QUADERNI DEL DIPARTIMENTO

DI ECONOMIA POLITICA E STATISTICA

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Employee Control, Work Content and Wages

n. 775 – Gennaio 2018

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Abstract

Recent contributions have highlighted a technological bias in the substitution of routine work as a cause of wage inequality. Technological progress is assumed to increase returns to abstract, cognitive work and reduce those related to physical, usually routine, work activities. This article puts forward an alternative interpretation whereby wages are related to employees' control over work, which is conditioned by the institutions that represent workers' interests. We use O*NET detailed occupational level data to build two measures of control over i.) physical or tangible work activities, ii.) abstract or non-tangible work activities and one of the direct impact over firm's profits and production. These are used to contest previous interpretations of this data as a measure of task intensity and the relevance of a disaggregation between routine and non-routine work, at least for wage outcomes. We develop a simple bargaining model that suggests employee control adds to the bargaining power of workers and has a negative relation to impact, which is used to a greater extent in industries where control over work is not sufficient to increase wages, a relation that is corroborated by random slopes multilevel models estimates. A comparison of these random coefficients with industry level characteristics provides evidence that institutions such as unions and professional associations increase the odds of receiving a wage premium related to employee control, but finds very limited support for a relation between technological change and the estimated wage *premia*.

Keywords: Labour Economics, Industrial Relations, Job Polarization, Wage Polarization.

JEL: *J*01, *J*31, *J*50, *O*33

Introduction

In the aftermath of the global financial crisis the soaring wage and income inequality in developed economies was brought into the spotlight and its causes have been a matter of great interest and controversy. Since the early 1990s technological change has championed economic attempts to make sense of wage inequality. The complementary between skill and new technologies[1] is in the core of Skill Biased Technological Change models (Acemoglu, 2002a, 2002b) that propose a long term upward slopping labour demand curve to explain the simultaneous increase of employment and wages in the top end of wage and skill distribution. Recently though the hypothesis of routine task automation (Goos, Manning and Salomons, 2009; Acemoglu and Autor, 2011) has become an increasingly popular explanation for the job polarization[2] patterns observed in the 1990s.

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[1]Specially information technology with the mass adoption of computers in the workplace.

[2]The term job polarization refers to the simultaneous increase of employment in both ends of the skill distribution relative to middle skill workers whose jobs consist mainly on routine, standardized and easier to automate, tasks. For a survey see Autor (2015). The technological explanation of job polarization has been questioned on empirical basis, particularly regarding the relation between automation of routine tasks and wages. Recent works by Schmitt at al. (2013) and Bárány and Siegel (2014) pointed out that the relative loss of middle skill jobs might date back to the 1950s, thus preceding widespread evidence of wage polarization by decades.

Alternatively, institutional factors such as de-unionisation and minimum wages have also provided a convincing explanation for the rise of wage inequality (Lemieux, 2008; Kristal and Cohen, 2016). In sociology, the focus on labour market stratification fostered research on social and occupational closure strategies such as unionisation, licensing and professional association representation as vehicle to restrict relative supply and sustain demand, demarcating activities to be performed, within occupations (Weeden, 2002).

The present study bridges the gap between technology and institutions introducing employee control as an additional source of wage inequality. It is argued that the amount of control a worker possesses over his activities and hence over the productive process and resources of a firm has a positive effect on her wage. That is, the capacity to affect production and profits increases the bargaining power of employees.

Our contribution is twofold. First, by building new variables from the Occupational Information Network (O*NET) work activities data and comparing them to previous measures by Acemoglu and Autor (2011) and Autor and Handel (2013) we challenge the common interpretation of O*NET data as task intensities[3]. Instead, it is claimed that they bear a closer association to the amount of control employees in each occupation have over their work. Moreover, assessing O*NET measures of task frequencies, which differ from the importance of work activities usually employed in the construction of routine and non-routine work variables, these two sets of measures often have very low or even negative correlation, as shown in figure (1).

It is also suggested that, at least with respect to wage outcomes, routine and non-routine disaggregations make little sense while the separation of physical or tangible and abstract or non-tangible work activities results in qualitatively different patterns. Figure (1) below illustrates our employee control variables on the left in comparison to their equivalents from Acemoglu and Autor (2011) on the right graph. The industry means[4] of the variables are plotted for 250 3-digit industries, in the x-axis, ordered according to the Census Industry codes from mining, construction and manufacturing industries to services, in the right-side of both graphs.

The two sets of variables show a striking similarity despite the conceptual differences in the choice of work activities that compose them, discussed in the following pages. Figure (1) illustrates how routine and non-routine physical or manual work activities, represented by squares and x's respectively, behave very much alike. Hence, the empirical analysis that follows distinguishes between physical and abstract instead of the usual routine and non-routine work as responsible for wage differentials among employees in distinct occupations.

On the left side of both graphs mining, construction and manufacturing industries present a higher score for the two variables related to tangible work, towards the right side of the x-axes service industries are characterized by a greater importance of abstract, non-tangible work in the occupations they employ.
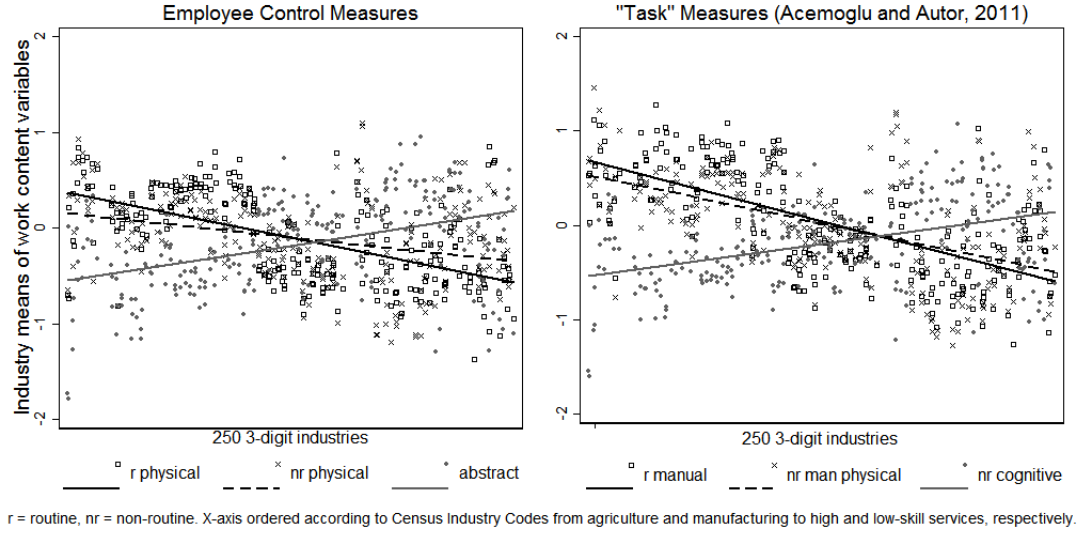
In our second contribution, the econometric analysis casts further doubt on previous results from the routine biased technological change literature. In addition of control over physical and abstract work activities, we asses the direct impact a worker in a specific occupation may have over firm's results, henceforth Impact, using O*NET work context data on i.) the consequence of committing an error and ii.) the importance of decisions. In contrast to employee control, which relates to the type of work activities, physical or abstract, carried out in an occupation, impact refers to the capacity to influence the development of these activities either improving or damaging performance which eventually affects directly production and profits.

Even though the regressions estimate the expected negative and positive wage *premia* associated with physical and abstract work activities, respectively, once these are interacted with employee impact the first is mitigated while the second increases even further.

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[3]Specifically, assuming O*NET work activities measured in scale of importance reflect the frequency in which theses activities (tasks) are performed in a certain occupation.

[4]Excluding workers in management occupations.

Figure 1: Comparison of physical and abstract employee control variables by industries to Acemoglu and Autor (2011) measures

Moreover, multilevel models with random slopes for the two employee control variables reveal a great degree of heterogeneity in the relation between physical and abstract control and wages in different industries, with an unexpected distribution. Although there is a clear negative relation between the estimated random slopes for physical and abstract control, hence workers in industries with high returns to physical control have low or negative wage *premia* from abstract control and vice versa, there is no clear concentration of production and manufacturing industries with positive returns to physical control and of high-skill services with greater random slopes for abstract control.

We also find evidence of a negative relation between the abstract and physical control random slopes and their respective interactions with Impact. That is, a lower or negative wage premium from control over work activities in a certain industry is associated with greater wage gains from an employee's capacity to directly impact production and profits.

The final step of the empirical analysis estimates a multinomial logit model regressing the industry random slopes for physical and abstract employee control on industry level institutional and technological characteristics. Both the level and especially the growth rate, between 2003 and 2016, of industry mean abstract and physical work content that reflect the current and the evolution of the employment composition in industries are poor predictors of the wage *premia* associated with the random slopes[5]. On the other hand, industry average Impact, unionisation rates and professional association representation are related to random slopes statistically greater or at least not smaller than zero, thus providing some evidence that institutions are an important factor that mediate the relation between technology and wages.

Another interesting result is drawn from the Impact variable. High industry mean Impact is related to positive employee control random coefficients according to the multinomial logit analysis, but in the multilevel estimates the interaction between Impact and control is associated to higher wages in industries where employee control alone has negative random slopes. Hence, when the overall level of Impact of workers in an industry is low, the few who can actually affect production and profits earn

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[5]Note that the random slopes estimated by industry in the multilevel models and used as the dependent variable in the multinomial logit does not depend on the industry mean of control over abstract and physical work activities but rather on the relation between occupational level abstract and physical control and individual wages.

higher wages and when average Impact is high employee control over work is more likely to be related to a positive wage *premium*.

The next section provides a brief overview of the literature on employee control and is followed by a simple economic model of wage bargaining where workers in different occupations have distinct bargaining powers according to their control over work activities and also occupation specific capacities to Impact firm's profits. We then describe the measures of employee control based on detailed occupational level data from the O*NET with particular attention to differences between our variables and other previously adopted in the literature and argue that these work activity measures better reflect employee control than task intensities using occupation specific task frequency data.

The empirical analysis follows. Combining occupational level employee control variables with individual level wage, demographic and educational data from the Current Population Survey Merged Outgoing Rotation Groups extracts (CPS-ORG) we first present simple regressions, exploring routine-non-routine disaggregations, and then perform a multilevel analysis which allows us to estimate different returns to employee control by industry. After discussing possible reasons for the technological or institutional nature of employee control over work we find some evidence in favour of the later but only very limited support for the former.

Labour and Control

The issue of employee control gained notoriety with Braverman's (1998) *Labour and Monopoly Capital* though it was preceded by the works of french sociologist Georges Friedmann. Both stressed a pessimistic view, of Marxian inspiration, according to which there was a common trend of decreasing employee control and deskilling of the labour force[6]. A contrasting theory emerged among American scholars such as Clarck Kerr and John T. Dunlop. Specialized skills together with increased voice and autonomy replaced the discouraging trends in labour standards envisioned by Braverman.

