Wage inequality and its effects on labor productivity

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Abstract

Can be wage inequality harmful for productivity growth? We present a simple theoretical model according to which workers concern on wage inequality affects their labor productivity. So labor productivity decreases if wage differentials among workers is increasing. Then, after to test for Panel Granger Causality we estimate a dynamic panel data estimator (Arellano-Bond), and we find that wage inequality reduces country's labor productivity. Moreover, the variables given by GDP per capita, annual hours worked per worker and total population employed over total population are of significant effect over labor productivity. This in a sample of 34 OECD countries from 1995 through 2007.

Keywords: Employment; dynamic panel; labor market and labor productivity; workers' effort.

JEL Codes: C23; J23; J24; J31; J41.

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1 Introduction

In a perfectly competitive labor market, wage is determined by labor productivity, so wage dispersion reflects the marginal contribution to the revenue product of each worker. According to this theory, treating wage inequality as an independent variable in a model of productivity did not find large consensus, and economists have posed little attention on this potential relation. So, the link between wage and labor productivity is well anchored in economic theory. Higher labor productivity should increase the demand for workers and result in an increase in wages as long as the labor supply curve is not perfectly elastic. Some theoretical models suggest that the causality between the two may also work in the opposite direction. Akerlof (1982, [4]), for instance, argued that higher wages lead to greater effort from workers. More recently, Helpman et al. (2008, [21]) find that greater firm heterogeneity increases unemployment, wage inequality and income inequality, whereas greater worker heterogeneity has an ambiguous effects on wage inequality. However, the literature is sparse regarding studies showing the potential impact of wage inequality on labor productivity.

The existing contributions (mainly theoretical and micro-level empirical studies) do not provide a unilateral answer to this issue: Hibbs and Locking (2000 [22]), for example, do not find empirical support that wage levelling within workplaces and industries may enhance productivity, although reduction of inter-industry wage differentials contributes positively to aggregate output and productivity growth. Another strand of literature assumes that managers choose the optimal 'wage structure" with regard to fairness and cohesiveness, to maximise productivity (Akerlov and Yellen, 1988 [7], Lazear 1989 [26], and Levine 1992 [29]), opening to the possibility that wage inequality may affect someway each workers effort. In this vein, Bandiera et al. (2007, [10]) found that the introduction of managerial performance pay raises both the mean and dispersion of worker productivity, and show that managers target their effort towards high ability workers, and the least able workers are less likely to be selected into employment.

So the question is: can be wage inequality a stimulus to work more productively? From one hand, at firm level, Becker (1964, [11]) suggests that greater wage inequality might reduce the incentives to invest in vocational education with possible detrimental effects on productivity growth. Akerlof and Yellen (1988 [7]), Akerlof (1984 [5]) and Cohn et al. (2010, [16]) say that agents who fell under-rewarded tend to supply corresponding fewer effort, and the evidence appears strongest with the provision of services by workers who are led to believe they are underpaid. Rehn and Meidner (1952), Agell and Lommerud, 1993 [1], and Moene and Wallerstein, 1997 [33], claim that squeezing pay differentials between industries and plants could enhance productive efficiency by speeding up the movement of labor and capital from low to highly productive activities. Levine (1991 [28]) states that "narrowing wage dispersion can increase cohesiveness, and in participatory firms cohesiveness can increase productivity".

At aggregate, country level, Medner and Rehn (1952, [32]) argued that wage solidarity - equal pay for equal works regardless the characteristic of the firm - could raise productivity. Their basic argument was that high wages in low productivity firms or sectors could force them to close, transferring resources to high productivity firms or sectors. Levine (1991 [28]) claims that raising low-end wages can increase national output, as long as the increase in labor costs balances the increase in productivity from higher cohesiveness. At the margin, an increase in low-end wages leaves profit unchanged, but raises productivity, output, and welfare for the low end of the wage distribution.

