---|---|---|
| **Primary Series** | **Code** | **Primary Series** | **Code** |
| Employment | 4 | Total hours worked by employees | H_EMPE |
| Wages and salaries (at current prices) | 5 | Gross value added at current basic prices | VA |
| Value added (at current prices) | 20 | Compensation of employees | COMP |
| Index numbers of industrial production | 51 | Gross value added, price indices | VA_P |
| **Industry** | **Code** | **Industry** | **Code** |
| Food and beverages | 15 | Food, Beverages, and Tobacco | 15t16 |
| Tobacco products | 16 | Textiles; Textile, Leather, and Footwear | 17t19 |
| Textiles | 17 | Wood and of Wood and Cork | 20 |
| Wearing apparel, fur | 18 | Pulp, Paper, Printing and Publishing | 21t22 |
| Leather, leather products and footwear | 19 | Chemical, Rubber, Plastics, and Fuel | 23t25 |
| Wood products (excl. furniture) | 20 | Other Non-Metallic Minerals | 26 |
| Paper and paper products | 21 | Basic Metals and Fabricated Metal | 27t28 |
| Printing and publishing | 22 | Machinery, n.e.c. | 29 |
| Coke, refined petroleum products, nuclear fuel | 23 | Electrical and Optical Equipment | 30t33 |
| Chemicals and chemical products | 24 | Transport Equipment | 34t35 |
| Rubber and plastics products | 25 | Manufacturing, n.e.c.; Recycling | 36t37 |
| Non-metallic mineral products | 26 | Total Manufacturing | D |
| Basic metals | 27 | | |
| Fabricated metal products | 28 | | |
| Machinery and equipment n.e.c. | 29 | | |
| Office, accounting and computing machinery | 30 | | |
| Electrical machinery and apparatus | 31 | | |
| Radio, television and communication equipment | 32 | | |
| Medical, precision and optical instruments | 33 | | |
| Motor vehicles, trailers, semi-trailers | 34 | | |
| Other transport equipment | 35 | | |
| Furniture; manufacturing n.e.c. | 36 | | |
| Recycling | 37 | | |
| Total manufacturing | D | | |

*Notes*: The codes are the standard 2-digit Isic classification codes. The Eu-Klems dataset uses a higher level of aggregation, as indicated. The series for total manufacturing (code D) were only used for plotting Figures A.1 and A.2.

Table A.2: EU-Klems: IPS and Meta-Analysis Panel Unit Root Tests

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **ln(product wage)** | | | | | | | | |
| $\bar{W}_t$ | 2.49 | 3.10 | 3.92 | 3.37 | -0.78 | -0.28 | 1.70 | 0.85 |
| p-value | 0.99 | 1 | 1 | 1 | 0.22 | 0.39 | 0.96 | 0.80 |
| **ln(labor productivity)** | | | | | | | | |
| $\bar{W}_t$ | 2.20 | 3.08 | 4.36 | 5.35 | -3.84 | -2.85 | 0.05 | 0.77 |
| p-value | 0.99 | 1 | 1 | 1 | 0 | 0 | 0.52 | 0.78 |
| **ln(wage share)** | | | | | | | | |
| $\bar{W}_t$ | -5.06 | -2.32 | 0.28 | 1.26 | -7.10 | -3.72 | -0.83 | 0.82 |
| p-value | 0 | 0.01 | 0.61 | 0.90 | 0 | 0 | 0.20 | 0.79 |
| **$\Delta$ln(product wage)** | | | | | | | | |
| $\bar{W}_t$ | -68.28 | -45.92 | -30.05 | -23.29 | -65.75 | -41.50 | -25.40 | -18.41 |
| p-value | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **$\Delta$ln(labor productivity)** | | | | | | | | |
| $\bar{W}_t$ | -72.24 | -48.09 | -33.52 | -25.16 | -68.55 | -42.77 | -28.40 | -19.72 |
| p-value | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Lags | bic | 1 | 2 | 3 | bic | 1 | 2 | 3 |
| Linear Trend | N | N | N | N | Y | Y | Y | Y |
| Country-Year Effects | Y | Y | Y | Y | Y | Y | Y | Y |
| Groups | 209 | 209 | 209 | 209 | 209 | 209 | 209 | 209 |
| Avg. Obs. per Group | 37.37 | 37.37 | 37.37 | 37.37 | 37.37 | 37.37 | 37.37 | 37.37 |
| **memo: Meta analysis test** | | | | | | | | |
| **ln(wage share)** | | | | | | | | |
| Z Statistic | -5.66 | | | | | | | |
| p-value | 0 | | | | | | | |
| L Statistic | -5.84 | | | | | | | |
| p-value | 0 | | | | | | | |
| Newey-West Lags | 3 | | | | | | | |

