Industry concentration and wage inequality: a directed technical change approach*

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Abstract

Despite several theoretical approaches linking rising market power to more income inequality, a theoretical-based empirical quantification of this relationship has not been made. We devised a directed technical change model and characterize this relationship. To test our model, we calculate concentration indexes and relate them with skill-premium using industry data per country for 40 countries from 1995 to 2011. In general, we show a negative and robust relationship between the market power index and wage inequality. Additional evidence shows that results tend to be different for countries with different income levels and for different initial values of skill-premium and market power.

JEL classification: O14, O50.

Keywords: Market Power, Industrial Concentration, Skill-premium, Inequality, Input-Output Matrices.

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"Understanding the origins of inequality, we can better grasp the costs and benefits of reducing it. (...) market forces help shape the degree of inequality"

Stiglitz (2012)

1 Introduction

Economic inequality recently has entered the political discourse in a highly visible way. Inequality was the centerpiece of President Obama's 2015 State of the Union address.[1] The effect of market power on income inequality has been eloquently mentioned by Stiglitz (2012) in his well-known book *The Price of Inequality.* In the book, Stiglitz associated the rise and high level of the US inequality to the failure of the market. Competitive forces should limit big profits and disproportionate high rewards (of CEO's of large companies, of high talented footballers, most skilled and specialized IT professionals, and so on). However, these competitive forces may not prevail even when they are efficient, as governments are not effective in controlling rent seeking. Thus, this argument of Stiglitz is in line with explanations provided by William and Smiley (1975) when they first studied the connection between market power and inequality. Monopoly power transfers wealth to the most influent members raising not only capital returns, which perpetuate inequality, but also distorting prices between larger and smaller producers. Our main research question is to study the relationship between market concentration and wage inequality.

Other authors modelled theoretically the effect of market power on income inequality. For example Creedy and Dixon (1999) have analysed the effect of monopoly rents in income inequality. They concluded that monopoly has a greater impact on the lower income groups, and therefore an inequality increasing effect. Notwithstanding, Rognlie (2015) argues that the concern about inequality should be shifted away from the overall split between capital and labour and toward other aspects of distribution, such as the within-labour distribution of income and scarcity of land. Bucci et al. (2003) found that the relationship between market power and income inequality may be positive or negative, depending on the initial values for both variables. The relationship tends

[1] see Remarks by the President in State of the Union Address (Jan. 25, 2015).

to be positive for high industrial concentration. Notably, empirical evidence does not cover the relationship between market concentration and income inequality, an issue that has been well noted both theoretically and politically. We contribute to fill this gap. In this paper we calculate a market concentration measure (Herfindahl-Hirschman Index) and relate it with the skill-premium across the world. For this purpose we start by developing a theoretical directed technical change model in which we reflect in R&D technology the impact of market concentration. That is, we assume that market concentration improves the R&D productivity in the face of expected higher profits associated with new designs. In general, we found a negative and robust relationship between the market power index and wage inequality but a positive and robust relationship between the market power variation and wage inequality. Taking the theoretical relationship into account, this means that while high markups tend to have long-run effects in decreasing wage inequality, evidence points to short-run effects tending to increase wage inequality. Robustness analysis tends to strongly validate the long-run negative effect of market power in wage inequality, meaning that an increase in market power would contribute to decrease wage inequality.

The paper is organized as follows. In Section 2 we review the literature on the determinants of income inequality with particular emphasis on the relationship between industry concentration (and market power) and income inequality. In Section 3, we describe the data. In Section 4 we present a model of directed technical change that can describe the relationship between market power and the skill-premium and that shapes our econometric specification. In Section 5 we use the model to specify the econometric regression and present the empirical results. In Section 6 we provide some robustness tests. Finally, Section 7 concludes the paper and highlights some policy implications.

2 On the empirical determinants of inequality

Technology has been one mechanism used to explain the connection between market concentration and inequality. The effect of technology in creating markets with property rights and intellectual property protection also has a role in the proliferation of concentrated markets. Additionally, industry concentration significantly raises skill premium by lowering total factor productivity in the unskilled-intensive sector Haskel and Slaughter (2001).

Because comparable cross-country data on inequality has become available in the last few years, the efforts to quantify the determinants of inequality are quite recent. In fact, according to Hornstein et al. (2005), there is a scarcity of empirical studies dealing with this issue. Empirical literature has focused on the effects of education and globalisation on inequality (Föster and Thó, 2015). The attempts to evaluate the relationship between education and inequality are mostly country-specific; for example Ding et al. (2011) and Rattsø and Stokke (2013) dealing with the effect of technology, and Birchenall (2001) dealing with the effect of human capital. Micro evidence on the relationship between education and income inequality is mixed. While Martins and Pereira (2004) found a positive sign for the effect of education returns in inequality due to an increase in returns to education throughout the wage distribution for 16 European Countries, Wang (2011) found returns to education in China that are more pronounced for individuals in the lower tail of the earnings distribution than for those in the upper tail, in stark contrast to the results found in some developed countries. In a study of the US Metropolitan areas Borjas and Ramey (1995) found that employment change in trade-impacted concentrated industries may explain part of the rise of wage inequality in the US during the 1980s.

Some papers evaluated this relationship using a large cross-section of countries. Some of these papers are concerned solely with the relationship between education and inequality. Milanovic (2000) reassessed the Kuznets (1955) initial contribution, adding institutional variables to the analysis of determinants of the income inequality. Teulings and van Rens (2008) found evidence for a negative relationship between increase in schooling and returns in a cross-section of countries, implying a contribution of schooling to reduce inequality, a result that goes in the same direction as that obtained by De Gregorio and Lee (2002). Another set of articles has been concerned with the effect of globalisation on inequality. For example, Bergh and Nilsson (2010) discovered positive and significant effects of freedom of trade on inequality. In the opposite direction, Jaumotte et al. (2013) and Asteriou et al. (2014) reported equalizing effects of trade openness as well as positive effects of financial openness in increasing inequality. Focusing on top earnings, Roine et al. (2009) discovered that financial development favours the richest persons while trade openness has no significant effect. Moreover, government spending has a negative effect on top earnings.

Three other papers relate income inequality in cross-sections with several controls. Barro (2000) presents fixed-effects estimations of equations of the Gini index on covariates such as GDP and GDP squared, schooling, democracy index, openness, rule of law index and several dummies. In his fixed-effects estimations, dummies for income or spending and secondary schooling are negatively related to inequality, and higher schooling and openness are positively related to inequality (with significant coefficients). Primary schooling and the dummy for individual or household data are not significantly related to the Gini coefficient. There is a strong inverted-U relationship with GDP (the so-called Kuznets curve) in Barro's estimations. Rodriguez-Pose and Tselios (2009) present positive and robust signs for secondary and tertiary education levels and income inequality among European regions. Additionally, these authors found that population ageing, female participation in the labour force, urbanisation, agriculture, and industry are negatively associated with income inequality, while unemployment and a specialisation in the financial sector positively affect inequality. Finally, income inequality is lower in social-democratic welfare states, in Protestant areas, and in regions with Nordic family structures. Although Jaumotte et al. (2013) focus on the effect of globalisation on inequality, they also conclude that information and communication technologies and credit deepening increases inequality, while the share of industry in the economy decreases inequality. Interestingly, education variables and initial GDP (when included) are insignificantly related to inequality. Sequeira et al. (2017) estimated a regression for income inequality with human capital and openness, while obtaining a positive coefficient for human capital, coefficients for TFP and openness were nonsignificant. In an empirical test of the skill-biased technical change theory, Santos et al. (2017) found that the interaction between human capital and technology presents a positive and significant coefficient. **Additionally, Antonelli and Gehringer (2017) test the relationship between technological progress (measured through patents) in income inequality and concluded that innovation decreases inequality, with a stronger effect for higher levels of inequality.**