On the other hand, however, Caroli and Van Reenen (2001 [14]) find that an higher ratio of skilled to unskilled pay is negatively associated with organizational changes, which in turn, have a positive association with productivity growth. Agell and Lommerud (1997 [2]) and Agell, (1999 [3]), claim that compressing wage distribution may reduce the number of low skilled jobs, acting as a signal to workers to invest in human capital, or face unemployment. In this view, the introduction of a minimum wage may lead to a greater human capital accumulation and productivity. Moene and Wallerstein (1997 [33]) provide a theoretical discussion according to which wage compression can raise profitability, increase the rate of new firm entry, and lead to a more modern capital stock (seminal paper by Salter, 1966 [35]).

In this paper we test whether wage dispersion may affect labor productivity. To the best of our knowledge, there are not empirical studies which test this hypothesis using country-level data. We empirically test for a panel of OECD countries whether the Gini index of wage inequality (as provided by ILO) has affected or not the average level of labor productivity, for the years 1995 through 2007.

In the remainder sections, firstly in section 2 we present a simple theoretical model to explain how changes in wage inequality affect labor productivity. Then, section 3 introduces the econometric model, explaining data sources and the descriptive statistics. Subsection 3.1 presents the econometric results. Finally section 4 concludes.

2 The model

It is important to stress that the main purpose of the next model is to illustrate the effect of wage inequality on labor productivity, and then to guide our empirical analysis. To this purpose we assume that wages are determined exogenously to the model, that effort entails disutility, and that firms maximize profits according to an optimal demand of the number of workers supplying different levels of effort depending on wage inequality. Workers are identical in terms of ability, and this is common knowledge.

Let us assume that N is total employment, for simplicity normalized to 1, and that there is no unemployment. Workers are indentical and wages are determined outside the model (i.e. through bargaining between representatives of employers and employees), so both firms and workers consider them as given.

Consider that worker j is paid a wage w_j which is greater than worker i's wage, $w_j < w_i$, and wages are positive numbers. That is, i-worker is underpaid while j-worker is high-paid.

Only i's worker effort is affected by wage inequality, which is measured by how much his/her salary is far from j's wage. Thus, changes in i's wage or in j's wage are equivalent to changes in wage inequality, which we assume have an effect on labor productivity. This is true for both types of workers, and since wage is determined exogenously, variations in one type of worker's wage means - taking constant the other worker's salary - a variation in wage inequality.

Let us enter now into the merits of the model. Let us assume that the effort function of the representative worker, let us say k, is:

$$e_k = \begin{cases} aw_k & \text{if } w_k \geq w_{-k} \\ aw_k + b(w_k - w_{-k}) & \text{if } w_k < w_{-k} \end{cases} \tag{1}$$

Equation 1 basically indicates that a worker k is susceptible to wage inequality only if his own wage is lower than the other's $(-k)$. In our model we assume that there exists two types of workers, i and j, and that j is overpaid with respect to i. This means that the equations for the effort those two individuals will supply are:

$$
\begin{aligned}
e_i &= aw_i + b(w_i - w_j) && (2)\\
e_j &= aw_j && (3)
\end{aligned}
$$

with $a > 0$, $b > 0$, $e_j \geq e_i > 1$ and, by hypothesis, $w_j \geq w_i$. Equations (2) and (3) imply that if the wage is the same between the two types of workers, they supply the same level of effort. Otherwise, the worker i supplies a lower level of effort because it is affected by wage inequality.

The unique and necessary input for production is represented by $E(e_i, e_j)$ and it is a linear combination of individual efforts (equations (2) and (3)) of the i^{th} and j^{th} workers. We assume here that the contribution to the total imputs necessary for production is different between low-paid and high-paid workers. This difference is not only due to differences in effort supplied, but high-paid workers contribute more to the E function than those underpaid or low-paid workers. One may wonder why identical workers may have different salaries. Here we justify this fact by assuming that high-paid people work for more technological and productive firms, so the effort of those people produces more input than people employed in firms which use a lower level of technology. This difference is embodied in the coefficient θ, which is assumed to be greater than one for high-paid workers (which therefore have an higher marginal productivity per unit of effort), and equal to one for the low-paid workers.

The equation determining the total input necessary for production is therefore determined by the following equation:

$$
E = qe_i + (1 - q)\theta e_j \tag{4}
$$

where $q \in [0, 1]$ represents the fraction of i-workers who are employed over the entire worker population, and $\theta > 1$ - as already anticipated - represents the greater contribution of high-paid workers to E due to the fact that they are employed in a more technological firm.