The advent of reliable, large scale quality of work surveys in the U.S. and Europe during the 1970s soon depicted a trend incompatible with both theories. While there has been a pronounced decline in discretion, skill requirements rose from mid 1980s to the 2000s (Gallie, 2013, p.335). This propelled research towards the concepts of flexibility and polarization of the labour market. That is, labour market segmentation between a core and a periphery of workers, the former characterized by great autonomy and skill and the later marginalized to low autonomy, non-standard employment arrangements.

Another notable inquiry into the origins of management control and firm organization is due to Marglin (1974). His argument, later contested by Landes (1986), highlights the role of power and control instead of technical efficiency in the emergence of the factory system. In his compelling historical argument Marglin asserts that the agglomeration of workers in factories and the relocation of control over the work process and the quantities produced from manufacturer(worker) to capitalists shifted the former's role in production. The decision of whether or not to work was replaced by whether or not to be employed, thus imposing greater discipline on the labour force.

Part of the labour process theory that spanned from Braverman's work, such as Burawoy (1985), was brought into question by Hyman (1987). While sustaining the relevance of power relations in the organization of production, Hyman (1987, p.38) questions whether forms of organization that restrict worker's control may be considered a conscious strategy from management arguing, for instance, that "*Deskilling involves costs as well as benefits for capital. The more fragmented the structure of tasks and the more limited the range of aptitudes possessed by individual workers, the greater the requirement of expensive managerial skills to integrate collective labour process*".

In economics, efficiency wage models are the most notable line of research to consider some form of control. Despite the focus on employer instead of employee control, the matter in question is not so different from ours. Monitoring is necessary due to workers' capacity to affect production through their choice of effort.

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[6]This and the following paragraph are based on Gallie (2013) and Gallie at al. (2004).

The supervision of work is explicitly considered in Shapiro and Stiglitz (1984) and Bowles (1985). Although there is evidence of extensive use of workplace monitoring (Dickens et al., 1989; Jayadev and Bowles, 2006), the wage-effort relation that underlies these models has proven to be notably challenging for empirical research which perhaps contributed to the reduced interest on issues of employer or employee control among economists.

Still there is more to workplace control than supervision and monitoring. Edwards (1979) identifies three systems of control used by employers: simple, technical and bureaucratic. The first highlights the role of managers direct supervision to elicit higher effort from employees and thus resembles efficiency wage models. In the second, technical control, machinery and the organization of production dictate the work pace, as in a large production lines for instance. Easier to supervise employees reduce the cost of monitoring, nevertheless the operation of expensive and integrated machinery also adds to the potential impact of eventual employee malfeasance[7]. Third, bureaucratic control is usually related to high-skill workers in firms characterized by internal labour markets. Promotions and seniority increase expected or actual wages and hence the cost of jobloss, which in turn induces workers to exert higher effort.

Drawing on the works of both Edwards (1979) and Braverman (1998) it is evident that the amount of control an employee has over work and firm's resources depends on the organization of work and the interactions of employees with machinery, management, clients and each other. Hence, employee control is strictly connected to occupations and the content of work performed as well as industries and the firms' resources to which employees have access.

A Simple Model of Wage Bargaining with Control

This section provides a model of wage bargaining to make sense of the relation between control, Impact and wages . The model developed below resembles efficiency wage models with two important differences. First, firms have the ability to set wages but not employment which depends on the quantity of final goods produced due to the fixed coefficients technology. This choice might seem unusual but is hardly at odds with empirical evidence, or at least is a valid alternative to the Cobb-Douglas technology, that has repeatedly estimated elasticities of substitution well below one at country (Antràs, 2004)[8], industry (Young, 2013) and firm level (Barnes et al., 2008; Chirinko et al., 2011).

Second, in our model the decision to pay higher wages does not imply an increase in productivity through higher effort with respect to equilibrium market clearing wages as in Akerlof (1982). Instead higher wages actually prevent workers from reducing firms profits by under-utilizing capital with respect to the profit rate that would be collected if employees had no control over the productive process.

In the simple economy considered identical firms produce a single good that is used both for consumption and as an input in production. We analyse the distribution of the value of a unit of output in a single production period, for a given quantity of inputs (K) and a level of production (y). For simplicity, the heterogeneity of labour is restricted to two occupations which are combined with firm's inputs or capital as perfect complements. Therefore, the three inputs are labour in occupations one and two, L_1, L_2 and capital K.

Worker's control over the firm's resources and, hence, production is given by the bargaining power in both occupations β and γ, the weights of the Nash product in equation (7). Parameters β and γ and, thus, also the employer's bargaining power ($\delta = 1 - \beta - \gamma$) are exogenous to the bargaining process. In other words, control over work activities depend on technology and the organization of work in production, not on the wages determined in the bargaining process. Employees potential Impact over profits is represented by a function $h(w_1, w_2, v_1, v_2)$, whose arguments are wages and the fallback positions[9] in the two occupations.

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[7] Either by its direct impact on firm's resources or its capacity to delay or reduce production.

[8] Specially in the presence of any bias towards one of the production factors in technology or non Hicks neutral technology.

[9] We will clarify the definition of v_1 and v_2 soon, but it should be understood as the (labour) income a worker has if

Thus, our framework associates employee control over physical and abstract work activities with the bargaining power of workers in each occupation as they hinge on the content of the work performed and, hence, are known and considered in the bargaining process. The Impact over profits in function $h(\cdot)$, on the other hand, depends on the wages paid in excess of the fallback positions. It is associated to employee sabotage or not performing the amount or quality of work desired by the firm.

Therefore, we implicitly assume that impact has a collective character. The capacity of an individual worker to detract from profits without punishment *"depends almost completely upon the willingness of his fellow workers to deter such actions through group pressure and to cooperate with legal authorities"* (Piore, 1973, p.378-379). Hence, being able to actually do so is in line with the interpretation of occupations as micro-classes with specific social norms and collective representation by occupational associations (Grusky and Galescu, 2005,p.5). As it will soon be clear, our Impact variable in the empirical analysis corresponds to the potential or capacity to reduce profits which is given by parameters α and $1-\alpha$ in the model.

Thus, Impact passes through the utilization of firm's resources or capital (K). Whether they choose to make use of this power will depend, negatively, on the wages paid. Therefore worker's Impact on profits is included in production technology (1).

$$y = min\{a_1 L_1, a_2 L_2, b\frac{K}{h(w_1, w_2, v_1, v_2)}\} \tag{1}$$
$$y = min\{a_1 L_1, a_2 L_2, bK^*\}$$

Where $a_1 = \frac{Y}{L_1}$, $a_2 = \frac{Y}{L_2}$ and $b = \frac{Y}{K^*} < 1$ are the labour and capital-output ratios. Note that the capital-output ratio b is not different for actual (K) and effective capital, given by $K^* = K/h(\cdot)$. This means employees' influence on utilization does not affect capital productivity, it rather changes the quantity of actual inputs necessary to produce a unit of output.

We shall further assume that function $h(\cdot)$ is strictly increasing and concave on the difference between wages and the fallback positions. Parameters α and $(1-\alpha) \in (0,1)$ represent the capacity of workers in occupations one and two, respectively, to detract from profits, and thus represent the variable Impact in the following empirical analysis. Indeed α and $(1-\alpha)$ are the elasticities of the amount of damage a worker may impose to the firm with respect to her wages relative to the outside option[10]. Therefore, if $\alpha > 0.5 > 1 - \alpha$ reducing w_1 will have a greater impact on profits than a decrease in w_2.

Moreover, the fallback positions are defined as the alternative income for a worker, hence, the wage of the same occupation in another firm $\left(w_1^A, w_2^A\right)$, which is exogenous to the bargaining process, multiplied by the probability of being employed, given by employment rates $e_1, e_2 \in (0,1)$. Equation (2) gives the explicit form of function $h(\cdot)$.

$$h(w_1, w_2, e_1, e_2, w_1^A, w_2^A) = (w_1 - e_1 w_1^A)^\alpha (w_2 - e_2 w_2^A)^{1-\alpha} \tag{2}$$

The total value of the product, normalizing the output price to 1, equals y, to be distributed between the two categories of workers and profits as in (Tavani and Vasudevan, 2014). Dividing (3) by y gives the same expressions for the value of a unit of output. Rearranging (4) we obtain the gross profit rate by unit of actual capital as a function of wages (5).

$$y = w_1 L_1 + w_2 L_2 + rK \tag{3}$$
$$1 = \frac{w_1}{a_1} + \frac{w_2}{a_2} + \frac{r}{b} \tag{4}$$
$$r = b(1 - \frac{w_1}{a_1} - \frac{w_2}{a_2}) \tag{5}$$

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not employed in the firm. It is assumed that $w_1 > v_1$ and $w_2 > v_2$

[10]Using equation (2) below: $\frac{\partial h(\cdot)}{\partial w_1} \frac{(w_1 - e_1 w_1^A)}{h(\cdot)} = \frac{\alpha(w_1 - e_1 w_1^A)^{\alpha-1}(w_2 - e_2 w_2^A)^{1-\alpha}(w_1 - e_1 w_1^A)}{(w_1 - e_1 w_1^A)^\alpha (w_2 - e_2 w_2^A)^{1-\alpha}} = \alpha$

However, the effective capital utilization also depends on function $h(\cdot)$. Therefore r represents the profit rate that would be obtained with efficient use of inputs. Since the effectively used inputs are given by $K^* = K/h(\cdot)$, the effective profit rate π will be given by $r.h(\cdot)$ and the reduction in profits with respect to r is equal to one minus the ratio between actual and effective capital $(1 - h(\cdot) = 1 - K/K^*)$.

$$\pi = b(1 - \frac{w_1}{a_1} - \frac{w_2}{a_2})h(\cdot) \tag{6}$$

This implies that $h(\cdot) \leq 1$ which will be the case since employers and employees bargain wages and profits over the value of a unit of output, normalized to 1, and the impact function $h(\cdot)$ is homogeneous of degree one. In other words, the bargained wages would have to be very high with respect to the total value that may actually be paid, given by the value of a unit of output. In order for the impact function to be greater than one $(h(\cdot) > 1)$ an unlikely combination of extremely high output-to-labour ratios and very large unemployment rates would be necessary[11].

Although it might seem strange that effective capital is greater than actual capital $(K^* > K)$, $h(\cdot) \leq 1$ represents the necessity of more inputs when these are not efficiently utilized. Consider a firm with a fixed amount of actual capital (K) that hires labour according to the technological requirements in equation (1). Paying higher wages and consequently obtaining a greater value of $h(\cdot)$ will ensure a more efficient use of capital or a smaller difference between effective and actual capital. Hence, for a given quantity of desired output, higher wages are related to a more (actual) capital-intensive production, a fact that finds support in empirical research such as Arai (2003) and Gittleman and Wolff (1993).