3 Data on Market Power and Skill Premium

To compute the Herfindahl-Hirschman Index[2] and the skill-premium we use the World Input-Output Database (WIOD). WIOD provides input-output tables for 40 countries classified into 35 industries from 1995 to 2011 [15] and collects the following variables: High-skilled labour compensation (share in total labour compensation); Medium-skilled labour compensation (share in total labour compensation); Low-skilled labour compensation (share in total labour compensation); Hours worked by high-skilled persons engaged (share in total hours); Hours worked by medium-skilled persons engaged (share in total hours); Hours worked by low-skilled persons engaged (share in total hours); Number of persons engaged (thousands); Number of employees (thousands); Total hours worked by persons engaged (millions); and Total hours worked by employees (millions). Using the input-output tables we find the share of each industry in the output and compute the HHI for each economy. Industries in WIOD are classified according to the International Standard Industrial Classification revision 3 (ISIC Rev. 3) as shown in Table 9 in Appendix. Figures 4 and 5 in Appendix illustrate the distribution of the Herfindahl-Hirschman Index across the globe.

We calculate two alternative measures of the skill-premium. One ($\frac{w_h}{w_l}$) is the ratio between the high-skilled labour compensation per hour worked and the low-skilled labour compensation per hour worked. The second ($\frac{w_h}{(w_m+w_l)/2}$) is the ratio between the high-skilled labour compensation per hour worked and an average of the low-skilled labour compensation per hour worked and the medium-skilled labour compensation per hour worked.

Table 1 shows first moments for these variables. Industrial concentration (HHI) oscillates from 0.041 to 0.107 with an average of 0.055, indicating that many industries have around average indexes. Skill-premium indicates that on average high skilled workers earn roughly two times more than low-skilled workers, but this premium oscillates considerably, between a minimum of near 1.2 (high-skilled earn 20% more than the low-skilled) to a maximum near 5 (high-skilled earn 500% more than the low-skilled).

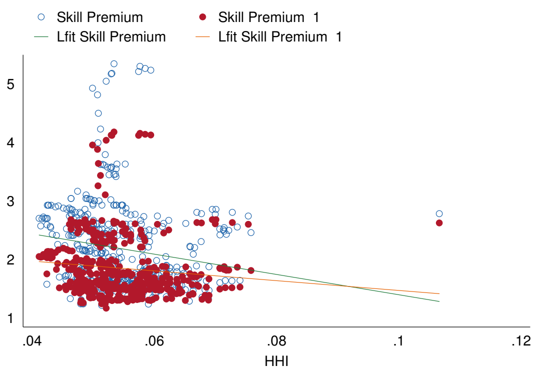
[2] The s_i is the share of industry i on the output, that is, $HHI = \sum_i^n s_i^2$, where n is the number of industries in the economy.

Table 1: Summary statistics Skill-Premium and Herfindahl-Hirschman Index

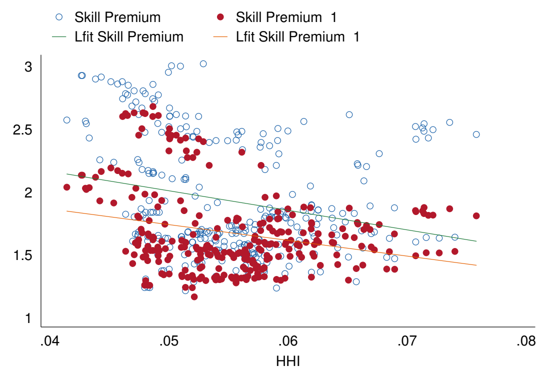
	$\frac{w_h}{w_l}$	$\frac{w_h}{(w_m+w_l)/2}$	HHI
average	2.17	1.83	.055
standard-deviation	0.76	0.53	.007
maximum	5.35	4.18	.107
minimum	1.22	1.17	.041

Figure 1: Skill-Premium against Herfindahl-Hirschman Index by income level

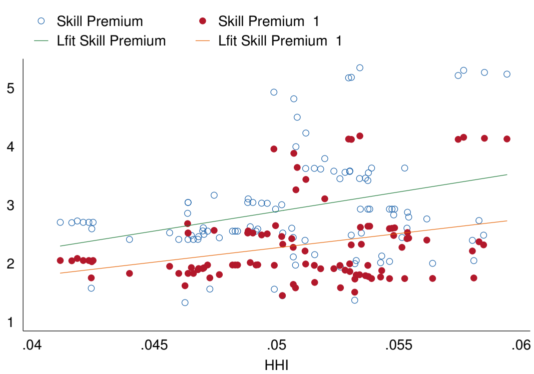
(a) All Countries



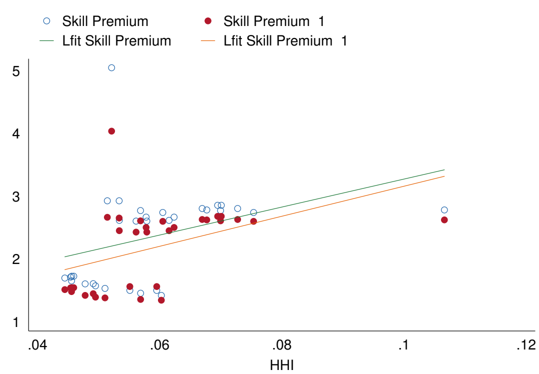
(b) High Income



(c) Upper Middle Income



(d) Lower Middle Income



Legend: Blue empty data points are for $\frac{w_h}{w_l}$ (Skill Premium) and red data points are for $\frac{w_h}{(w_m+w_l)/2}$ (Skill Premium 1). Each data point is the average for all sectors for a country per year.