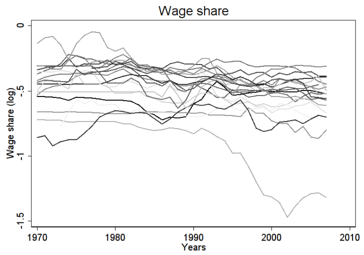
*Notes:* The null hypothesis is that all groups contain unit roots, while the alternative hypothesis is that at least one group is stationary. 'Lags' denote the number of lagged differences included in equation (2) to parametrically correct for autocorrelation, with 'bic' indicating a group-specific choice of lags based on the Schwartz information criterion. 'Linear Trend' indicates whether a linear trend was included in the specification of (2). Finally, 'Country-Year Effects' indicates the use of country-demeaned data, as described in section 3. The meta-analysis test is based on group-specific Phillips-Perron tests, whose p-values are combined according to the methodology of Choi (2001). It embodies the same null hypothesis of the IPS test.

Table A.3: Unido: IPS Panel Unit Root Tests

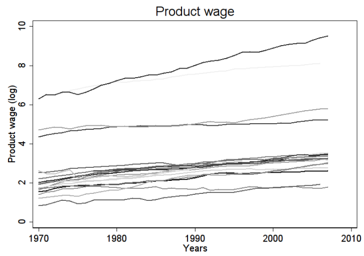
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **ln(product wage)** | | | | | | | | |
| $\bar{W}_t$ | 0.22 | 2.20 | 2.92 | 1.59 | -6.49 | -0.03 | 1.65 | -0.37 |
| p-value | 0.59 | 0.99 | 1 | 0.94 | 0 | 0.49 | 0.95 | 0.36 |
| **ln(labor productivity)** | | | | | | | | |
| $\bar{W}_t$ | -3.77 | -0.94 | 1.59 | 2.02 | -10.11 | -4.63 | -0.60 | -1.51 |
| p-value | 0 | 0.17 | 0.94 | 0.98 | 0 | 0 | 0.27 | 0.07 |
| **ln(wage share)** | | | | | | | | |
| $\bar{W}_t$ | -17.43 | -11.25 | -6.90 | -5.63 | -15.71 | -8.15 | -3.80 | -3.73 |
| p-value | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **$\Delta$ln(product wage)** | | | | | | | | |
| $\bar{W}_t$ | -64.57 | -35.10 | -19.03 | -13.36 | -56.87 | -26.38 | -11.84 | -6.37 |
| p-value | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **$\Delta$ln(labor productivity)** | | | | | | | | |
| $\bar{W}_t$ | -69.29 | -40.52 | -22.21 | -16.51 | -58.66 | -30.71 | -14.06 | -9.45 |
| p-value | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Lags | bic | 1 | 2 | 3 | bic | 1 | 2 | 3 |
| Linear Trend | N | N | N | N | Y | Y | Y | Y |
| Country-Year Effects | Y | Y | Y | Y | Y | Y | Y | Y |
| Groups | 412 | 412 | 412 | 412 | 412 | 412 | 412 | 412 |
| Avg. Obs. per Group | 19.92 | 19.92 | 19.92 | 19.92 | 19.92 | 19.92 | 19.92 | 19.92 |

*Notes:* The null hypothesis is that all groups contain unit roots, while the alternative hypothesis is that at least one group is stationary. 'Lags' denote the number of lagged differences included in equation (2) to parametrically correct for autocorrelation, with 'bic' indicating a group-specific choice of lags based on the Schwartz information criterion. 'Linear Trend' indicates whether a linear trend was included in the specification of (2). Finally, 'Country-Year Effects' indicates the use of country-demeaned data, as described in section 3.