In this economy, the country's labor productivity funcion is $Y/N = Y(E)$. This function $Y(E)$ is increasing (the marginal product of E is positive) and concave (diminishing returns exist in E). Labor productivity is basically total output produced (Y) over the total population (N). Since total population is normalized to one, labor productivity is equal to total output. The equation representing both output and labor productivity is:

$$Y = E^{\alpha} \tag{5}$$

where $\alpha \in (0, 1)$. As we mentioned, in this model unemployment is set to zero while profit maximising firms actually choose the combination of i and j workers to hire, that is to say q.

Total profits are given by equation (6):

$$\Pi = pY - qw_i - (1-q)w_j \tag{6}$$

where $p > 0$ represents the given price vector or output price that clears markets. Hence, given the price p, the problem involves choosing the optimal $q \in [0, 1]$ (share of i-workers to hire) for the maximization program, $\max_q \Pi(q)$. Substituting equation (5) into equation (6) we get the expression for profits expressed in terms of efforts, wages and the fraction of i-workers

$$\Pi = p(qe_i + (1-q)\theta e_j)^{\alpha} - qw_i - (1-q)w_j, \tag{7}$$

which must be differentiated with respect to q to find the optimum.
So, taking the first derivative of equation (7) with respect to q and rearranging, we get:

$$\frac{\partial \Pi}{\partial q} = 0 \Rightarrow \alpha p \cdot E^{\alpha-1}(e_i - \theta e_j) = w_i - w_j \tag{8}$$

which basically says that marginal revenues (left hand side of the equation) must be equal to marginal costs (right hand side). It follows, after the necessary substitutions and rearrangements,

$$q^* = \frac{1}{\eta} \cdot \left[\left(\frac{w_i - w_j}{\alpha p \eta} \right)^{\frac{1}{\alpha - 1}} - \theta a w_j \right] \tag{9}$$

where

$$\eta \equiv a(w_i - \theta w_j) + b(w_i - w_j)$$

that is, the share of i-workers to hire depends on wage inequality $(w_i - w_j)$ which affects the effort functions e_i and e_j. Notice that η represents the marginal variation of E (the necessary input for production) with respect to variations of q, that is to say, $\eta = \partial E / \partial q$. This means that increasing the share of low paid workers in the population, the necessary input for production will decrease, if wages are kept constant.

In order q^* be nonnegative, the following condition must hold:

$$\left[\left(\frac{w_i - w_j}{\alpha p \eta} \right)^{\frac{1}{\alpha - 1}} - \theta a w_j \right] < 0, \tag{10}$$

Equation 10 can be rewritten as

$$\underbrace{\left(\frac{\alpha p a + \alpha p b - (\theta a w_j)^{1-\alpha}}{\theta \alpha p a + \alpha p b - (\theta a w_j)^{1-\alpha}} \right)}_{\Omega} w_i - w_j > 0 \tag{11}$$

which is satisfied if and only if the following two conditions hold:

$$\theta a w_j \quad > \quad \big(\alpha p(\theta a + b)\big)^{\frac{1}{1-\alpha}} \tag{12}$$

$$\Omega \quad > \quad \frac{w_j}{w_i}. \tag{13}$$

Equation (12) says that q* is nonnegative if the contribution of the single j-worker to the production of the necessary input E ($\theta a w_j$) is greater than a certain parameter that involves the price of the product, p, the output elasticity, α and the constants terms (a and b) of the worker's effort functions. Equation (13) basically says that the ratio Ω must be greater than the ratio of the wages earned by the j and the i-workers. This happens when θ is sufficiently large.
Another characteristic of q^* is that it is increasing in w_j, so $\partial q^*/\partial w_j > 0$, and this indicates that - given the salary of the low-paid worker, the higher is wage inequality, the greater is the demand for low-paid workers.

Now, country's labor productivity is given by:

$$\frac{Y}{N} = Y = \quad (q^* e_i + (1-q^*)\theta e_j)^{\alpha}. \tag{14}$$

Hence, it is crucial here to check what happens to the country's labor productivity when w_j (i.e. the level of wage inequality) increases.