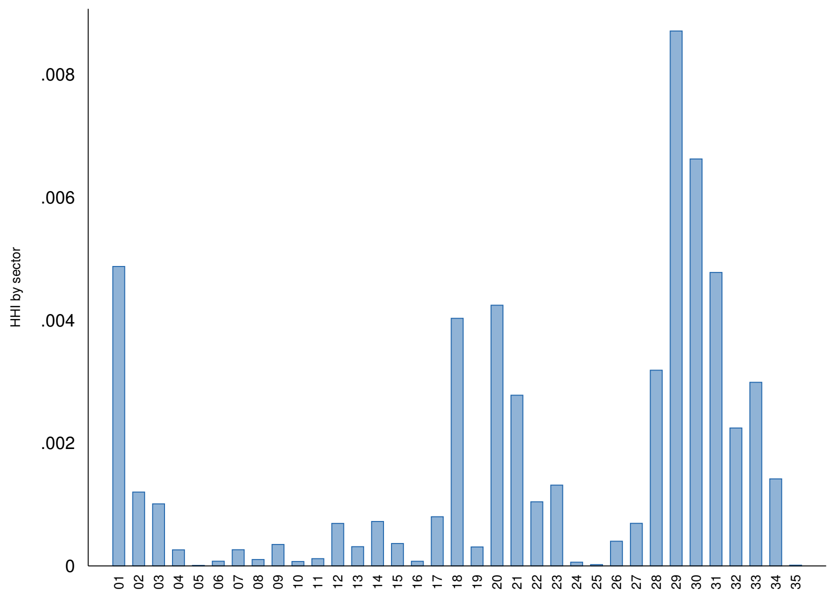
Figure 1 shows a negative relationship between skill-premium and the HHI, which is observed for the set of countries in our sample[3]. This Figure highlights that this relationship in the high-

[3] To classify countries by income groups we use the GNI per capita calculated using the World Bank Atlas method and its respective thresholds.

income countries is negative (dominating the sign in the whole sample) and in the upper-middle and lower-middle income countries is positive.

Figure 2: Sector Share and Skill-Premium

(a) Share by sector



Legend: The corresponding list of sectors, numbered here from 1 to 35, is described in Table 9 in Appendix.

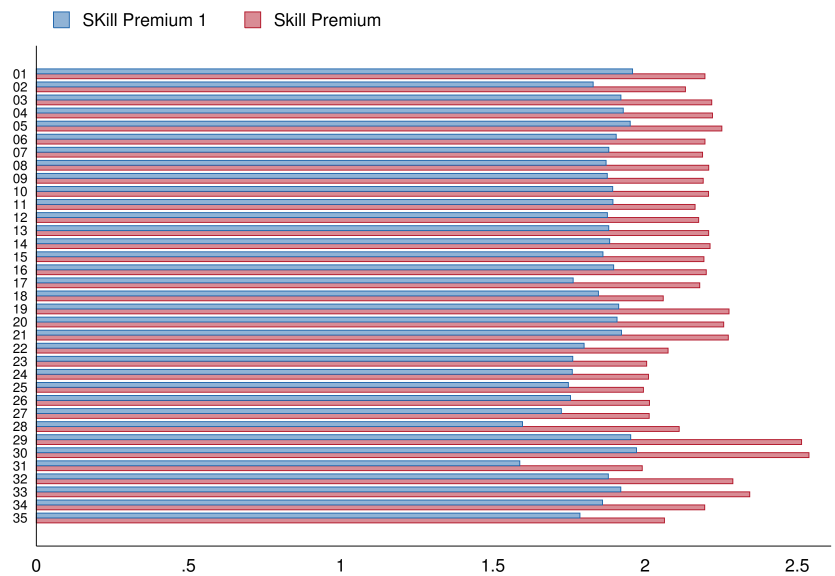
Figures 2-3 show that different sectors in the economy present very different weights and skill-premium.[4] For example, the sectors with higher weight in the economy are: real estate activities (29), renting of machines and equipment and other business activities (30), public administration and defense (31), and agriculture hunting, forestry and fishing (1). These sectors also present high skill-premium ratios with the sectors real estate activities (29) and renting of machines and equipment and other business activities (30) being those with highest skill-premium in our sample. Thus, as shown by Figures 2-3 there are important differences in terms of skill-premium and sector weights suggesting that, given the straight and positive relationship between sectors weights and HHI, the industry is the correct unit of analysis when relating market power with income inequality.

In the next Section we devise a directed technical change growth model that will help to properly

[4]Figures 2-3 show the average weight and skill-premium by sectors for the set of 40 countries included in our sample and the period 1995-2011.

identify the regression model. In particular, devising this model will establish the direction of causality to be tested as well as decrease the concern about omitted variables. Thus the empirical tests presented in Section 4 have to be interpreted as a test of the devised model. In fact, this decreases the potential endogeneity concerns of the empirical specification due to potential reverse causality and omitted variables.[5]

Figure 3: Sector share and Skill-Premium



Legend: The corresponding list of sectors, numbered here from 1 to 35, is described in Table 9 in Appendix. Skill Premium and Skill Premium 1 denote the ratios $\frac{w_h}{w_l}$ and $\frac{w_h}{(w_m+w_l)/2}$, respectively.

4 A stylized model of directed technical change

We set up a dynamic macroeconomic model that closely follows Acemoglu (2002) except that we use the human capital provided to the market by a given group in a specific occupation as a productive input rather than using the quantity of labour supplied by individuals of different human-capital levels. The model is solved for the wage per unit of labour since wages per unit of human capital

[5] We cannot exclude certain forms of reverse causality that could be potentially suggested by alternative theoretical relationships.

are not observed.

The aggregate output, Y, is produced competitively with specific intermediate final goods Y_i by sector i:

$$Y = \left(\sum_i Y_i^{\frac{\varepsilon - 1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon - 1}}. \tag{1}$$

Intermediate final goods are produced competitively using non-durable intermediate goods x_i, and labour L_i that are specific to the intermediate final good:

$$Y_i = \frac{1}{1-\alpha} L_i^{\alpha} \int_0^{N_i} x_i(j)^{1-\alpha} dj, \tag{2}$$

where α is the labour share in production and $1 - \alpha$ is the intermediate-goods share. The labour types are occupation groups and we can therefore consider these intermediate final goods, indexed by i, as composite sets of services offered to the market by workers in different occupations. There is a continuum of length N_i of intermediate goods, indexed by j, representing the technological-knowledge level in the occupation i; i.e., technology is complement to a measure of human capital. The output Y_i is sold at price P_i, intermediate goods of the type j can be rented at the price $p_i(j)$, and workers of the i-group are paid at the wage w_i.

The monopolist with the design for an intermediate good used in occupation i produces and maintains each unit of the intermediate good with a unit of capital rented at price R. That is, one unit of capital can produce one unit of the intermediate good per unit of time and then intermediate goods depreciate fully, but capital does not. Hence, intermediate goods can be understood as capital that has been temporarily repurposed for a specific occupation. Thus, the stock of capital is always equal to the stock of intermediate goods. To capture the entire market, as in Grossman and Helpman (1991, Ch. 4), for example, we assume that limit pricing strategy is binding and thus is used by all monopolists $p_i(j) = \bar{p}$. Assuming that first-order conditions hold with equality, the profit maximization condition for demand for the intermediate good in occupation i for a given capital rental rate is $x_i(j) = x_i = \left(\frac{P_i}{\bar{p}}\right)^{\frac{1}{\beta}} L_i$; i.e., x_i is independent of the intermediate good.

Profit maximization in intermediate goods and in intermediate final goods gives a specification for demand wages conditional on technological-knowledge, N. Considering hereinafter two occupations by intermediate-final-goods-sector, skilled ($i = h$) and unskilled ($i = l$), we have:

$$\frac{w_h}{w_l} = \left(\frac{N_h}{N_l}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{L_h}{L_l}\right)^{-\frac{1}{\sigma}}; \tag{3}$$

where: $\sigma = 1 + (\varepsilon - 1)\,\alpha$ is the elasticity of substitution between groups of workers conditional on fixed technological knowledge. We could stop here if technological knowledge were observable, but one of our aims is to discuss the impact on estimates of σ from not observing N and failing to understand that changes in technological knowledge are implicit in wage and labour supply. Concerning the technological-knowledge progress, we assume that a country builds its own technological-knowledge level with R&D expenditures (forgone consumption) with the following innovation possibilities frontier:

$$\dot{N}_i = \delta_i Z_i \tag{4}$$

where, considering a lab-equipment model type, $Z = \sum_i Z_i$ is the amount of aggregate final good used in R&D, and δ_i represents the group-specific innovative productivity.