Wages are determined by generalized Nash bargaining between employees in both occupations and the employer. The adopted production technology with fixed coefficients allows for the determination of factor demands without unique equilibrium prices given by the marginal products of labour and capital. Nash bargaining provides thus an instrument to set bargained wages as a linear combination of the value of a unit of output of the firm and wage floors given by the fallback positions (Tavani, 2012, p.118-119). The correspondent bargaining powers in occupations one and two, that represent our measures of employee control in the empirical analysis ahead, are the weights of the Nash product:β, γ, while $\delta = 1 - \beta - \gamma$ expresses employers control over work. The wage bargaining in a certain period of time will be described by (7).

$$\max_{\{w_1, w_2\}} : S = (w_1 - e_1 w_1^A)^\beta (w_2 - e_2 w_2^A)^\gamma (r.(w_1 - e_1 w_1^A)^\alpha (w_2 - e_2 w_2^A)^{1-\alpha})^\delta \tag{7}$$

Taking the first order conditions with respect to the two wages and combining them gives the bargained wages (8) and (9)[12].

$$w_1 = \frac{a_1(\beta + \alpha\delta)}{1 + \delta} + \frac{e_1 w_1^A(\delta + \gamma + (1-\alpha)\delta)}{1 + \delta} - \frac{a_1}{a_2}\frac{e_2 w_2^A(\beta + \alpha\delta)}{(1 + \delta)} \tag{8}$$

$$w_2 = \frac{a_2(\gamma + (1-\alpha)\delta)}{1 + \delta} + \frac{e_2 w_2^A(\delta + \beta + \alpha\delta)}{1 + \delta} - \frac{a_2}{a_1}\frac{e_1 w_1^A(\gamma + (1-\alpha)\delta)}{(1 + \delta)} \tag{9}$$

Bargained wages will be increasing in each occupation's labour-output ratio (a_1, a_2), employee control (β, γ), Impact $(\alpha, 1 - \alpha)$ and on their outside options. They are also decreasing on employer's bargaining power (δ) and on the other occupation's outside option.

In market equilibrium wages bargained by all the identical firms are the same, as in Skott and Guy (2007). Hence, the alternative wages in the fallback positions will be equal to the bargained ones[13]. Rearranging equations (8) and (9) into the system below we may apply Cramer's rule to get the market wages.

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[11] A more detailed explanation is provided in the final section of Appendix A.

[12] The derivations and algebra are presented in Appendix A.

[13] $w_1 = w_1^A$ and $w_2 = w_2^A$.

$$\begin{bmatrix} 1 + \delta - e_1(\delta + \gamma + (1-\alpha)\delta) & \frac{a_1}{a_2}e_2(\beta + \alpha\delta) \\ \frac{a_2}{a_1}e_1(\gamma + (1-\alpha)\delta) & 1 + \delta - e_2(\delta + \beta + \alpha\delta) \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} a_1(\beta + \alpha\delta) \\ a_2(\gamma + (1-\alpha)\delta) \end{bmatrix}$$

The final expressions for wages in both occupations will then be given by (10) and (11)[14]:
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$$w_1 = \frac{a_1(\beta + \alpha\delta)}{(1 + \delta(1 - e_1)) + (e_2 - e_1)(\beta + (1-\alpha)\delta)} \tag{10}$$

$$w_2 = \frac{a_2((\gamma + (1-\alpha)\delta)}{(1 + \delta(1 - e_2)) + (e_1 - e_2)(\gamma + \alpha\delta)} \tag{11}$$

Wages are still strictly increasing in their own control over work and Impact and, therefore, decreasing on the other occupation's. There is also a compensating effect between employee control and Impact. A higher α $(1 - \alpha)$ for occupation one (two) will result in higher wages the lower is the sum $\beta + \gamma$. Namely, the wage reduction that would follow a high bargaining power of the employer (δ) is mitigated by workers capacity to impact directly firm's profits by choosing to perform poorly or sabotage work.

Wages in (10) and (11) are also increasing on their own and decreasing on the other occupation's employment rate. However, due to the production technology adopted employment rates e_1 and e_2 must increase in line with production. Hence, if both e_1 and e_2 increase as a function of total output (Y) there will be an interval in which both occupations obtain higher wages following a growth in Y. Such an interval is increasing in the employer's bargaining power (δ). If, however, there is a great disparity in the output-to-labour ratio in the two occupations, the one with the higher ratio will see a greater employment expansion and obtain higher wages while the other could have a decrease in wages as a result of higher output. The underlying logic behind this movements is that a much stronger growth in, say, e_1 with respect to e_2 also increases the outside option in occupation one, inducing employers to negotiate higher wages these employees in order to avoid their direct impact on profits[15].

Taking the ratio between (10) and (11) a simpler expression for wage inequality is obtained (12)[16].

$$\frac{w_1}{w_2} = \frac{a_1(\beta + \alpha\delta)(1 - e_2)}{a_2(\gamma + (1-\alpha)\delta)(1 - e_1)} \tag{12}$$

It is evident from the expression above that a polarization of the Impact over profits $(\alpha, 1 - \alpha)$ increases inequality. Employee control will also increase inequality if the growth of β, for instance, implies a decrease in γ. The effect of an equal and simultaneous increase in β and γ on wage inequality depends on parameter α. If $\alpha > 0.5$, a fall in $\delta = 1 - \beta - \gamma$ will reduce the w_1/w_2 and reduce inequality if wages in occupation one were initially higher or increase it otherwise.

An expansion of aggregate demand and output, supposing a fixed supply of labour in both occupations, will reduce inequality if wages in the occupation with the highest labour-output ratio is initially lower. In other words, if $a_1 < a_2$ and $w_1 > w_2$, an increase in Y will generate greater demand for $L_2 = a_2 Y$ than for L_1, provided that none of the occupations is near full employment or that there is some degree of mobility between them. Hence, not only there is a pro-cyclical trend in wages, as empirical evidence suggests (Shin and Solon, 2007; Martins, 2007), but under reasonable conditions for the model's parameters wage inequality is counter-cyclical.

Despite the simple consequences of an output increase on wages and inequality outline above, this simple model serves to characterize the bargaining process between two different types of workers and employers in a single period, static environment. Three features of the model distinguish it from the more usual efficiency wage setting. First, it provides a change in perspective. Employees' control

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[14] The denominator in the two expression is the same, they were rearranged for an easier interpretation.

[15] The effects of output (Y) on wages is analyzed in greater detail in the end of appendix A.

[16] The terms $(1 - e_2)$ and $(1 - e_1)$ are present in both the numerator and denominator of equations (10) and (11), respectively and, hence, are omitted above. Appendix A provides the complete calculations to obtain market wages.

over work and their capacity to impact profits negatively lead to an inefficient use of firm's resources instead of increasing labour productivity as in efficiency wage models. Second, due to the heterogeneity of workers in our model it describes not only a conflict between employers and employees, but also between different groups of workers. The third and final contribution of this simple model regards the interaction between employee control and impact. Parameters $\alpha\delta$ and $(1-\alpha)\delta$ in equations (10) and (11), respectively, provide a testable hypothesis: impact (α and $1-\alpha$) should have a greater effect on wages when employee control over work (β and γ) is low.

The next section begins the empirical analysis describing the variables that compose our measures of employee control and impact. I also discuss their relation with the intensity or frequency of work activities performed by workers and, hence, contrasts our interpretation of O*NET variables as measures of employee control and impact with previous uses of the same dataset.

Measures of Work Content and Employee Control

The bulk of wage inequality is traditionally found within-occupation or between-firm and researchers, such as Barth et al. (2014) for example, have concentrated a great deal of attention in it. The growth of between-occupation inequality since the late 1970s, however, has been equally impressive and did not pass unnoticed. According to Williams (2013) although most of wage inequality in the U.K. is still found within-occupation, it was between-occupation inequality that grew the most between 1975 and 2008.

A similar picture emerges in the U.S. From 1992 to 2002, the 66 percent of wage inequality increase took place between occupations (Mouw and Kalleberg, 2010, p.422). Accounting for a longer period Weeden et al. (2007, p.721) found similar results[17] for the period ranging from 1973 to 2005[18]. Both of these studies measure inequality through the decomposition of wage variance between and within occupations.

These figures provide sufficient motivation to use occupational level characteristics to explain wage inequality. Hence, to construct measures of control by occupation we use data from the Occupational Information Network (O*NET 21.3[19]), developed by the U.S. Department of Labor and released in May 2017 containing detailed characteristics on 974 occupations[20]. In 2000 the O*NET replaced the Dictionary of Occupational Titles (DOT), which gained notoriety among economists with Autor, Levy and Murnane's (2003) analysis of routine task substitution due to the introduction of information technology, as the main source of occupational information in the U.S. Since then O*NET data itself was employed in studies about automation (Frey and Osborne, 2017) and offshoring (Blinder, 2009; Blinder and Krueger, 2013).

Each occupation is described by variables classified into eight major groups: *i.*) abilities, *ii.*) interests, *iii.*) knowledge, *iv.*) skills, *v.*) work activities, *vi.*) work context, *vii.*) work styles and *viii.*) work values. The O*NET job content model (Onetcenter, 2017) is based on organizational analysis and reflects characteristics of occupations (*v.* and *vi.*) and of the people employed in those (*i.*, *ii.*, *iii.*, *iv.*, *vii.* and *viii.*).

We rely on occupational requirement characteristics included in work activities (*v.*), for employee control, and work context (*vi.*) for Impact[21]. The O*NET variables used to build our two measures of

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[17] The authors consider two kinds of within occupation inequality: between (big) class and between occupations/within class. Big class is defined as a group of several occupations.

[18] A contrasting view was presented by Kim and Sakamoto (2008) arguing that the increase in wage inquality in the past few decades was better explained by within occupation trends. Mouw and Kalleberg (2010, p.403), however, show that the increase in residual wage inequality in the CPS sample of Kim and Sakamoto was mainly caused by imputed missing wages, obtained based on aggregate categories of occupations, thus artificially reducing between occupation inequality. For further information refer to the Wages and Task Control section.

[19] The data is freely available at https://www.onetcenter.org/db_releases.html

[20] The O*NET codes are based on the U.S. Bureau of Labour Statistics Standard Occupational Classification (SOC) codes.

[21] Work activities include the set of general activities common to all job families and industries like analyzing data and monitoring processes while work context reflects the physical and social factors that influence the nature of work such

employee control over physical and abstract activities were selected using a bottom down approach as in other studies that rely on the same dataset (Firpo et al., 2010; Blinder, 2009; Autor and Handel, 2013). All the variables attribute a scale of importance, from 1 (not important) to 5 (extremely important), to a specific activity in a given occupation[22].