Proposition 1. *As wage inequality increases, the effect on country's labor productivity is negative.*

To prove the above statement, we simply must find that $\frac{\partial Y}{\partial w_j} < 0$. Note that, substituting equation (9) into country's labor productivity and rearranging, we get:

$$Y^* = \left[\left(\frac{w_i - w_j}{\alpha p [a(w_i - \theta w_j) + b(w_i - w_j)]} \right)^{\frac{1}{\alpha - 1}} \right]^{\alpha} = \left(\frac{w_i - w_j}{\alpha p \eta} \right)^{\frac{\alpha}{\alpha - 1}}, \tag{15}$$

and then, the derivative of labor productivity with respect to inequality[1] is given by:

[1]Since the determination of the levels of wages is assumed to be exogenous, taking as given the salary of the low paid workers, an increase in wage inequality is equivalent to an increase in the salary of the high paid workers.

$$\frac{\partial Y}{\partial w_j} = \frac{a\alpha w_i(\theta-1)\left(\frac{w_i-w_j}{\alpha p\eta}\right)^{\frac{\alpha}{\alpha-1}}}{(w_i-w_j)(\alpha-1)\eta} < 0. \tag{16}$$

Basically, this result (16) is negative because: $\eta < 0$, $(\alpha-1) < 0$ and $w_i - w_j < 0$. Equation 16 basically indicates that the greater the inequality, the greater the negative impact on country's labor productivity. Otherwise, when wage differentials are zero ($w_i = w_j$), labor productivity is not affected.

In the next section, we conduct the empirical study to validate the result stated here.

3 Empirical evidence and econometric model

There can be several factors that may influence labor productivity. In the previous section, we already stressed the fact that one might be wage inequality (see **Proposition 1**), so the first variable that we will consider is this one.

Then, it must be realized that labor productivity may be affected by other variables, too. Then, we consider GDP per capita, the level of employment and the total of hours worked as determinants of labor productivity.

Relatedly, the level of employment can be also responsibile for variations in productivity levels. Gust and Marquez (2002, [20]) identify a negative relationship between changes in the employment rate and productivity growth. The authors attribute this effect to the fact that a rise in the employment rate is accompanied by the arrival of lower skilled workers in the workforce, which crimps productivity. Another reason could be that periods of high unemployment increase workers' productivity for the stronger incentive to the latter to keep their job, since outside opportunities to find a new occupation are low. Oulton (1995, [34]) and Eltis and Higham (1995 [18]), in the analysis of UK productivity since 1980, find that harsh recessions (of course associated to high levels of unemployment) in the early 80's may have caused inefficient business to exit (rising average level of productivity) and, at firm level, the least productive workers may be made redundant first, once again rising average productivity.

However, note that GDP per capita can affect productivity because it may enhance investments both in human and physical capital. Therefore, some problem of endogeneity is remedied by using instrumental variables. For instance, GDP per capita is an instrument used its first lagged value). Remember that the estimators of a dynamic panel data uses internal instruments, and they are defined as instruments based on previous realizations of the explanatory variables, and this is in order to consider better the potential joint endogeneity of the regressors.

Given the above considerations, now let us descrive our database and the especification of the econometric model. Data for labor productivity (which is expressed per hour worked), GDP per capita (1990 US $) and total percapita hours worked are from the Conference Board and Groningen Growth and Development Centre (Total Economy Database, september 2008). Data for employment (measured by total population employed over total population, 15+) is from World Bank. Data on wage inequality (measured by Gini index of wage inequality) is from the International Labor Organization (ILO, Global Wage database, 2010).

Using these data we study empirically the effect of wage inequality on labor productivity. Denoting by:

1. LP - labor productivity per hour worked in 1990 US$,
2. $Gini$ - Gini index of wage inequality,
3. GDP - GDP per capita in 1990 US$,
4. H - annual hours worked per worker,
5. E - total population employed over total population.