Along the balanced growth path (BGP), free entry into the innovation sector gives us the relative technological-knowledge level or the technological-knowledge bias $\frac{N_h}{N_l} = \left(\frac{L_h}{L_l}\right)^{\sigma-1} \left(\frac{\delta_h}{\delta_l}\right)^{\sigma}$, which gives us the endogenous technological-knowledge value to put into equation (3) to obtain the long-run relationship between wages and labour supplies:

$$\frac{w_h}{w_l} = \left(\frac{\delta_h}{\delta_l}\right)^{\sigma-1} \left(\frac{L_h}{L_l}\right)^{\sigma-2}. \tag{5}$$

Equations (3) and (5) highlight the difficulty of estimating the relevant demand elasticities. Linear regressions of the logs of relative wages on the logs of relative labour supply, as, for example, in Card and Lemieux (2001), would produce coefficients whose meaning is ambiguous. Suppose the regression coefficient is β. If the time frame for the data were short enough that technological knowledge had not had a chance to adjust to a supply shock, then transforming β into σ as in equation (3), considering $\left(\beta = -\frac{1}{\sigma}\right)$, would be justified. However, if technological knowledge has been able to adjust close to the BGP, we would want to transform β into σ as implied by equation (5), considering $(\beta = \sigma - 2)$. This is not a minor difference: the shift in relative factor demand from increased relative technological knowledge could create a positively-sloped relationship between prices and quantities, indicating to the casual statistician a negative elasticity of substitution.

To identify the regression models we follow Murphy and Welch (1992), Card and Lemieux (2001), and Jerzmanowski and Tamura (2015) and think of the group-specific innovative productivity parameter δ_i as being captured by a full set of occupation indicators and a full set of year indicators; in particular, we thus reflect in R&D technology (4) a crucial feature of our model, and, in line with Acs and Audretsch (1987), Blundell et al. (1999), Nolan et al. (2012), and Castiglione and Infante (2014), among others, we assume that the R&D productivity also reflects the concentration of the market. As argued by Blundell et al. (1999), the total industry profits decrease when more firms share the market. Thus, the efficiency effect both in monopolist and oligopoly markets leads to greater incentives to innovate and to produce higher quality innovations rising the R&D productivity. Hence, for reasons of simplicity, a crucial feature of our model is reflected in R&D technology, by assuming that R&D productivity in each sector i also reflects the concentration of the market:

$$(1-\sigma)\ln\left(\frac{\delta_{h,t}}{\delta_{l,t}}\right) = \gamma_o + \lambda_t + \mu_{h,t} \tag{6}$$

where $\mu_{h,t}$ has conditional mean zero and we have indicated that the base occupation is indexed by l. Taking the log of equation (5) and adding time subscripts yields us the following regression equation:

$$\ln\left(\frac{w_{h,t}}{w_{l,t}}\right) = (\sigma - 2)\ln\left(\frac{L_{h,t}}{L_{l,t}}\right) + \gamma_o + \lambda_t + \mu_{h,t} \tag{7}$$

5 Specification and Results

To analyse the effects of industry concentration on the skill-premium and according to the model devised above, we specify the following econometric model:

$$\ln\left(\frac{w_h}{w_l}\right)_{ijt} = \alpha + \beta\ln\left(\frac{H}{L}\right)_{ijt} + \zeta HHI_{jt} + \varphi Z_{jit} + \nu_{ji} + \rho_t + \epsilon_{jit} \tag{8}$$

where w_h is the wage per hour paid to high-skilled workers in each sector, w_l is the wage per hour paid to low-skilled workers in each sector, H is the number of hours worked by high-skilled labourers in each sector, L is the number of hours worked by low-skilled labourers in each sector, HHI_{it} is the Herfindahl-Hirschman Index and the variable we are interested in, Z_{jit} is a vector with control variables, ν_{ji} is the $i-$sector, $j-$country fixed effect, ρ_t is the time fixed effect, and ln denotes natural logarithm. Note that as equation (8) is derived from the model, the empirical estimations refer to the causality relationship indicated by the model.

As control variables we consider economic factors that can affect the skill-premium, which were suggested by the literature. We include the share of employment in each sector measured as a share of total population in each country ($share_{ijt}$), and the country trade openness measured as share of GDP ($open_{jt}$).[6] These controls and the market power should help to explain R&D productivity and thus the skill-premium (recall equations 6 to 7). With this we also aim to reduce the potential omitted variable bias.

To estimate the panel regression specified in equation (8) we include both panel (sector by country)

[6]To compute the employment share we use the number of persons engaged and the population data from the PWT 9.0 and, to compute the country trade openness we use the imports and exports share also from the PWT 9.0.

and time fixed-effects. In this way the estimated results account for both unobserved time-invariant heterogeneity in countries (ν_i) such as socio-cultural factors and any global shock (ρ_t) such as a financial crisis.

Table 2 presents descriptive statistics for the variables used in the regressions.

Table 2: Summary statistics for the econometric analysis

Total	$ln(\frac{w_h}{(w_m+w_l)/2})$	$ln(\frac{H}{M+L})$	$ln(\frac{w_h}{w_l})$	$ln(\frac{H}{L})$	$ln(share)$	$ln(HHI)$	$ln(Open)$
average	0.563	-1.741	.712	-.451	1.864	-2.916	-.059
St-dev	.240	.649	.301	1.107	.1567	.128	.117
max	1.379	-.380	1.631	1.995	2.209	-2.239	.112
min	.150	-3.574	.194	-3.021	1.313	-3.190	-.609
count	434	434	434	434	434	434	434
High							
mean	.490	-1.578	.617	-.286	1.884	-2.900	-.0631
sd	.180	.589	.226	1.043	.1214	.1223	.133
max	.959	-.380	1.098	1.995	2.175	-2.579	.112
min	.1497	-3.209	.1938	-3.021	1.559	-3.184	-.609
count	286	286	286	286	286	286	286
Upper Middle							
mean	.784	-2.018	1.023	-.542	1.794	-2.983	-.068
sd	.255	.403	.297	1.001	.205	.088	.0723
max	1.379	-.808	1.631	1.250	2.147	-2.823	.026
min	.366	-2.997	.278	-2.796	1.350	-3.190	-.405
count	97	97	97	97	97	97	97
Low Middle							
mean	.660	-2.928	.7449	-2.338	1.851	-2.870	-.008
sd	.316	.274	.325	.4458	.193	.212	.047
max	1.351	-2.173	1.578	-1.531	2.023	-2.238	.051
min	.297	-3.383	.352	-3.021	1.312	-3.113	-.117
count	23	23	23	23	23	23	23

Note: All variables are in logarithms (ln). $(\frac{w_h}{(w_m+w_l)/2})$ measures skill-premium in terms of the medium and low skilled; $(\frac{H}{M+L})$ measures the skilled-unskilled ratio where unskilled include low and medium skilled workers; $(\frac{w_h}{w_l})$ measures skill-premium in terms of the low skilled; $ln(\frac{H}{L})$ measures the skilled-unskilled ratio where unskilled include only low skilled workers; $(share)$ measures the share of employment in each sector; (HHI) measures the Herfindahl-Hirschman Index and $(Open)$ measures the openness ratio per country. All statistics are average values by country.