The present analysis differs from previously developed variables, particularly those in Acemoglu and Autor (2011) and Autor and Handel (2013), in two aspects. First, in order to be as consistent as possible with the original O*NET model each of our variables is built with data from a single category, namely work activities for physical and abstract employee control and work context for Impact. Additionally, employee control is based on a far greater number of work activities, 13 for physical[23] and 16 for abstract, as seen in table (1)[24].

Although this choice does reduce variation in the control measures between occupations and industries, to some extent, it also reduces the risk of introducing an undesired bias towards some occupations when dealing with a more restricted set of work activities. Analyzing data or interpreting information for others, both included in abstract control, are certainly relevant and fairly general work activities. But there is no obvious criteria to choose these over processing information or making decisions and solving problems. Considering more work activities is a conservative decision that attempts to capture important characteristics for a greater number of occupations without changing dramatically the industry average of the variables, with respect to the Acemoglu and Autor (2011), as previously seen in figure (1).

The second and more meaningful difference is one of interpretation. Our use of these work activities, in a scale of importance, to measure employee control differs from previous interpretations of the same data. We have thus far intentionally avoided the use of the term tasks to refer to the O*NET work activities and work context variables for it is exactly as a measure of tasks intensity that they have been interpreted by other works such as Autor and Handel (2013).

Therefore, assuming that O*NET variables correspond to tasks immediately leads us to task based models (Gorssman and Rossi-Hansberg, 2008) that underlie the routine task automation hypothesis to explain job and wage polarization (Acemoglu and Autor, 2011, p.1079; Acemoglu and Restrepo, 2016). Empirical applications of these models assume that variables based on the same O*NET data we use reflect the frequency in which these work activities are performed in each occupation. That is, jobs that are intensive in a certain routine tasks are also more susceptible to automation because those tasks are easier to translate into a coded and standardized procedures to be performed by machines.

Hence, identifying the O*NET measures of work activities and context as tasks implies that they reflect the frequency or intensity of those in an occupation. Fortunately the O*NET database also contains information on tasks which are, in contrast to work activities, specific to each occupation and measured in a scale of frequency.

These are also associated to work activities, but not to work context. We compare our selected work activity measures of importance with the sum of the frequencies of all tasks associated to them.

Table (1) lists the work activities that compose the two employee control measures[25]. Furthermore, physical control is separated into routine and non-routine. All of the omitted work activities from O*NET are either too ambiguous to be assigned to our two variables or regard managerial aspects of

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as freedom to make decisions and the degree of automation in an occupation.

[22]The O*NET questionnaires contains a short description of the work activity followed by the question and an horizontal scale with numbers 1,2,3,4 and 5 labeled as not important, somewhat important, important, very important and extremely important. The questionnaires may be either administered by occupational experts (22.7%), analysts (0.3%) or responded by incumbents alone (77.3%), the percentages regard the work activities reported in O*NET 21.2. Let us consider the work activity 4.A.1.a.1: getting information. The question "How important is getting information to the performance of your current job?" is preceded by the description of this activity: "observing, receiving and otherwise obtaining information from all relevant sources".

[23]Which is further disaggregated into routine (6) and non-routine (5).

[24]Autor and Acemoglu (2011, p,1079) have argued that restricting the number of work activities and other occupational characteristics avoided overlap between the variables built from O*NET. Still, since we use only two variables with qualitatively different characteristics, it is unlikely that one of the selected work activities reflects both abstract and physical activities of an occupation.

[25]A more detailed description of each work activity is provided in Appendix B.

work which are not of direct interest[26]. For each of the work activities listed below we present the correlation (ρ) between their measure of importance, used to build both our employee control variables and the measures of task intensities used in other work on the literature, and the sum of the frequencies of the actual tasks from O*NET data associated to them.

Table 1: Composite measures of control and correlation (ρ) between work activities in scale of importance and their respective task frequencies

Physical Work Activities	ρ	N	Abstract Work Activities	ρ	N
Monitor Processes, Materials, or Surroundings (a)	.22	429	Getting information (a)	.10	508
Inspecting Equipment, Structures, or Material (a)	.04	456	Identifying objects, actions and events (a)	-.30	89
Operating vehicles, mechanized devices, or equipment (a)	.33	82	Estimating the Quantifiable Characteristics of Products, Events, or Information (a)	-.17	241
Assisting and Caring for Others (a)	.47	202	Judging the Qualities of Things, Services, or People (a)	-.04	252
Monitoring and controlling resources (a)	-.06	352	Processing information (a)	-.08	207
Controlling machines and processes (b)	.31	284	Evaluating Information to Determine Compliance with Standards (a)	-.11	99
Drafting, laying out, and specifying technical devices, parts and equipment (b)	-	-	Analyzing data or information (a)	-.05	297
Repairing and maintaining mechanical equipment (b)	.26	323	Making decisions and solving problems (a)	-.08	401
Repairing and maintaining electronic equipment (b)	-	-	Thinking creatively (a)	.16	424
Documenting/Recording Information (b)	.19	749	Interpreting the Meaning of Information for Others (a)	.13	193
Performing administrative activities (b)	-.19	182	Communicating with Persons Outside Organization (a)	-.16	164
Performing general physical activities (c)	.12	383	Establishing and Maintaining Interpersonal Relationships (a)	-.08	33
Handling and moving objects (c)	.32	486	Selling or Influencing Others (a)	.33	145
			Resolving Conflicts and Negotiating with Others (a)	-.01	96
			Performing for or working directly with the public (a)	.21	76
			Provide Consultation and Advice to Others (a)	.01	340
Non-routine Physical (a)			Non-routine Abstract (a)		
Routine Physical (b)					
Not classified Physical (c)					
Physical Control (a) + (b) + (c)			Abstract Control (a)		

ρ computes the correlation between the reported importance of each work activity in the table and the sum of the frequencies of all the tasks associated to this work activity. N refers to the number of O*NET occupations that have at least one task associated to the listed work activity.

O*NET data encompasses 974 occupations using a classification based on the Standard Occupation Classification (SOC) code. The two measures of employee control are constructed by adding-up the values of the O*NET work activities that compose it, by occupation, and then standardizing them such that all have mean zero and a standard deviation of one.

A similar procedure is applied to O*NET tasks. A measure of frequency in seven categories from 1, yearly or less, to 7, hourly or more, represents the proportion of respondents that report them and is available for each task. We calculate an average of times per year that task is performed[27] weighted by the frequency in which they were reported. These values are then used to calculate the frequency of each task. Then, the sum of the frequencies of all tasks that correspond to each work activity in table (1) is computed.

Table (1) presents the correlations (ρ) between work activities, in scale of importance, and the frequency of their respective tasks with mostly low and often negative correlations. We interpret these as evidence that work activity measures of importance do not reflect the intensity or frequency of those in an occupation, but rather the relevance of such an activity to the overall productive process, which is closely related to the control an employee has over that activity rather than the time spent performing it.

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[26] All the following empirical analysis will be conducted excluding managers.

[27] A table with the values attributed to each category is available in appendix B.

Most work activities are associated to several different tasks, but not all occupations have tasks matching work activities, since the former are occupation-specific. Let us consider, for example, *processing information* which is part of our abstract control variable. For workers in occupation Advertising and promotions managers[28] processing information corresponds to two tasks: *i.*) gather and organize information to plan advertising campaigns and *ii.*) confer with department heads or staff to discuss topics such as contracts, selection of advertising media, or product to be advertised. On the other hand, for Operations research analysts[29] processing information is related to *i.*) collaborate with senior managers and decision makers to identify and solve a variety of problems and to clarify management objectives and *ii.*) define data requirements and gather and validate information, applying judgement and statistical tests. Columns (N) present the number of occupations with at least one task-work activity match[30].

The third and last variable to be used in the empirical analysis assesses the Impact employees may have over firm's resources and profits, represented by parameter α in the model. We select two work context characteristics, in scale of importance as well, namely *i.*) consequence of committing an error and *ii.*) the impact of decisions on co-workers or company results. These portray how critical a certain occupation is with respect to the impact an employee may have on final products according to the O*NET content model (Onetcenter, 2017, p.32). Just as the two employee control variables, these two work context characteristics are summed by occupation and the final Impact variable in then standardized.

Wages and Employee Control

In order to make the variables compatible with individual wage data we aggregate them into CPS occupational titles. First, O*NET occupations data is converted to slightly more aggregated SOC codes taking simple averages, then those are converted into CPS 2010 Census Occupation Codes using averages weighted by the total employment of each occupation[31]. The final sample, excluding public sector, contains 466 occupations.

Wages and other individual characteristics are obtained from the 2016, 2015 and 2014 Current Population Survey's Outgoing Rotation Group (Center for Economic and Policy Research. 2017)[32][33]. A cross-section is pooled from these three specific year because they share similar occupation and industry codes. CPS-ORG extracts have been extensively employed in the analysis of wage inequality (Card and DiNardo, 2002; Lemieux, 2006; Mouw and Kalleberg, 2010).

The analysis is based on a sample of employed, full time[34], private sector, non self-employed workers aged between 18 and 65 with real hourly wages ranging from 3 to 100 USD. We further exclude individuals in managerial occupations since these are more likely to have wages related to firm performance and the supervision of other employees to focus exclusively on workers whose earnings are more likely to be influenced by their control over work.

The dependent variable is the log of real hourly wages calculated for both hourly and non hourly workers. The final restriction imposed in the sample is to exclude observations with imputed wages and hours. Missing wages are imputed based on reported wages by workers that present a similar set of characteristics like sex, race and, of greater relevance for us, major occupational group. Hence,

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[28]Which is occupation 0040 in 2010 COC.

[29]Which is occupation 1220 in 2010 COC.

[30]For instance, 508 out of the 974 O*NET listed occupations contain a task that is related to the work activity Getting information. Additionally, two of the selected work activities have no associated tasks.

[31]The crosswalk files are provided by the U.S. Bureau of Labor Statistics and is available at https://www.bls.gov/emp/ep_crosswalks.htm.