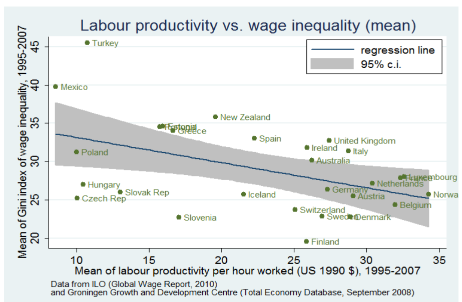
A first look at our data, we explain the main statistics. Table 1 shows the main summary statistics of the variables we have used (thus, we get the median, standard deviation and minimum and maximum data, this for each of our above enumerated variables.)

Table 1: Summary statistics of the main variables

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
$Year$	-	-	1995	2007	442
LP	22.21	8.08	7.44	37.65	429
$Gini$	29.79	6.11	18.9	46	254
GDP	17,617	6,538	5,623	39,976	442
H	1,778	216	1,398	2,497	429
E	55.26	6.89	38.9	75.10	442

In our panel of 35 OECD countries, plotting the mean of wage inequality (represented by Gini index) over labor productivity, we observe a tendency to have higher productivities associated to lower wage inequalities, and this can be seen through time as well as through countries:

Figure 1. Relations between Wage Inequality and Labor Productivity.



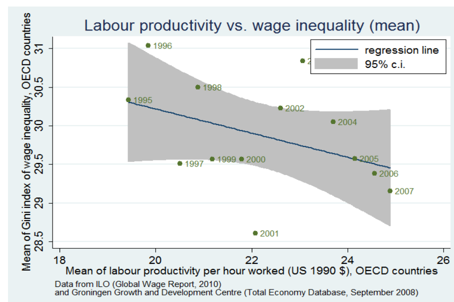


Figure 1 [which is a plot of the theoretical result given by Proposition1 (equation (13-14))] on the left hand side, shows that a cross country regression of labour productivity over Gini index of wage inequality would predit a negative coefficient, indicating that a positive variation of wage inequality is associated to a negative variation in labor productivity. The dots in the graph indicates each country's position in the inequality - productivity relationhip. On the right hand side of the figure, we have a similar graphs, but this time the mean of wage inequality and labor productivity has been calculated over years, and not countries. From 1995 to 2007 we assist at an average decrease in wage inequality and a increase in labor productivity, and this is more evident for the years 2004 through 2007.

3.1 Causality

To address the question of whether is wage inequality that causes productivity or viceversa, we use a recently developed methodology for assessing non - causal homogeneity in a panel Granger framework based on the procedure developed by Dumitrescu and Hurlin (2012, [17]).

Causality tests with panel data[2] are performed - similarly to what happens in time-series data - by regressing k lagged values of the dependent variable y for *k=1,...,K* and k lagged values of another independent variable x (for *k=1,...,K*). If one or more of the lagged values of x is significant, we are able to reject the null hypothesis that x does not Granger cause y. In panel frameworks, however, employing the conventional Granger tests raises two important inferential issues, both dealing with the potential heterogeneity of the individual cross-section units. The first (and the easiest to address) is the possibility of distinctive interceipts across individual cross-section units, but this problem may be easily solved by means of fixed effect models. The second and more problematic issue concerns the possibile differential causal relations across units. In more practical terms, the fact that causality goes in one determined direction for one country does not mean that this direction must be the same (with equal coefficients) for all countries in the sample, as older tests of causality for panel data assumed (Holtz-Eaking et al., 1988 [23]).

Dumitrescu and Hurlin (2012, [17]) propose a simple test of homogeneous non causality, which, under the null, assumes that there is no causal relationship for any of the units of the panel and considers a heterogeneous panel data model with fixed coefficients (in time). They also specify the alternative hypothesis as heterogeneous causality, which assumes that there is a causal relationship from x to y for a subgroup of individuals only (possibly all). The statistics they propose is based on averaging standard individual Wald statistics of Granger non causality tests (as used in first generation panel unit root tests), which - under the assumption of cross-section independence - is shown to converge sequentially in distribution to a standard normal variate when the time dimension T tends to infinity, followed by the individual dimension N. In case of T and N fixed, they also provide critical values generated by simulations of the semi-asymptotic distribution of the average statistics.