Table 3 presents the baseline regressions for the skill-premium. Columns (1) to (4) present regressions for the skill-premium measured in relation to the low-skilled. We obtain positive and significant relationships with openness, indicating that a higher trade openness tends to increase wage inequality, a result that may be consistent with the arguments in Epifani and Gancia (2008), which focus on the importance of scale effects when compared to the Heckscher-Ohlin effects.[7]

Interestingly, the coefficient the Herfindahl-Hirschman Index is marginally significant, with a neg-

[7] A positive relationship between income inequality and openness was also obtained in Barro (2000).

ative sign, suggesting that higher industrial concentration decreases inequality due to an efficiency wages argument, a result that is suggested by the theoretical approach in Bucci (2003), but seems to be at odds with the current political and scientific discourse (see, e.g., Stiglitz, 2012).[8] This negative and significant coefficient is even stronger when instead of the current value for the Herfindahl-Hirschman Index, one introduces the lagged value (column 2). However, once we introduce the first-difference of the Herfindahl-Hirschman Index (columns 3 and 4), the relationship becomes positive and highly significant. This suggest that increases in the industrial market power may help to increase wage inequality, and even that the level of it helps to decrease inequality, indicating that the same effect may not hold for all the distributions of the skill-premium and the concentration index. Another possible interpretation is that the while industry concentration may be associated to decreases in wage inequality in the long-run, the effect in the short-run may act inversely: more industry concentration may be associated with high inequality.[9] The last four columns in Table 3 (columns 5 to 8) use the skill-premium measured in relation to the low and medium-skilled as the dependent variable. In these regressions, the skilled-labour ratio coefficient becomes negative and highly significant, indicating that the usual negative demand-side effect prevails when compared with the skill-technological bias. As noted above, this means that the regression coefficient β should be equivalent to $\sigma - 2$, thus yielding values for the elasticity of substitution below but close to 2 (as the estimated coefficients are near 0.03 in Table 3: columns 5 to 8, then the implied σ would be 1.97), which are in line with empirical estimations for the elasticity of substitution provided elsewhere.[10]

The positive and significant sign is also maintained for the coefficient of the first difference of the HHI in columns (5) to (8) in Table 3.

[8] Bucci (2003) use the efficiency wages argument to explain the negative relationship between market concentration and wage inequality. In the research market there are monitoring problems that imply that the firms with lower markups have to set a higher efficiency wage, An alternative explanation may be the labor unions strength.

[9] Introduction of the lagged value and first-differences help to prevent potential reverse causality to be a source of empirical endogeneity. Introduction of time and sector-country dummies helps to consider heterogeneity effects or idiosyncratic shocks by sector-country, time effects and of course, omitted variables.

[10] For example, Duffy and Papagiorgiou (2000) present estimates for σ using a panel database for 82 countries over a 28-year period. Nonlinear estimations for σ oscillate between 1.2 and 2.3, while linear estimations oscillate around 1.4.

Table 4 presents results for subsamples of countries classified by their *per capita* income level. In this Table, results highlight that the higher significant coefficient of the HHI level comes from the lower-middle income countries with an elasticity from -9 to -12, meaning that a 1% increase in the HHI would lead to a 9% decrease in the skill-premium (see columns (3) and (6) in Table 4). Results for high-income countries show a negative and significant coefficient but with a much lower elasticity (see columns (1) and (4) in Table 4). In upper-middle income countries the coefficient for the concentration index is positive and significant: a 1% increase in the HHI would lead to a 0.2%-0.4% increase in the skill-premium (see columns (2) and (5) in Table 4). The positive coefficient for openness and the negative effect of the skilled-labour ratio are maintained as in Table 3.

Table 3: Panel regression results for skill-premium

	(1) $ln(\frac{w_h}{w_l})$	(2) $ln(\frac{w_h}{w_l})$	(3) $ln(\frac{w_h}{w_l})$	(4) $ln(\frac{w_h}{w_l})$	(5) $ln(\frac{w_h}{(w_m+w_l)/2})$	(6) $ln(\frac{w_h}{(w_m+w_l)/2})$	(7) $ln(\frac{w_h}{(w_m+w_l)/2})$	(8) $ln(\frac{w_h}{(w_m+w_l)/2})$
$ln(HHI)_{jt}$	-0.0682*				-0.0185			
	(-1.64)				(-0.56)			
$ln(HHI)_{jt-1}$		-0.0840**		-0.0626		-0.0265		-0.0143
		(-2.09)		(-1.45)		(-0.79)		(-0.40)
$\Delta ln(HHI)_{jt}$			0.157***	0.123***			0.0776***	0.0700***
			(7.40)	(5.01)			(5.27)	(3.62)
$ln(\frac{H}{L})_{ijt}$	0.00584	-0.00315	-0.00198	-0.00317				
	(0.59)	(-0.32)	(-0.20)	(-0.32)				
$ln(\frac{H}{L+M})_{ijt}$					-0.0282**	-0.0344***	-0.0339***	-0.0345***
					(-2.54)	(-3.12)	(-3.04)	(-3.13)
$ln(share)_{ijt}$	0.00209	-0.00332	-0.00102	-0.00315	0.0127*	0.0106	0.0112	0.0107
	(0.22)	(-0.35)	(-0.11)	(-0.33)	(1.76)	(1.46)	(1.52)	(1.47)
$ln(Open)_{jt}$	0.213***	0.185***	0.187***	0.187***	0.213***	0.192***	0.193***	0.193***
	(4.22)	(3.63)	(3.70)	(3.69)	(4.84)	(4.37)	(4.41)	(4.41)
Constant	0.543***	0.506***	0.749***	0.568***	0.464***	0.437***	0.514***	0.471***
	(4.37)	(4.22)	(39.14)	(4.42)	(4.62)	(4.29)	(20.44)	(4.34)
Sample-Size	15027	13953	13953	13953	15027	13953	13953	13953
R^2	0.211	0.221	0.221	0.222	0.154	0.160	0.161	0.161
F	78.196	80.803	86.937	81.932	51.149	53.028	71.293	66.837

Notes: Time and sector-country dummies are included in the regressions but omitted from the Table.
Robust t-statistics are presented in parentheses with significance as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Next, our aim is to evaluate if the effects obtained so far change for different initial values of the skill-premium and of the concentration index (HHI). With this, we wish to investigate if the effects of increasing the market power of a sector change depending on the sector being initially concentrated or not and on the sector being characterised by an initial high or low skill-premium. These results are presented in Tables 5 and 6. Both tables confirm the positive and significant coefficient for openness as well as the almost always negative and significant coefficient for the skilled/unskilled ratio. The exceptions are obtained in regressions in columns 2 in both Tables 5