[32]The data is freely available. A prepared version of the CPS-ORG extracts starting from 1979 is available at http://ceprdata.org/cps-uniform-data-extracts/cps-outgoing-rotation-group/cps-org-data/

[33]The O*NET 21.3, released on 2017, contains occupational measures collected in different years. Hence, although there were frequent releases of new version of O*NET since its first version, is is not possible to couple it with a longitudinal database to consider changes in occupational task characteristics in time.
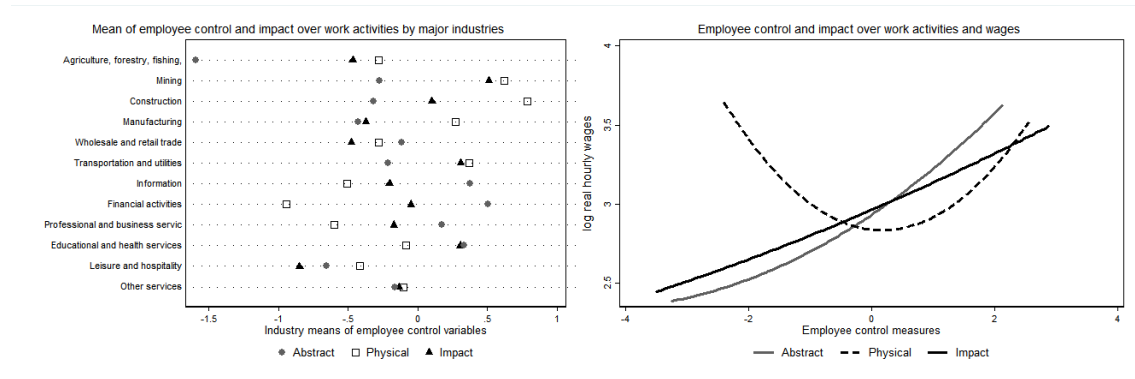
[34]35 hours per week or more in the week before the interview.

this imputation procedure artificially reduces wage difference between occupations by imputing wages based on a more aggregate group occupations than the 3-digit codes associated with our employee control and Impact variables (Mouw and Kalleberg, 2010, p.413)[35].

The final sample has 146,067 observation with workers classified in 466 occupations. Figure (2) provides some intuition on the behaviour of our three variables once they are combined with the CPS-ORG data. The left graph plots the average of our three variables by twelve major industry groups. Employee control over physical activities is higher, in average, among manufacturing and infrastructure industries such as mining and construction and lower in typically high-skill services like financial and information industries. The inverse is true for abstract control. Employees in some industry groups have relatively lower average control over both physical and abstract activities like agriculture, leisure and hospitality and wholesale and retail trade. Impact presents a mixed pattern across industries with high and low values in both production and service industries.

The right graph of figure (2) plots the quadratic fit of our three variables against log real hourly wages. Both abstract control and impact are monotonically increasing a rather linear. Physical employee control instead has a u-shape. That together with the significant variation of our three measures, even in very aggregated industry groups, suggests there is at least some degree of heterogeneity in the relation between employee control , impact, and wages worth considering in the following empirical analysis.

Figure 2: Major industries mean employee control and impact (left) and their relation to wages (right)

The first estimates are presented in table (2) and suggest that employee control and Impact are indeed related to wages. Column (1) regresses the two measures of control on log real hourly wages without other controls. The two coefficients are statistically different from zero but physical control is negative while abstract control has the expected positive sign. In particular, a one standard deviation increase in abstract control implies a substantial wage increase of about 25%.

Once the interactions between employee control and Impact are introduced in column (2) physical and abstract control coefficients remain virtually unaltered. Their interactions with Impact suggest that being able to affect firm's profits to a greater extent is related to a small wage premium, thus mitigating the overall negative effect of physical and further increasing the positive one related to control over abstract work.

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[35]Our sample of full time, private sector workers contains about 41.5% of imputed wages, slightly higher than the 33.4% reported by Mouw and Kalleberg (2010, p. 412) for the full CPS-ORG sample of 2008.

Table 2: OLS regressions of log real hourly wages on employee control and impact variables

	(1)	(2)	(3)	(4)
Abstract	0.253***	0.259***	0.105***	0.110***
	(0.00154)	(0.00162)	(0.00213)	(0.00219)
Abstract*Impact		0.0124***		0.0123***
		(0.00155)		(0.00150)
Physical	-0.0590***	-0.0549***	-0.0704***	-0.0655***
	(0.00181)	(0.00184)	(0.00292)	(0.00297)
Physical*Impact		0.0201***		0.00943***
		(0.00174)		(0.00161)
Union			0.195***	0.194***
			(0.00427)	(0.00427)
Female			-0.138***	-0.138***
			(0.00298)	(0.00298)
Age			0.0284***	0.0291***
			(0.00407)	(0.00407)
Age^2			0.0000283	0.0000254
			(0.0000250)	(0.0000250)
Potential experience			-0.00260	-0.00313
			(0.00371)	(0.00371)
Potential experience^2			-0.000453***	-0.000452***
			(0.0000244)	(0.0000244)
Black			-0.106***	-0.106***
			(0.00399)	(0.00399)
Hispanic			-0.0646***	-0.0647***
			(0.00363)	(0.00363)
Asian			0.0153**	0.0146*
			(0.00573)	(0.00573)
Other			-0.0905***	-0.0910***
			(0.0109)	(0.0110)
U.S. citizen			0.104***	0.104***
			(0.00468)	(0.00468)
HS graduate			0.0450***	0.0441***
			(0.00752)	(0.00751)
Some college			0.0781***	0.0765***
			(0.0123)	(0.0123)
College degree			0.218***	0.216***
			(0.0210)	(0.0210)
Advanced degree			0.383***	0.378***
			(0.0281)	(0.0281)
Constant	2.948***	2.937***	1.841***	1.854***
	(0.00155)	(0.00169)	(0.0673)	(0.0673)
22 2-digit occupations			✓	✓
250 3-digit industries			✓	✓
N	146,067	146,067	146,067	146,067
R^2	0.197	0.199	0.539	0.540

Robust standard errors in parentheses. All models are weighted by sampling weights.

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

Column (3) of table (2) adds demographic and educational characteristics of individual workers as well as industry and occupation dummies without the impact interactions. Both employee control variables remain good predictors of wages but while physical control suffers only a minor change in magnitude, from -0.06 to -0.07, abstract control estimated coefficient falls from .26 to .10. In the final regression (4) the interaction terms are estimated together with other covariates. Even though the increase in fit is marginal the two interaction coefficients remains positive and statistically different from zero as in column (2).

This descriptive results thus far seem to corroborate the usual interpretation that abstract work content boosts earnings while manual or physical, which often coincide with routine work, is related

to lower wages. Moreover, Autor and Handel (2013, p.S87) point out that *"occupations that have high returns to Abstract tasks have low returns to Manual and Routine tasks"*, a fact that also happens to industries in our analysis given the considerable variation in employee control and Impact measures by major industry groups on the left graph of figure 2. But before presenting a more thorough analysis of the heterogeneity in employee control and impact between industries we consider the difference between control over routine and non-routine physical activities and compare our employee control variables to those developed by Acemoglu and Autor (2011), both already shown in figure (1).

In the last decade it has become increasingly consensual that technological change is biased towards the substitution of routine, easier to automate tasks. As these concentrate in blue collar, office and administrative jobs in the middle of the skill and wage distribution, the automation of routine work would explain the higher relative growth of employment in both high a low-skill occupations which are more intensive in non-routine manual and abstract work, respectively and stagnant wages in the middle.

Our use of O*NET variables to infer employee control over work does not correspond to the most common usage of this data. We have shown in table (1) that the correlations between the control measures in scale of importance and the frequency of their respective tasks is limited and often negative. The results in table (3) pose further questions on the relevance of the routine-non-routine disaggregation. Figure (1) in the introduction showed a very similar distribution of control over physical routine and non-routine control between industries as well as of routine manual and non-routine manual physical "task" measures.

Table 3: OLS regressions of log real hourly wages on employee control with routine/non-routine disaggregations

	(1)	(2)		(3)	(4)
Abstract	0.266***	0.103***	Non-routine cognitive	0.244***	0.0771***
	(0.00155)	(0.00240)		(0.00183)	(0.00187)
Physical routine	0.132***	-0.0314***	Routine manual	-0.0913***	-0.0668***
	(0.00223)	(0.00293)		(0.00301)	(0.00374)
Physical non-routine	-0.158***	-0.0199***	Non-routine manual physical	0.0450***	-0.0120**
	(0.00224)	(0.00300)		(0.00255)	(0.00381)
Controls		✓	Controls		✓
22 2-digit occupations		✓	22 2-digit occupations		✓
250 3-digit industries		✓	250 3-digit industries		✓
N	146,067	146,067	N	146,067	146,067
$t\ \beta_{routine} = \beta_{non-routine}$	5195.6***	5.3*	$t\ \beta_{routine} = \beta_{non-routine}$	697.3***	65.1***
R^2	0.223	0.538	R^2	0.207	0.542

Robust standard errors in parentheses. All models weighted by sampling weights.

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

Controls include, as in table 2; union, sex, age, age^2, potential experience and its square,

race/ethnicity, U.S. citizenship and education.

However, once we regress these two sets of variables on wages, columns (1) and (3), only routine manual has a negative coefficient in (3) as expected, but this relations is reversed using our employee control variables in (1) with physical routine greater and non-routine employee control smaller than zero.

After accounting for the same covariates included in table (2) routine and non-routine physical (2) and routine manual and non-routine manual physical (4) become negative. Although the Wald tests in the bottom of both tables reject the hypothesis that routine and non-routine variables are equal in models (2) and (4), once a great number of different work activities is considered in the construction of our employee control variables the difference in the relation between routine and non-routine physical control and wages is small and both have the same negative sign.

Hence, the assumption that routine activities are related to lower wages seems to apply just as well to non-routine physical work. Yet the simpler distinction between control over abstract and physical activities appears to be more relevant for earnings. The simple regressions analysis carried thus far suffers, however, from an important limitation. They mask a considerable degree of heterogeneity between industries, which we consider in the following section.
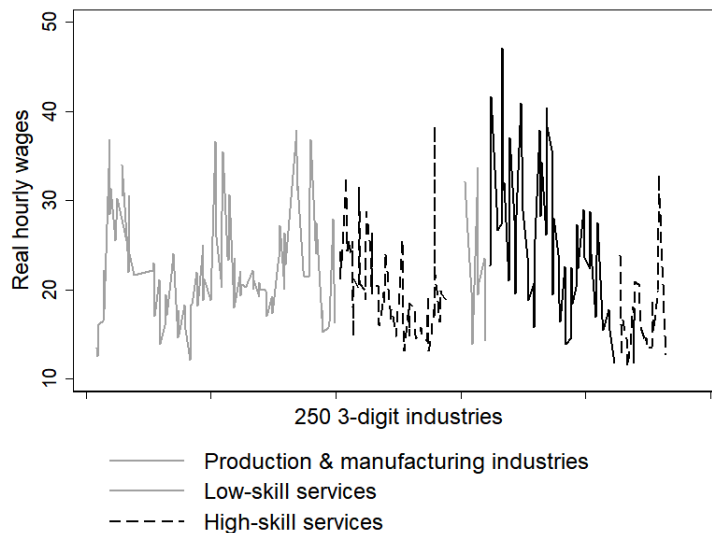
Multilevel Models

The OLS regressions presented above implicitly assume an homogeneous population of workers but the data employed in the previous section has a hierarchical structure with workers nested in industries with possible different returns to employee control and Impact. Ignoring such hierarchy often leads to biased, underestimated standard errors.