Let us consider x and y two stationary variables. For each individual $i = 1, ..., N$ at time $t = 1, ..., T$, they consider the following linear model:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \epsilon_{i,t} \tag{17}$$

with the number of lags is denoted by $K \in \mathbb{N}$ and $\beta_i = (\beta_i^{(1)}, ..., \beta_i^{(K)})'$. For simplicity, the individual effects α_i are supposed to be fixed in the time dimension, and the initial conditions $(y_{i,-K}, ..., y_{i,0})$ and $(x_{i,-K}, ..., x_{i,0})$ of both individual processes $y_{i,t}$ and $x_{i,t}$ are given and observable. The lag orders K are

[2] This procedure applies under the hypothesis that all series to be tested do not contain a unit root.

assumed to be identical for all cross-section units, but they allow the autoregressive parameters $\gamma_i^{(k)}$ and the regression coefficient slopes $\beta_i^{(k)}$ to differ across groups (but are kept constant through time).

Under the following assumptions: (1) normality and identically distributed across groups of individual residuals and (2) both individual variables $x_i = (x_{i,1}, ..., x_{i,T})'$ and $y_i = (y_{i,1}, ..., y_{i,T})'$ are covariance stationary with finite variance, the average statistics $W_{N,T}$ associated with the null of homogeneous non causality hypothesis is defined as

$$W_{N,T} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T} \tag{18}$$

and asymptotically, for T first and then N tending to infinity, the following distribution approaches to a standard normal.

$$Z_{N,T} = \sqrt{\frac{N}{2K}}(W_{N,T} - K) \xrightarrow{d} N(0,1) \tag{19}$$

Equation 18 represents a simple average of the individual Wald statistics $W_{i,T}$ for the i^{th} cross-section unit corresponding to the individual test $H_0 : \beta_i = 0$. This individual Wald statistics $W_{i,T}$ follows a χ^2 distribution with K degrees of freedom as $T \to \infty$. Equation 19 follows from the assumption of independent distribution across grous of individual residuals. This allows the individual $W_{i,T}$ statistics for $i = 1, ..., N$ be identically and independently distributed with finite second order moments as $T \to \infty$, and therefore, by Lindber-Levy central limit theorem under the homogeneous non causality hypothesis, the average statistic $W_{N,T}$ sequentially converges in distribution.

For large N and T samples, if the realization of the standardized statistic $Z_{N,T}$ is superior to the corresponding normal critical value for a given level of risk, the homogeneous non causality hypothesis is rejected.

In practical terms, however, when we deal with real data we always face fixed T and fixed N distributions. Dumitrescu and Hurlin (2012, [17]) computed the exact empirical critical values for the corresponding sizes N and T via stochastic simulations. These critical values must be compared with the mean Wald statistic $W_{N,T}$ defined in equation 18, and if the value of $W_{N,T}$ results to be greater than the simulated critical value, the null of homogeneous causality is rejected. Here I do not report the table of the simulated critical values since the reader can easily refer to their original publication.

In the following, we discuss our procedure to determine the direction of causality.

$H0_1$: Wage differentials does not cause variations in labor productivity

We then proceeded to the estimation of the single Wald statistics for each unit in our sample. For each of our 34 OECD countries, we estimated two models, the first (unrestricted) in which two lagged values of the dependent variable "labor productivity per hour worked" and two lagged values of gini index of wage inequality are regressed over the actual value of labor productivity per hour worked and we stored the sum of squared residuals (SSR_u) of the regression. We then estimated another model, a restricted one, in which the β_i coefficients attached to the lagged values of gini index of wage inequality are bounded to zero (or - alternatively - excluded from the model) and, again, we stored the sum of squared residuals (SSR_r) of the regression. The individual Wald statistics were computed according to the following formula:

$$W_{i,T} = \frac{(SSR_r - SSR_u)/K}{SSR_u/(T - 2K - 1)} \tag{20}$$

and then they was averaged trough all the units availabe [3] The statistics $W_{N,T}$, computed according equation 18, displays a value of 4.22, which is greater than the simulated critical value of 2.68 (this critical value assumes 15 units and 10 observation for each unit), and then $H0_1$ is rejected. This means that the index of wage inequality causes variations in labor productivity for at least one (and possibily more) country in the sample.