Table 4: Panel regression results for skill-premium by income

	(1) $ln(\frac{w_h}{w_l})_{HI}$	(2) $ln(\frac{w_h}{w_l})_{UM}$	(3) $ln(\frac{w_h}{w_l})_{LM}$	(4) $ln(\frac{w_h}{(w_m+w_l)/2})_{HI}$	(5) $ln(\frac{w_h}{(w_m+w_l)/2})_{UM}$	(6) $ln(\frac{w_h}{(w_m+w_l)/2})_{LM}$
$ln(HHI)_{jt}$	-0.303***	0.416***	-12.37***	-0.0723**	0.268***	-9.559***
	(-5.09)	(3.09)	(-27.01)	(-1.47)	(2.42)	(-22.75)
$\Delta ln(HHI)_{jt}$	0.0247	0.107	0.227***	0.0897	-0.0793	0.219***
	(0.28)	(1.05)	(4.67)	(1.20)	(-1.23)	(5.01)
$ln(\frac{H}{L})_{ijt}$	-0.0421***	-0.0123	0.0128			
	(-3.47)	(-0.74)	(0.63)			
$ln(\frac{H}{L+M})_{ijt}$				-0.0809***	0.00177	-0.0417***
				(-5.83)	(0.07)	(-1.45)
$ln(share)_{ijt}$	-0.00381	-0.0139	-0.00548	0.0147	0.00195	-0.00322
	(-0.30)	(-1.14)	(-0.23)	(1.48)	(0.19)	(-0.18)
$ln(Open)_{jt}$	0.0927***	-0.128	11.51***	0.176***	-0.157***	9.073***
	(1.50)	(-0.84)	(23.43)	(3.28)	(-1.48)	(21.80)
Constant	-0.271**	2.326***	-33.65***	0.142	1.612***	-26.07***
	(-2.42)	(9.01)	(-28.41)	(1.59)	(11.06)	(-26.83)
Sample-Size	9355	3097	704	9355	3097	704
R^2	0.187	0.516	0.843	0.161	0.411	0.845
F	114.619	171.538	174.081	95.273	112.187	176.801

Notes: Time and sector-country dummies are included in the regressions but omitted from the Table.
Robust t-statistics are presented in parentheses with significance as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and 6, where the coefficient is nonsignificant in Table 5 and significantly positive in Table 6. This means that for a skill-premium that initially is above the median, then the skill-biased technical change mechanism tends to overcome the usual demand mechanism. The implied value for the elasticity of substitution oscillated between 1.89 (coefficient of -0.11 in Table 5, column (3)) and 2.03 (coefficient of 0.03 in Table 6, column (2)) which are again consistent values with the empirical estimates for the elasticity of substitution.

The coefficients for the level of the concentration index tend to be significantly positive for low values of initial skill-premium (Table 5, column (1)) and for low values of initial market concentration (Table 6, columns (1) and (3)) and tend to be significantly negative for high values of initial skill-premium (Table 5, columns (2) and (4)) and for high values of initial market concentration (Table 6, columns (2) and (4)). Moreover, variations (first-differences) in the concentration index tend to present significantly negative coefficients for low values of initial skill-premium (Table 5, column (1)) and present significantly positive coefficients for high values of initial skill-premium (Table 5, column (3) and (4)). Thus taking the identification led by the model into account, results in Table 5 indicate a short-run increase in market power for high levels of wage inequality tends to increase wage inequality while a long-run increase in market power tends to decrease wage inequality (columns (2) and (4) in Table 5). Moreover, results in Table 6 indicate that a short-run increase in market power for high levels of market power tend to increase wage inequality while a long-run increase in market power tends to decrease wage inequality (columns (2) and (4) in Table 6).

Table 5: Panel regression results for skill-premium (conditional initial median of skill-premium)

	(1) $ln(\frac{w_h}{w_l})_{\overline{Median}}$	(2) $ln(\frac{w_h}{w_l})_{\underline{Median}}$	(3) $ln(\frac{w_h}{(w_m+w_l)/2})_{\overline{Median}}$	(4) $ln(\frac{w_h}{(w_m+w_l)/2})_{\underline{Median}}$
$ln(HHI)_{jt}$	0.233***	-0.286***	-1.063***	-0.0565
	(5.16)	(-6.98)	(-12.67)	(-1.61)
$\Delta ln(HHI)_{jt}$	-0.110***	0.346***	0.171	0.107***
	(-4.00)	(7.42)	(0.74)	(4.26)
$ln(\frac{H}{L})_{ijt}$	-0.0459***	0.0117		
	(-3.38)	(1.06)		
$ln(\frac{H}{L+M})_{ijt}$			-0.112*	-0.0390***
			(-1.84)	(-3.56)
$ln(share)_{ijt}$	0.000146	0.00389	-0.00230	0.0140**
	(0.01)	(0.34)	(-0.03)	(1.97)
$ln(Open)_{jt}$	0.153**	0.191***	-1.912***	0.237***
	(2.12)	(3.83)	(-4.09)	(5.47)
Constant	1.783***	-0.318***	-1.785***	0.318***
	(12.90)	(-2.64)	(-6.31)	(2.99)
Sample-Size	5004	8949	203	13750
R^2	0.133	0.263	0.736	0.169
F	14.392	82.798	13.67	68.976

Notes: Time and sector-country dummies are included in the regressions but omitted from the Table. Robust t-statistics are presented in parentheses with significance as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $\overline{Median}$ means the regression is for observations below the Median. $\underline{Median}$ means the regression is for observations above the Median.

Table 6: Panel regression results for skill-premium (conditional on initial HHI)

	(1) $ln(\frac{w_h}{w_l})_{\overline{MedianHHI}}$	(2) $ln(\frac{w_h}{w_l})_{\underline{MedianHHI}}$	(3) $ln(\frac{w_h}{(w_m+w_l)/2})_{\overline{MedianHHI}}$	(4) $ln(\frac{w_h}{(w_m+w_l)/2})_{\underline{MedianHHI}}$
$ln(HHI)_{jt}$	0.0931*	-0.204**	0.0919*	-0.246***
	(1.67)	(-2.47)	(1.86)	(-3.83)
$\Delta ln(HHI)_{jt}$	-0.0242	0.654***	-0.0186	0.225***
	(-0.71)	(9.08)	(-0.60)	(4.32)
$ln(\frac{H}{L})_{ijt}$	-0.0292**	0.0300**		
	(-2.27)	(2.39)		
$ln(\frac{H}{L+M})_{ijt}$			-0.0474***	-0.0250*
			(-4.06)	(-1.75)
$ln(share)_{ijt}$	-0.00917	-0.00648	0.00806	0.00670
	(-0.59)	(-0.50)	(0.60)	(0.74)
$ln(Open)_{jt}$	0.316***	0.0997	0.398***	-0.122*
	(4.64)	(1.22)	(6.88)	(-1.81)
Constant	0.924***	0.241	0.727***	-0.178
	(5.73)	(0.96)	(5.12)	(-0.88)
Sample-Size	6427	7526	6427	7526
R^2	0.194	0.319	0.195	0.203
F	38.274	60.470	28.358	41.756

Notes: Time and sector-country dummies are included in the regressions but omitted from the Table. Robust t-statistics are presented in parentheses with significance as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. $\overline{MedianHHI}$ means the regression is for observations below the Median of the HHI. $\underline{MedianHHI}$ means the regression is for observations above the Median of the HHI.