To circumvent this issues and account for heterogeneous coefficients of employee control and Impact in different industries this section extends the previous analysis using multilevel models, for a general text see Snijders and Bosker (1999). Also known as mixed effects, these models account for the hierarchical structure of the data and allows us to disentangle effects from variables defined at different levels. In the present case level 1 corresponds to the individual workers and aggregations of workers within industries define higher levels[36]. Additionally, the estimates presented in table 4. provide a variance decomposition among the different levels, such that level one estimates within and level two between industry wage variance.

Average wages, in the y-axis, by the 250 3-digit industries that define our level 2, in the x-axis, are plotted in figure (3) There is significant wage variation among groups, even between production and manufacturing, low-skill and high-skill service industries.

Figure 3: Average real hourly wages by 3-digit industries

In contrast to the previous OLS regressions the multilevel analysis no longer considers sampling weights. There are two distinct reasons for that. First, the hierarchical levels of interest, industries, are different from the ones in the CPS survey structure which may lead to problems in the maximum

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[36]The hierarchical levels are conventionally numbered bottom-up.

likelihood estimation. Second, omitting the weights is likely to be a problem only if the survey design is informative, that is, if the errors are correlated to the weights. Furthermore, Stapleton and Kang (2016) argue that ignoring both the stratification and sampling, which is the case here, does not introduce a severe bias on estimates since the former implies an overestimation and the later an underestimation of standard errors that compensate each other.

The estimates are reported in table (4) The null model in column (1) is equivalent to a random effects ANOVA and provides the variance decomposition between the two levels, about 8% of wage variation is found between industries.

In column (2) employee control over abstract and physical work activities are included in the model with average coefficients similar to those in the OLS regression. There is a significant reduction of the estimated wage variance in both levels that result in a intra-class correlation of 6.2%. Individual demographic and educational characteristics as well as occupation dummies are introduced in column (3) with results similar to those of model (3) in the OLS regressions, just as model (4) in which the impact interactions are included once again with positive but small coefficients.

Table 4: Multilevel regressions of log real hourly wages on employee control and impact

	(1)	(2)	(3)	(4)	(5)	(6)
Abstract		0.196^{***}	0.106^{***}	0.111^{***}	0.0961^{***}	0.0940^{***}
		(0.00146)	(0.00183)	(0.00187)	(0.00378)	(0.00368)
Abstract*Impact				0.0143^{***}		0.00909^{**}
				(0.00131)		(0.00337)
Physical		-0.0705^{***}	-0.0684^{***}	-0.0629^{***}	-0.0638^{***}	-0.0583^{***}
		(0.00167)	(0.00243)	(0.00246)	(0.00501)	(0.00455)
Physical*Impact				0.00901^{***}		0.0189^{***}
				(0.00135)		(0.00423)
Controls			✓	✓	✓	✓
22 2-digit occupations			✓	✓	✓	✓
Random effects						
level 2: σ_u^2	0.071	0.054	0.021	0.022	0.019	0.018
	(0.0065)	(0.0049)	(0.0020)	(0.0021)	(0.0002)	(0.002)
level 2: $\sigma_{abstract}^2$	-	-	-	-	0.0020	0.0016
					(0.0004)	(0.0002)
level 2: $\sigma_{abstract*impact}^2$	-	-	-	-	-	0.0014
						(0.0002)
level 2: $\sigma_{physical}^2$	-	-	-	-	0.0035	0.0023
					(0.0004)	(0.0003)
level 2: $\sigma_{physical*impact}^2$	-	-	-	-	-	0.0028
						(0.0004)
level 1: σ_e^2	0.238	0.210	0.152	0.152	0.150	0.148
	(0.0009)	(0.0008)	(0.0006)	(0.0006)	(0.0005)	(0.0005)
N	146,067	146,067	146,067	146,067	146,067	146,067
Likelihood ratio test	$44,696.3^{***}$	$8,140.0^{***}$	$56,986.3^{***}$	176.1^{***}	$1,476.7^{***}$	$1,823.5^{***}$
AIC	205,891.7	187,755.6	140,837.3	140,665.1	139,194.4	137,392.8
BIC	205,921.3	187,805.1	141,223.1	141,070.7	139,629.6	137,936.9

Standard errors in parentheses, all models include a constant.

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

Controls include, as in table 2; union, sex, age, age^2, potential experience and its square,

race/ethnicity, U.S. citizenship and education.

The likelihood ratio tests the models against the one in the column to the left and against a linear model in (1).

The last two model in table (4) estimate random slopes for physical and abstract employee control (5) and also for their interaction with impact (6). Both the information criteria and the likelihood ratio test in the bottom of the table confirm that the introduction of the random slopes do increase the fitness of the models. Although there is no considerable change in the estimated coefficients for
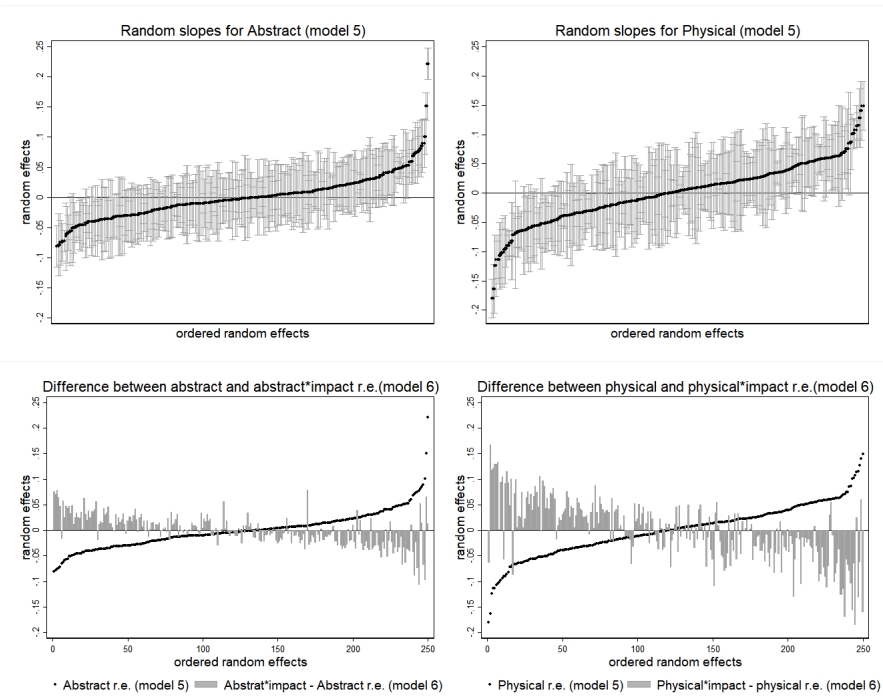
the means or the fixed part of the model in (5) and (6), the random slopes in both models provide valuable insights on the relation between employee control, Impact and wages between industries.

Figures (4) and (5) plot the estimated random slopes to illustrate three important results. First, indeed there is a great heterogeneity in the relation between employee control and wages in different industries. Second, as suggested in the bargaining model there is a negative relation between the estimated random slopes of employee control and their respective interactions with Impact. And third, there seems to be no clear cut intuitive pattern relating industries to wage *premia* from employee control. Several typically high-skill industries have negative random slopes for abstract control just as some manufacturing industries have effective wage gains from abstract and not physical control.

The two graphs in the first row of figure (4) present the estimated random slopes for abstract and physical control from model (5) in an increasing order with their 90% confidence intervals. Several industries have positive random slopes for physical control that compensate the negative mean coefficient and others have a negative correlation between abstract control and wages that reduce the wage *premia* of about 9% for a one standard deviation increase in abstract. Out of the 250 industries 29 have abstract control random slopes statistically greater than zero and other 29 negative ones. On the north-east plot of figure (4) a total of 40 industries have positive and 47 negative slopes for employee control over physical work activities.

Our second result is seen in the second row of figure (4) in a slightly different manner. The black dots plot again the slopes estimated for model (5) and the difference between the estimated random slopes of the interaction with Impact and the employee control variables from model (6) is shown in the grey bars[37]. As in the bargaining model the increase in earnings for employees with the capacity to directly impact firm's production and profits is larger in industries where employee control does not translate into higher wages. Thus, when employers hold great bargaining power employees sabotage or their capacity to do so plays a more prominent role in wage determination.

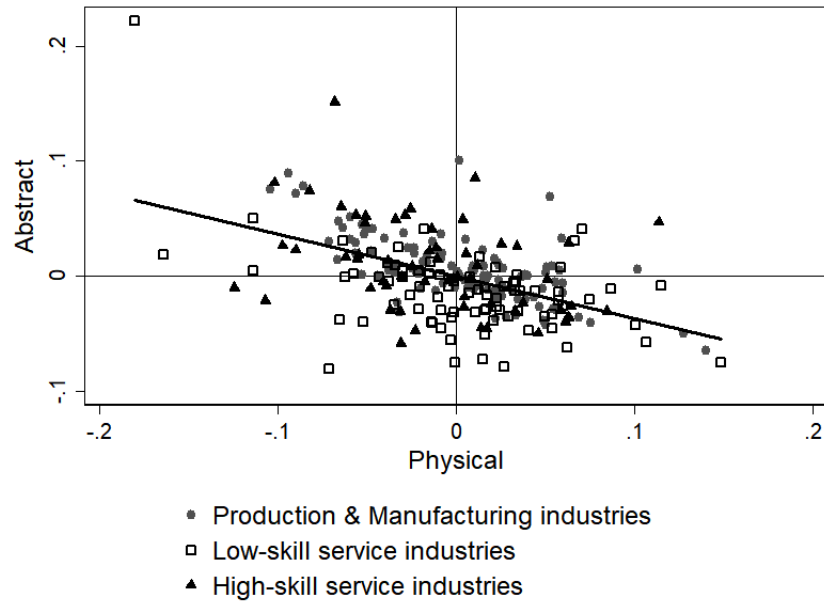Figure 4: Estimated random coefficients from models (5) and (6) (table 4)

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[37]Hence, the bars on the south-west graph are equal to $\beta_{Abstract*Impact} - \beta_{abstract}$ for each industry.

A simple example aids the interpretation in the difference between control over work activities and Impact. Take an automotive production line which is highly automated nowadays. A production worker does not have a great deal of control over her work activities whose discipline and pace are largely dictated by the machinery itself and the speed at which it is programmed to perform. Still, an error or a deliberate act of sabotage may have costly consequences to the firm and halt the whole line, at least for some time.

The third result is presented in figure (5) in a scatter plot of the abstract and physical employee control random slopes from model (5). It confirms that, just as for occupations, also industries with high returns to physical have low returns to abstract control and vice-versa for most of the coefficients lie on the north-west and south-east quadrants of the graph. However some high-skill industries (triangles) have a negative correlation between abstract control while wages and some low-skill service (squares) and manufacturing industries (circles) rank among the highest in abstract control. The physical control coefficients are equally mixed with a fair share of industries in these three major categories enjoying positive wage returns.