$H0_2$: labor productivity differentials does not cause variations in wage differentials

Similarly, we proceeded to the estimation of the single Wald statistics for each unit in our sample. For each of our 34 OECD countries, we estimated two models, the first (unrestricted) in which two lagged values of the dependent variable "gini index of wage inequality" and two lagged values of labor productivity per hour worked are regressed over the actual value of gini index of wage inequality and we stored the sum of squared residuals (SSR_u) of the regression. We then estimated another model, a restricted one, in which the β_i coefficients attached to the lagged values of labor productivity are bounded to zero (or - alternatively - excluded from the model) and, again, we stored the sum of squared residuals (SSR_r) of the regression. The individual Wald statistics were computed according to equation 20, and then they was averaged trough all

[3] It was not possible to use all the countries in the sample because of missing observations, and only 17 (with an average of 9 observations per unit) were employed in this test.

the units availabe [4] The statistics $W_{N,T}$, computed according equation 18, displays a value of 5.53, which is greater than the simulated critical value of 2.68 (this critical value assumes 15 units and 10 observation for each unit), and then $H0_2$ is rejected. This means that also labor productivity causes variations in the distribution of wages for at least one (and possibily more) country in the sample.

3.2 The econometric specification and results

Here we use Arellano-Bond (1991) estimator to account for the role of wage inequality on the level of productivity. This procedure is appropriate - by estimating the model in first differences - to account for individual, time invariant effects, and it is based on the method known as Generalized Method of Moments (GMM) in first differences. First differences are calculated from the equation for removing observed and permanent individual heterogeneity. Subsequently, lagged levels of the series are used as instruments for the endogenous variables in first differences. That is, the estimators of dynamic panel data use internal instruments, defined as instruments based on previous realizations of the explanatory variables to consider better the potential joint endogeneity of the regressors. In sum, Arellano-Bond GMM estimator introduces dynamic effects into the standard model of panel data by including a lag of the dependent variable on the right hand side, while correcting the endogeneity problem, fixed effects, short time span and possible autocorrelation.

The equation we estimate is then:

$$
\begin{aligned}
\Delta LP_{i,t} &= \beta_0 + \beta_1 \Delta LP_{i,t-1} + \beta_2 \Delta GDP_{i,t} + \beta_3 \Delta GDP_{i,t-1} \\
&+ \beta_4 \Delta H_{i,t} + \beta_5 \Delta H_{i,t-1} + \beta_6 \Delta E_{i,t} \\
&+ \beta_7 \Delta E_{i,t-1} + \beta_8 \Delta Gini_{i,t} + \Delta u_{i,t} \qquad (21)
\end{aligned}
$$

$$\Delta u_{i,t} = \Delta v_{i,t} + \Delta e_{i,t}. \qquad (22)$$

where the subscripts $i = 1, ..., N$; $t = (1, ..., T)$ indicate the number of observations and the period of time,

[4] It was not possible to use all the countries in the sample because of missing observations, and only 17 (with an average of 7.29 observations per unit) were employed in this test.

and $u_{i,t}$ is the random error of the model containing fixed effects (like country-specific effects) decomposed into unobservable effects, $\Delta v_{i,t}$, and omitted observable effects, $\Delta e_{i,t}$. By transforming the regressors by first differencing the fixed effect is removed, because it does not vary with time.

The next table 2 shows the output results of the econometric model (equation (17)).

Table 2: Regression coefficients

	(1)
	lp_hours
$\Delta LP_{i,t-1}$	0.775***
	(11.54)
$\Delta GDP_{i,t}$	0.00112***
	(10.96)
$\Delta GDP_{i,t-1}$	-0.000926***
	(-7.03)
$\Delta H_{i,t}$	-0.0113***
	(-10.20)
$\Delta H_{i,t-1}$	0.00581***
	(4.67)
$\Delta E_{i,t}$	-0.319***
	(-7.95)
$\Delta E_{i,t-1}$	0.216***
	(5.14)
$\Delta Gini_{i,t}$	-0.0305*
	(-1.97)
N	172

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Estimations are corrected by heteroskedasticity through the White method.

Importantly, the results indicate::

1. While controling for endogeneity, all the coefficients are statistically significant, and the resulting standard errors are consistent with panel-specific autocorrelation and heteroskedasticity in one-step estimation.