6 Robustness checks

We implemented two different sets of robustness tests as in Dorn et al. (2018) and Dorn and Schinke (2018). First, in order to account for first-order autocorrelation in residuals and omitted variable bias from dynamic relations we apply panel data models with an autoregressive error form of order 1.[11] Then, we test whether our results are sensitive to other control variables and single countries in our sample. Results on the first test are shown in Table 7. Results on the second set of tests are commented on the text and are not presented due to space considerations. In this case, they are available upon request.

In Table 7, columns 1 to 4 replicate the first four columns in Table 3 and columns 6 to 9 replicates the last four columns in Table 3 with the AR(1) error structure. Columns (5) and (10) include a lagged depend variable in the regression. There are several points to be noted. First, a negative and significant coefficient of market concentration is obtained throughout all the specifications. Quantitatively, this means that a 1% increase in market concentration would decrease inequality from near 0.1% to 0.27%, a result that is maintained whether the current or the lagged level of market concentration is used. The short-run effect seen by the coefficient is now decreased and most results are not significant. This may mean that this previously significant result is absorbed by the autoregressive structure of the error term. Notwithstanding, the introduction of the lagged dependent variable as a regressor (columns 5 and 10) – which are highly significant – does not decrease the significance of the level of the market concentration.

Second, there is a negative and significant effect of the relative skilled labor stock, which is quite consistent with previous results, pointing to an elasticity of substitution that range from 1.83 to 1.98, which are again reasonable values according to empirical estimates.

Third, openness is now consistently negative and statistically significant which is more according to the Heckscher-Ohlin argument according to which more openness tend to decrease inequality.

[11] Note that our panel is large in N and small in T being robust standard errors the best option to lead with heteroskedasticity and/or autocorrelation, which is already made in the baseline regressions presented in Tables 3 to 6.

Finally the share of employment of each sector in each country is positively associated with market concentration.

Table 7: Panel regression results for skill-premium (robustness analysis)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$ln(\frac{w_h}{w_l})$	$ln(\frac{w_h}{w_l})$	$ln(\frac{w_h}{w_l})$	$ln(\frac{w_h}{w_l})$	$ln(\frac{w_h}{w_l})$	$ln(\frac{w_h}{(w_m+w_l)/2})$	$ln(\frac{w_h}{(w_m+w_l)/2})$	$ln(\frac{w_h}{(w_m+w_l)/2})$	$ln(\frac{w_h}{(w_m+w_l)/2})$	$ln(\frac{w_h}{(w_m+w_l)/2})$
$ln(HHI)_{jt}$	-0.267***				-0.0981***	-0.154***				-0.0947***
	(-31.77)				(-3.37)	(-22.72)				(-5.20)
$ln(HHI)_{jt-1}$		-0.270***		-0.276***	-0.0836***		-0.152***		-0.161***	-0.0325*
		(-31.15)		(-31.39)	(-2.88)		(-22.37)		(-23.09)	(-1.82)
$\Delta ln(HHI)_{jt}$			0.0387	-0.118***				0.000508	-0.0975***	
			(1.28)	(-4.02)				(0.03)	(-5.71)	
$ln(\frac{w_h}{w_l})_{ijt-1}$					0.268***					
					(49.38)					
$ln(\frac{w_h}{(w_m+w_l)/2})_{ijt-1}$										0.142***
										(32.01)
$ln(\frac{H}{L})_{ijt}$	-0.0301***	-0.0336***	-0.0689***	-0.0309***	-0.0211***					
	(-6.52)	(-6.86)	(-13.85)	(-6.26)	(-4.46)					
$ln(\frac{H}{L+M})_{ijt}$						-0.0714***	-0.0745***	-0.126***	-0.0694***	-0.0588***
						(-15.43)	(-15.62)	(-29.54)	(-14.31)	(-12.01)
$ln(share)_{ijt}$	0.00540	0.00486	0.127***	0.00275	0.00416	0.0132**	0.0148***	0.0671***	0.0120**	0.00936*
	(0.75)	(0.63)	(18.50)	(0.36)	(0.60)	(2.57)	(2.76)	(13.69)	(2.24)	(1.85)
$ln(Open)_{jt}$	-0.247***	-0.250***	-0.218***	-0.257***	-0.207***	-0.243***	-0.241***	-0.256***	-0.246***	-0.229***
	(-6.36)	(-6.06)	(-5.08)	(-6.23)	(-5.17)	(-9.54)	(-8.95)	(-9.32)	(-9.15)	(-8.38)
Constant	-0.107***	-0.122***	0.442***	-0.134***	-0.0437***	-0.0519***	-0.0558***	0.209***	-0.0710***	-0.0272***
	(-8.70)	(-9.16)	(55.38)	(-10.00)	(-5.57)	(-8.24)	(-8.33)	(47.18)	(-10.47)	(-6.02)
Sample-Size	13953	12879	12879	12879	11037	13953	12879	12879	12879	11037
F	420.550	416.496	161.124	336.781	887.745	494.065	515.619	373.319	418.836	693.232

Fixed Effects model with AR(1) disturbances with significance as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

With respect to the second set of robustness tests, the inclusion of government expenditure share of GDP as control variable in all our regressions has no effect in the sign and statistical significance of the market concentration index. Finally, when we analyze the effect of single countries within each subsample, the results are quite consistent and the main inference remains unchanged. However, when we drop the United Kingdom, Malta, Brazil and Turkey in the regressions of skill-premium measured in relation to the low skilled the first difference in the concentration index become positive and statistically significant, which recovers the results in the previous Section. When we measure the skill-premium in relation to the low and medium-skilled and drop single countries, our results are also quite robust. Only when we drop, the USA, Austria, the United-Kingdom, Greece, Malta and the Netherlands the first differences in the concentration index become positive and statistically significant, again recovering the results obtained in the previous Section. In these case we may state that at least in the short-run there is a positive relation between market concentration and inequality. Yet when we drop Latvia and Mexico, the first difference in the concentration index become negative and statistically significant means that within the upper middle countries there is a inverse relation between inequality and market concentration while in the long-run the relation is positive as observed in Table 4. These results reinforce the long-run positive relation and short-run negative relation for the high and low-middle income countries and the opposite for the upper-middle countries and the point we made for the causality direction purposed by the model.

Within this empirical exercise it was impossible to consider wealth inequality has the database has not sufficient years to allow for a consistent measure of families wealth. Additionally note that income inequality in the empirical work is restricted to wage inequality which excludes e.g. bequests and capital (property or dividend) income.