Figure 5: Relation between physical and abstract random slopes by 250 3-digit industries (model 5, table 4)

This section has extended the empirical analysis applying multilevel models to account for the hierarchical structure of the data with workers nested within 250 3-digit industries. The estimates in table (4) and figures (4) and (5) provide further evidence that abstract and physical control are good predictors of wages and support our hypothesis that some degree of control over work and the capacity to impact firm's production and profits constitute a source of bargaining power for workers. In particular lower effects of employee control on wages are partially compensated by Impact for those workers in occupations with a considerable ability to influence firm's results.

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The estimated random coefficients also confirm there is great heterogeneity in the relation between employee control and wages. To the extent that it might be misleading to conclude that control over abstract work pays a wage *premium* while control over physical work activities have a deleterious effect on earnings. Hence, the last part of the empirical analysis investigates which industry characteristics explain such heterogeneity in the relation between control and wages.

Technological or Institutional?

It is not clear so far whether employee control and its relation to wages is determined by the technology employed in production or by institutional factors, subject to changes promoted by employers, employees and their organizations. We refer once again to Braverman (1998) to argue that employee control has an institutional character.

The influence of machinery on the labour process depends on how an occupation is organized in production and on how workers interact with machines and with each other. Strictly speaking, it is not relevant for the purpose here exposed if different forms to organize workers in a productive process constitute distinct technologies, the crucial point is that such an organization is not a necessary consequence of technological development. It is subject to influences from the parties involved in production.

It might seem like a subtle difference, but it is fundamental for the relation between worker and the control over the labour she performs. Whether a coal miner uses a pick and her own physical strength or a hand held electric coal drill does not change fundamentally the labour process. Regardless of the increase in productivity achieved with the electric equipment the relation between worker and his job is practically the same. The development of technology and machinery entails an increase in human control over the environment and could also result in an expansion of human capacity to control the labour process.

This capacity, however, according to Braverman (1998, p.133) *"is seized upon by management from the beginning of capitalism as the prime means whereby production may be controlled not by the direct producer but by the owners and representatives of capital"*. Therefore the technological development that increases human capacity to control machinery and transform the environment has also increased, through different forms of workplace organization and division of work, employer's control over employees in capitalist society.

Three factors, according to Braverman, contributed to the decline of worker's control over production: *i*.) the separation between producer (worker) and the property of the means of production, *ii*.) the way workers interact and operate machinery, which is decided to a great extent by employers and *iii*.) the creation of a labour force adapted to this social organization of labour where only a specialized few have knowledge over the whole productive process.

Thus, the division of labour and the separation between intellectual and physical work in particular, in addition to its classical effects on productivity also favours the hierarchical organization of production due to increased substitutability of workers. Let us recover the coal mining example. Once the very capital intensive continuous longwall mining technology replaces individual miners, not only the number of workers is drastically reduced but the specialized skills to scoop soft and crumbling underground coal tunnels previously required of miners are no longer necessary for most of the workers that now operate the almost fully automated machinery. Detailed knowledge about the coal mining process itself, that was formerly at least in part a responsibility of each miner is now coded on the machines that carry the mining process and the engineers that design them.

Some evidence that control may be institutionally shaped is provided by the inclusion of managerial relations in collective bargaining. According to Marginson (2015, p.651) until the early 1990s negotiations over staffing levels and redeployment[38] were present in about half of the unionised firms in the U.K. as reported by the Workplace Employment Relations Survey. Storey (1976) analysed the extent to which different managerial issues were included in firm level collective bargaining in the U.K.

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[38]Redeployment refers to the reassigning of employees to new positions or work activities.

Apart from traditional topics such as shifts, overtime and dismissals a large proportion of the surveyed establishments reported having negotiated speed of work (48%), layout of equipment (8%), discipline (41%), production techniques and methods (26%) and job content (51%)[39]. Although managerial relations lost ground within the bargaining agenda in the past decades[40], its mere existence reveals how issues directly related to how work activities are performed and the organization of the workplace, which are directly connected to employee control, may be affected by employers and workers through collective bargaining instead of following directly from the state of technology.

Another source of anecdotal evidence comes from the short lived Volvo assembly plant in Uddevalla[41], near Gothenburg in Sweden, described in detail by Sandberg (2007). After only four years of operations the Uddevalla plant was closed in 1993 together with its innovative work organization that posed a challenge to Toyotism. The Uddevalla plant, that was conceived in cooperation with unions and academic researchers, relied long cycle-time work where parallel groups of workers assembled whole cars performing a great range of different tasks with no assembly line whatsoever. Workers were granted great control and autonomy over their activities[42] which resulted in a great capacity to customize the final products with good quality.

The development of high quality jobs in the Uddevalla plant addressed specific issues of the Swedish labour market at the time of its conception. In a tight labour market with highly educated workers the improved working conditions intended to attract qualified employees while avoiding absenteeism and turnover. The closure decision is credited to Volvo's overcapacity in face of lower market demand in the early 1990s. The firm opted to continue operations at the larger plant of Torslanda, Gothenburg, shutting down the smaller plants of Kalmar and Uddevalla. It should be noted, however, that in its short lifespan the Uddevalla plant quickly increased its productivity, achieving performance levels at least as good as those of the more traditionally organized Torslanda plant. Therefore, independent of whether employee control was crucial for the termination of Volvo's innovative plant[43], this experience illustrates how it is possible to organize production in a way that allows employees a great degree of control over their work without sacrificing productivity, thus reinforcing the institutional character of employee control.

Therefore, we consider the relation between two forms of employee organization, unions and professional associations, and the employee control random coefficients estimated in the multilevel model. The next section describes these variables as well as previous research on the effects of collective worker organizations on labour market segmentation and earnings.

Occupational Closures   The study of earnings inequality between occupations is a classical theme in the sociology of work that focus on stratification and social closures. Once we take into account stratification, wage inequality can not be determined by individual characteristics alone as in human capital theory, it depends also on characteristics of the groups to which individuals belong (Mouw and Kalleberg, 2010, p.404). A great part of the wage inequality found between firms and industries may be

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[39] The reported percentages refer to manager reports. The percentage of the same negotiated topics as reported by stewards are of 13%, 23%, 63%, 38% and 48%, respectively.

[40] This hollowing out of the bargaining agenda (Marginson, 2015) should be understood within the wider context of collective bargaining decentralization, largely driven by management and opposed by unions. In the particular case of the U.K. the shift to firm level bargaining is connected to reducing the scope of union action and the development of organization specific employment policies (Purcell, 1991).

[41] And to a lesser extent from the Kalmar plant.

[42] A description of the work activities is provided by Sandberg (2007, p.3): *"In a typical example, a group of nine workers assembled a car from beginning to end. They conferred with each other while working, resulting in the completion of the entire car before the morning coffee break. This team like all others in the plant had no supervisor. And the first level manager of this and the seven other teams in the product workshop, was on vacation; the groups could clearly manage their own work."*

[43] The official explanation of a slack market does not address why Uddevalla was closed instead of other Volvo establishments. The company presented a series of cost calculations that were later shown to be contestable. Sandberg (2007, p.13) offers another perspective on this issue: *"One aspect that was not raised in the calculations has to do with the issue of control. The productivity and learning in the Uddevalla concept, dependent to a large degree on the individuals and groups, could not be easily controlled by management.".*

explained by the type of workers they employ and the occupation-specific institutional arrangements such as unions and professional associations that represent their interests.

These are the mechanisms of social closure that allow workers within an occupation to collectively improve their position within a hierarchy (Weeden, 2002, p.56). The term closures refers to imposing barriers that exclude outsiders from the occupational group in order to protect or boost their remuneration. This may take the form of licensing, formal educational requirements or training through unionisation and professional associations. Weeden (2002, p.61) specifies channels through which these closures affect the relative earnings of an occupation: restricting supply, increasing demand and signalling the quality of services.

A supply side restriction decreases the unemployment rate of an occupation, rendering the substitution of a worker more costly and difficult. The requirement of a specific degree, often from specific universities in high pay jobs, constitutes a barrier of entry that guarantees those already in possession of the demanded degree a higher probability to find a job and a favourable position to bargain better wages. Increasing demand concerns long-term actions to delimit the activities performed by an occupation, thus guaranteeing demand through professional associations or unions that might lobby for government regulations and licenses. The last aspect of how closures affect wages is signalling the quality of a service. Again licenses and formal education are a signal that members of an occupation attain a desired degree of quality rendering them more attractive to the public or employers than others willing to provide similar services for an equal or lower compensation.

We consider two forms of social closure as a possible explanation for the heterogeneity in the effects of employee control on wages: unionisation and professional associations. While union affiliation data is already available at the individual worker level in the CPS-ORG a list of professional associations and the occupations they represent in the U.S. is provided by CareerOneStop (2017), sponsored by the U.S. Department of Labor.

Multinomial Logit   This final empirical exercise performs multinomial logit regressions of the two estimated random slopes for abstract and physical employee control on industry technological and institutional characteristics. Discrete dependent variables are build grouping the estimated random slopes from model (5) in table (4)[44] in three categories: smaller, equal and greater than zero using a 90% confidence interval.

Besides the industry averages of employee control over abstract and physical work activities, and impact we consider their growth rates between 2003 and 2016 for non-managerial workers. As there is no longitudinal measure for O*NET work activity variables[45] we use industry and occupation crosswalks to convert 2003 data to the 2016 codes then assign the O*NET 21.3 values to the occupations in 2003 and take industry averages. The growth rates of these variables in the multinomial logit estimates reflect changes in the extensive margin only and express whether industries now employ more workers in occupations with greater abstract, physical content and impact.

Industry unionisation rates are calculated for non-managerial workers as well as the change in its percentage since 2003[46]. The second institutional characteristic is the weighted average number of professional associations per worker per industry. First we take the sum of the number of professional associations related to each occupation and then the average of those per worker in each industry. Thus, this measure corresponds to the average number of associations per occupation, weighted by the employment of those occupations within an industry. Although this is not an accurate measure it does reflect whether an industry employs workers in occupations with greater representation.