2. Wage inequality measured by Gini index has a negative coefficient indicating that it has a negative effect "ceteris paribus" on country's labor productivity. That is, more wage inequality implies less

labor productivity. This result indicates that, for the period studied, inequality affects labor productivity. Hence, the economic policy says that in order to increase productivity, inequality should decrease.

3. $\Delta GDP_{i,t}$ is significant at 5% level, indicating that income increases labor productivity as it allows to save and invest more in new technologies which in turn allow workers to work faster and more efficiently. Differenced lagged GDP is however negative, indicating a decreasing rate of productivity growth (although positive).

4. Percapita hours worked have a negative impact on labor productivity, as it is highlighted by the coefficient attached to $\Delta H_{i,t}$ in table 2. This effect is probably due to the fact that the level of attention and performance decreases as the individual gets tired and tired. This variable lagged one period, however, shows that there exists a sort of "learning process" through wich the same worker gets used to work hard, increasing in the long period his level of productivity. An alternative interpretation is simply that, percapita hours' effect is not inmediate on labor productivity (although lag is positive), because as in any process, when you start a job initially invested time tends to reduce labor productivity (and that in the beginning still not harvested results), however, after some time the impact becomes positive (when these working hours begin to yield results).

5. Employment ratio has a negative effect on labor productivity because high unemployment makes outside opportunities of work less frequent and therefore workers who have a job tend to work more in order to lower the probability to get fired. The lagged differenced employment ratio has however a positive effect, indicating that although employment ratio decreases labour productivity, it does at an increasing rate.

Hence, we have obtained a consistent estimator indicating the major effects on labor productivity during the period 1995-2007 for the OECD countries.

However, because of the above Panel Granger Causality test one may argue that labor productivity affects wage inequality. That is, according to the standard neoclassical view the wage structured (i.e. the price of a unit of labor of a given quality), by a competitive market, is caused by productivity (rather than vice versa as we pointed out). Next Table 3 presents the empirical results on this relationship (being wage inequality the dependent variable, on the LHS of equation (17)). It should be noticed that any of the coefficients is not statistically significant.

Table 3: Regression coefficients

	(1) gini_wage
L.gini_wage	0.131
	(1.41)
cgdp1990	-0.000988
	(-1.27)
L.cgdp1990	0.000658
	(0.95)
chours_worked	0.00197
	(0.22)
L.chours_worked	-0.000261
	(-0.05)
empl_to_pop_ratio_15	-0.166
	(-0.64)
L.empl_to_pop_ratio_15	-0.164
	(-0.69)
lp_hours	0.581
	(1.63)
N	147

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In sum, our results are consistent with the view that, in order to maintain high productivity, OECD countries must be concerned with the social legitimacy of their wage distributions by reducing wage inequality. Hence we investigated how aspects of wage inequality affect country's labor productivity.

4 Concluding remarks

In this paper, with a simple theoretical model, we show that wage inequality has a negative effect on country's labor productivity. Then, we study an econometric model to analyze the effects of wage inequality on labor productivity for a panel of 35 OECD countries during 1995 through 2007. Using Arellano - Bond GMM estimator for dynamic panel data models, we found that wage inequality (expressed by Gini index) do affects negatively labor productivity in this sample.

The reason we believe is driving this result is due to the fact that wage inequality may induce workers who believe their wage is unfair to supply less effort. This is consistent with the view of Akerlof and Yellen (1986 [6]), Akerlof (1984, [5]) and Cohn, Fehr and Gotte (2010, [16]) which find that pay raised up to the fair wage lead to higher work effort. When wage inequality is high, it is also more likely that people who receive a low wage believe it is unfair, that's why an increase in wage inequality (i.e. a decrease of low wages or an increase in high wages) are associated to a reduction of low paid workers' effort. According to Cohn et al., pay raises above the fair wage are not associated to corresponding increases in effort, and the reduction of wage inequality in this sample of OECD countries must be one reason why the global level of productivity has increased. As our model suggests, even though an increment in pay for increasing effort proportionally, if the production function is concave, that is to say, has decreasing returns to scale, labor productivity intended as output per unit of effort (hour, if effort = hours) may decline too.

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