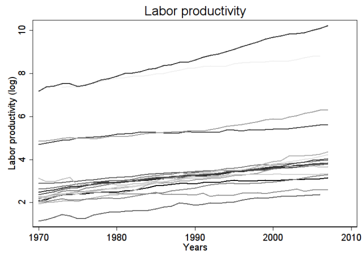
## Figure A.1: Klems



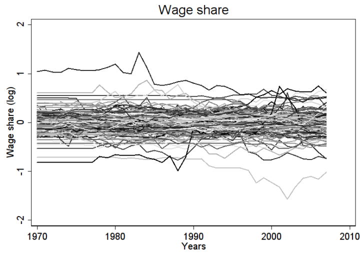
Wage share (all manufacturing)



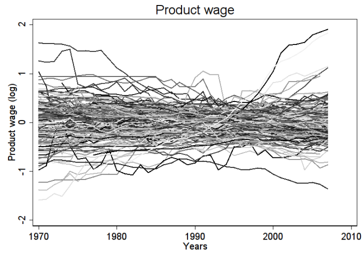
Real product wage (all manufacturing)



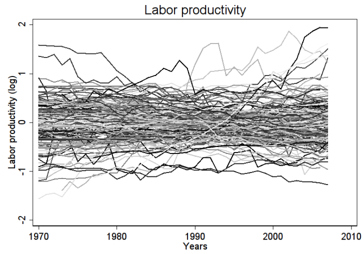
Labor prod. (all manufacturing)



Wage share (deviation from country mean)

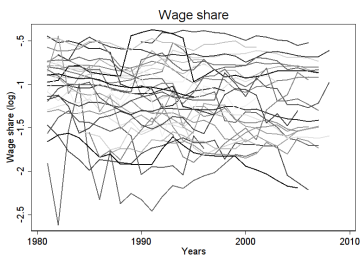


Real product wage (deviation from country mean)

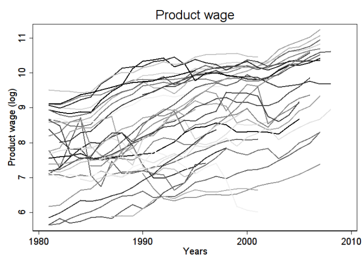


Labor productivity (deviation from country mean)

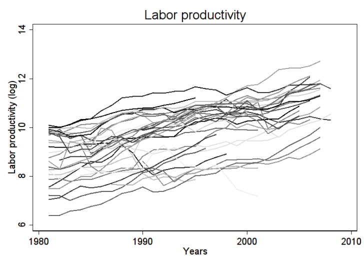
## Figure A.2: Unido



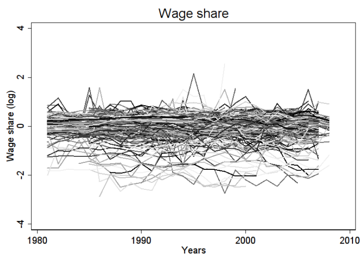
Wage share (all manufacturing)



Real product wage (all manufacturing)



Labor prod. (all manufacturing)



Wage share (deviation from country mean)

Real product wage (deviation from country mean)

Labor productivity (deviation from country mean)

*Notes:* The top panels in figures A.1 and A.2 show the wage share, the real product wage, and labor productivity in logarithmic scale for the aggregate manufacturing sector (industry code D). Each line refers to a country in the sample. The bottom panels show the same measures at the sub-industry level within manufacturing, expressed as deviations from the country-wide means for each year. Each line refer to an industry and country.