7 Discussion

There are different channels through which concentration can influence inequality. First, the relationship between concentration and profitability should increase income inequality assuming – as seems plausible – high levels of wealth inequality. The larger the concentration, the larger the profits distributed as dividends and hence the larger rent inequality and income inequality. At the same time, moreover, concentration is associated to the large size of firm. This in turn affects wage inequality and the inducement to the introduction of capital intensive technologies that increase the share of revenue paid to capital. Again, we should see that large firms pay larger wages and because of them use more capital intensive technologies that, for high levels of wealth inequality, increase income inequality. **This would indicate a positive relationship between concentration and inequality, which we obtain in the short-run. Second, the slowing pace of technological progress happened in the last quartile of the XXth century may be responsible for the observed rising income inequality, as Antonelli and Gehringer (2017) pointed out. This article relates the explanation of the found empirical regularity with the Schumpeterian theory. In fact slow rates of technological progress are associated to low levels of creative destruction and, as a consequence, to the maintenance of higher levels of market power. Thus following this argument, higher levels of market power**

may be associated with (low pace of technological progress and thus to) higher levels of income inequality. This would indicate a positive relationship between concentration and inequality, which we obtain in the short-run.

Secondly, this explanation misses that taken the economy as a whole, more innovation may be associated more sectors operating with markups and thus the association between innovation and market concentration is through this channel, positive. Additionally, as discovered by Aghion et al. (2005), the relationship between market concentration and innovation is not monotonic. According to the authors, "competition discourages laggard firms from innovating but encourages neck-and-neck firms to innovate". If innovation is positively related with market concentration (for higher levels of concentration following Aghion et al., 2005), then we should expect a negative influence of market concentration on income inequality, as we pointed out for the long-run.

Third, as firms facing more competition in the R&D market have to set higher efficiency wages due to monitoring problems – see Bucci (2003). Thus, less concentrated R&D industries set higher wages, then we should expect a negative influence of market concentration on income inequality, as we pointed out for the long-run.

All in all, this shows that the theorectical explanations for the relationship between concentration and income inequality are to be directly tested and with this paper we present new evidence that contributes to this discussion.[12]

[12] We thank a referee this interesting discussion.

8 Conclusion and Policy Implications

Despite the recent and spirited discourse concerning the relationship between market concentration and wage (or income) inequality, we did not find an empirical assessment of this relationship in the surveyed literature. This paper contributes to that discussion. To that end, we calculated the Herfindahl-Hirschman index and skill-premium for the 35 industries in 40 countries from data in the World Input-Output Database (WIOD) and described their relationship.

In order to identify the regression for the wage premium to be estimated, we devised a simple directed technical change model with industry-specific labour. Then, we estimated the equation yielded by the model. The results from regressions highlight an overall negative coefficient of the Herfindahl-Hirschman index in the regression for the skill-premium. According to the model, this means that the higher the industry concentration, the less the wage inequality. Long-run effects of rising market power tend to decrease wage inequality except for upper-middle income countries and when either wage inequality or market concentration are low. These long-run effects may be explained by the long-lasting effects of labor market institutions (e.g. efficiency wages) in the economies. Short-run effects usually act on the opposite direction. These results highlight that regulatory anti-trust policies targeted at historically highly concentrated and high skilled sectors would have redistributive effects. However, in general anti-trust policies may be combined with income policies to avoid a rise in inequality.

The study of the institutions (e.g. labor market and product market) on the relationship between wage inequality and the market power **as well as the relationship between concentration and inequality mediated by technological progress** are promising avenue of future research as also the use of firm-employees data to access this important relationship.

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A Country sample

Table 8: WIOD countries, regional aggregation and income classification

Euro-zone		Non-Euro EU	NAFTA	China	East Asia	BRIIAT
Austria^{d}	Italy^{d}	Bulgaria^{a,b}	Canada^{d}	China^{a,b,c}	Japan^{d}	Brazil^{a,b}
Belgium^{d}	Luxembourg^{d}	Czech Rep.^{b,d}	Mexico^{b}		Korea	Russia^{a,b}
Cyprus^{d}	Malta^{b,d}	Denmark^{d}	USA^{d}		Taiwan	India
Estonia^{b,d}	Netherlands^{d}	Hungary^{b,d}			Indonesia	
Finland^{d}	Portugal^{d}	Latvia			Australia^{d}	
France^{d}	Slovakia^{b,d}	Lithuania			Turkey^{a,b}	
Germany^{d}	Slovenia^{d}	Poland^{b,d}				
Greece^{d}	Spain^{d}	Romania^{a,b}				
Ireland^{d}		Sweden^{d}				
		UK^{d}				

The countries classification is based on World Bank Atlas method and during the sample period some countries moved from one income group to another. Legend: a denotes Low Middle Income, b denotes Upper Middle Income, c denotes Low Income and d denotes High Income.

B List of sectors

Table 9: List of sectors at two-digit level

1-Agriculture, Hunting, Forestry and Fishing	2-Mining and Quarrying
3-Food, Beverages and Tobacco	4-Textiles and Textile Products
5-Leather, Leather and Footwear	6-Wood and Products of Wood and Cork
7-Pulp, Paper, Paper , Printing and Publishing	8-Coke, Refined Petroleum and Nuclear Fuel
9-Chemicals and Chemical Products	10-Rubber and Plastics
11-Other Non-Metallic Mineral	12-Basic Metals and Fabricated Metal
13-Machinery, N.e.c.	14-Electrical and Optical Equipment
15-Transport Equipment	16-Manufacturing, Nec; Recycling
17-Electricity, Gas and Water Supply	18-Construction
19-Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel	20-Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles
21-Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods	22-Hotels and Restaurants
23-Inland Transport	24-Water Transport
25-Air Transport	26-Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies
27-Post and Telecommunications	28-Financial Intermediation
29-Real Estate Activities	30-Renting of M&Eq and Other Business Activities
31-Public Admin and Defense; Compulsory Social Security	32-Education
33-Health and Social Work	34-Other Community, Social and Personal Services
35-Private Households with Employed Persons	

C HH index map in 2011 and 1995

Figure 4: HHI 2011

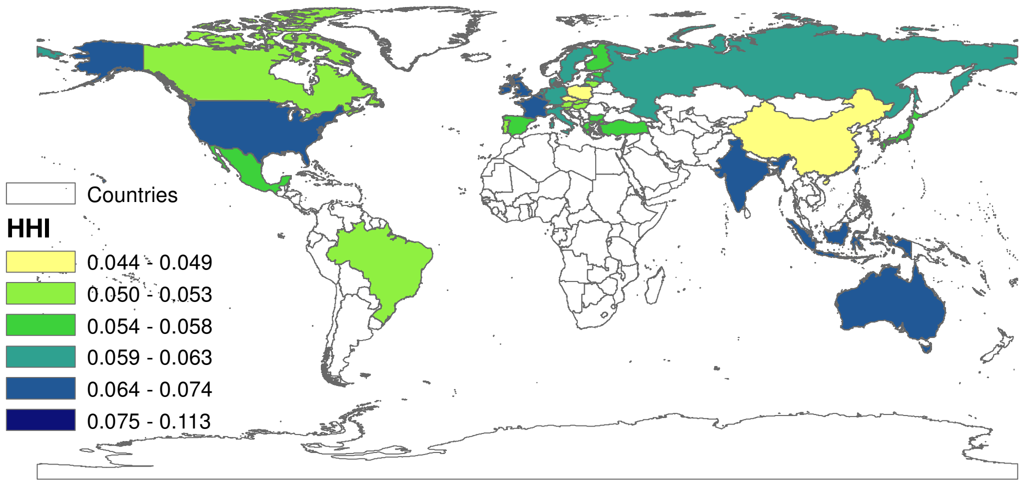

Figure 5: HHI 1995