All the growth rates described above regard the period between 2003 and 2016 due to a major overhaul in CPS industry and occupation codes in 2003. An attempt to build crosswalks to earlier versions of the CPS-ORG extracts would need aggregation in industries and occupations incompatible
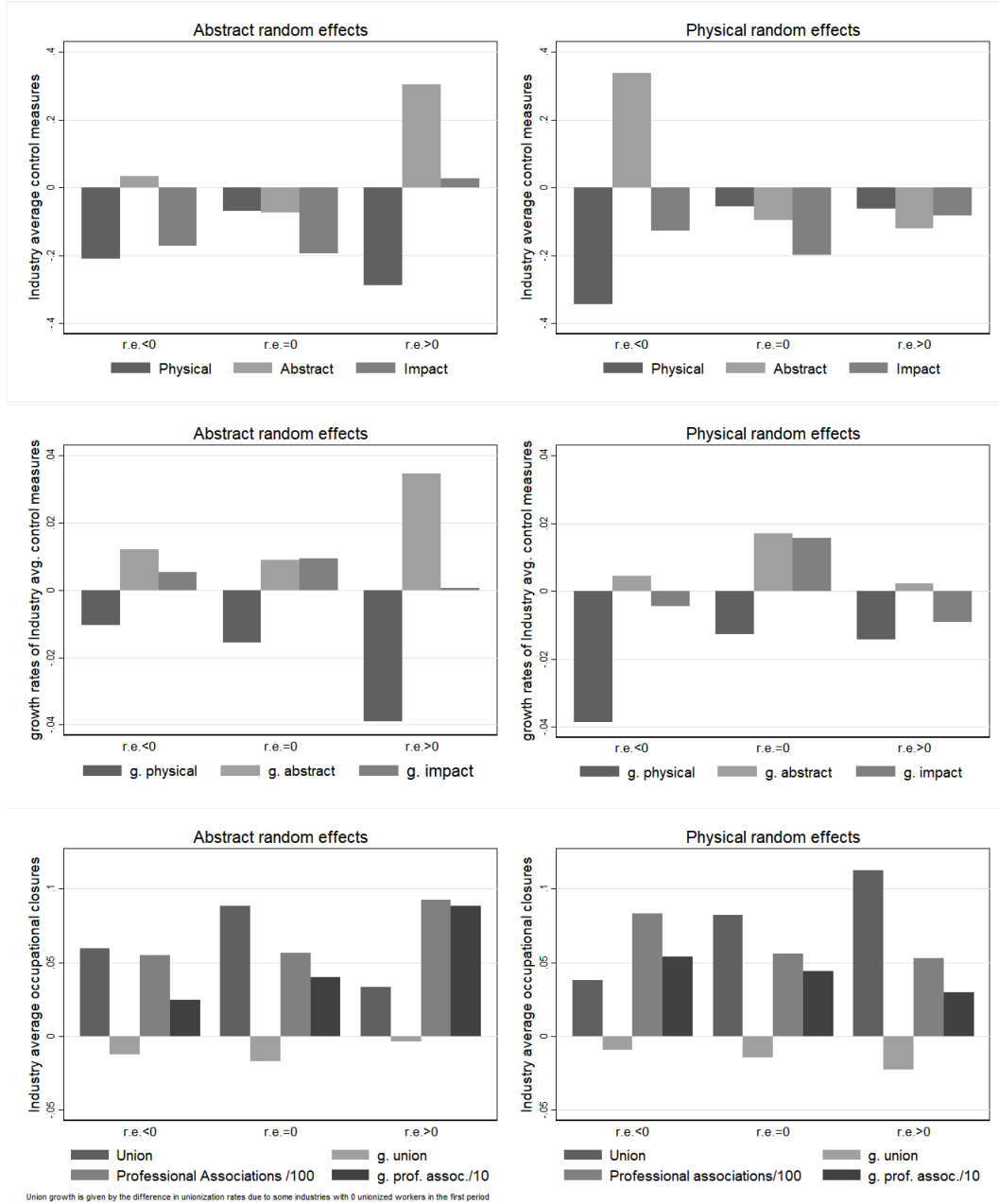
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[44]And displayed in the first row of figure 4. and on figure 5.

[45]The measures in the O*NET data are calculated using observation obtained in different years.

[46]Instead of a proper growth rate due to the many industries with no unionized workers in the survey.

to the one in which our depend variables are based on[47]. A first glance into the industry variables is presented in figure (6) that plots the average of the industry characteristics by the three categories of the depend variables.

Figure 6: Industry characteristics by sign of the random slopes

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The first row of the figure shows positive random effects for abstract and physical control are related to higher industry averages of abstract and physical control. In other words, industries where control is related to a higher pay in occupations also seem to be those where average level of employee control is higher. We do not identify however a similar behaviour for Impact which is somewhat higher for industries with positive abstract control random effects but have no clear increasing or decreasing behaviour on physical random effects.

As for the growth rate of the same variables, in the second row, the graph to the left show industries with a abstract random effect grater than zero experienced an increase in their average abstract and a decrease in physical employee control since 2003. The only distinctive feature on the right graph is that industries where physical control is negatively related to wages faced a much sharper decrease in unionisation in the last fifteen years or so.

It should be noted that in these first four graphs industry means of employee control over physical activities and its change in time are always negative. The negative averages in the first row graphs reflect the fact that the average physical employee control is negative in the whole sample due to a greater number of employees in occupations with below average physical control. Regarding the growth rates the second row show us how occupations with higher abstract content increased and those with high physical content decreased in the composition of employment of the U.S. economy in the period considered.

The last two graphs depict the contemporary industry averages and growth rates of unionisation and professional associations[48]. There seems to be an inverse relation with positive abstract random effects related to more professional association representation and reduced unionisation. On the physical random effects graph positive random coefficients are followed by higher unionisation rates and less professional associations.

Their growth rates follow a less obvious trajectory. Industries with more professional associations are also the ones where these type of worker representation grew the most. Industries with a greater proportion of unionised workers, in contrast, saw a sharper decrease in union representation. This is probably a consequence of the historically low unionisation rates in the U.S. where only a selected few industries still have room for significant reduction in unionisation.

A more accurate look into the relation between these variables and employee control random effects is given by the multinomial logit estimates in table (5) To ease interpretation and comparison all estimates are presented in odds ratios that correspond to a one standard deviation increase in the covariates. Hence, an odds ratio greater (smaller) than one corresponds to a positive (negative) coefficient. In both regressions the selected base outcomes are random effects statistically equal to zero. We also control for contemporary and growth of industry average wages and wage variation.

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[48] The professional association averages are only divided by 100 and 10 to make sure they are kept in similar scale to the unionization variables.

Table 5: Multinomial logit estimates of random slopes signs (model 5, table 4)

	(1) Abstract r.e. (model 5)		(2) Physical r.e. (model 5)	
	$r.e. < 0$	$r.e. > 0$	$r.e. < 0$	$r.e. > 0$
Physical	0.633	1.407	2.076^{+}	0.502^{*}
	(0.737)	(1.178)	(0.859)	(0.657)
Δphysical	1.051	1.506	0.870	1.272
	(2.876)	(4.861)	(3.521)	(2.974)
Abstract	1.385	0.503	2.758^{*}	0.662
	(0.584)	(1.052)	(1.002)	(0.585)
Δabstract	1.058	1.369	0.451^{**}	0.952
	(2.959)	(3.951)	(3.016)	(2.442)
Impact	1.414	2.023^{*}	0.662	1.812^{*}
	(0.691)	(0.907)	(0.820)	(0.691)
Δimpact	0.856	0.611^{+}	1.015	0.566^{**}
	(3.088)	(3.982)	(3.696)	(2.903)
Union	0.837	0.061^{**}	0.295^{**}	1.215
	(2.664)	(10.75)	(4.291)	(2.228)
Δunion	0.853	3.514^{*}	1.180	0.766
	(3.562)	(9.253)	(4.761)	(2.858)
Professional associations	0.796	1.956^{*}	1.310	0.706
	(0.139)	(0.109)	(0.124)	(0.139)
Δprofessional associations	0.783	1.694^{**}	1.320	0.805
	(0.285)	(0.265)	(0.270)	(0.250)
Industry mean wages	0.722	0.762	1.167	1.965
	(0.0880)	(0.0885)	(0.0647)	(0.0563)
Δindustry mean wages	1.284	1.713	1.302	1.090
	(2.785)	(3.216)	(2.125)	(2.284)
Industry wage dispersion	0.704	5.123^{*}	2.961^{+}	0.608
	(0.0936)	(0.131)	(0.0956)	(0.0703)
Δindustry wage dispersion	0.868	0.362	0.376^{*}	1.171
	(0.821)	(1.508)	(1.033)	(0.822)
Percentage correctly predicted	0.00	0.41	0.45	0.48
overall		0.79		0.69
N		249		249
Log likelihood		-132.9		-171.1
McFadden pseudo R^2		0.242		0.226

Results in Odds Ratios that correspond to a one standard deviation increase in covariates.

Robust standard errors in parentheses, all models include a constant.

Omitted base outcome in both models is random effects statistically equal to zero.

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The regression results do not fully confirm the graphical intuitions in figure (6) Industry average physical and abstract control as well as their growth rates are not good predictors of the random slopes signs, specially in model (1). Industry average impact instead increases the odds of having a positive wage *premia* from control in both models. Institutional characteristics have the expected correlations with more professional associations and its growth rate increasing the probability of positive abstract random effects and higher unionisation rates related to a reduced probability of negative physical control random effects.

Model (1), for the abstract random effects, performs rather poorly on the left column estimates. In fact, none of the covariates is a good predictor of industries with negative abstract random effects, so much so that no observation is predicted to fall into that category. Nevertheless, the overall percentage of industries whose categories are correctly predicted is of 79%, mostly due to observations correctly attributed to the base outcome ($r.e. = 0$).

On the right column of model (1) while industry mean Impact increases the odds of a positive abstract random effects, its growth rate decreases it, with a marginally significant coefficient. The earlier multilevel estimates in column (6) from table (4) reported an apparently contradictory result, that employee control interactions with Impact were related to higher wages in industries with lower

random slopes for employee control itself while table (5) relates higher employee control random slopes to greater *industry averages* of Impact. We interpret this results as evidence that there is a wage *premium* for workers in occupations with high Impact in industries with low average Impact. However, industries that have a great proportion of its workers with a good capacity to affect profits and production tend to negotiate higher wages based on their employees' control over work activities

The two industry institutional characteristics play a role in model (1). As expected workers in industries employing occupations with greater professional association representation are more likely to enjoy a positive wage premium from abstract control, as well as those in industries where this type of employee representation grew the most. Higher unionisation rates reduce the probability of earning higher wages due to abstract control. A final distinctive feature is that industries with positive abstract control random effects have a more pronounced wage inequality.

In model (2) our covariates have predictive power in both categories and some of the industry average control variables are statistically significant. In contrast to figure (6), the estimates point out to that higher (lower) industry average physical control actually decreases (increases) the odds of having positive (negative) random slopes for physical control. This could mean that controlling physical activities to a greater extent is only an effective tool to bargain higher wages if only a few occupations in an industry have it, thus making those workers harder to substitute or relatively more important to the overall productive process. Industries where workers have higher abstract control in average are more likely to have negative physical random effects, as expected.

Nevertheless, changes in the occupational employment composition within industry, expressed by the physical and abstract growth rates, still perform rather poorly with one exception. On the left column (*r.e.* < 0) of model (2) an increase in the share of workers performing complex abstract activities, given by the growth of abstract control, reduces the odds of negative random slopes for physical control.

Being represented by professional associations does no affect the odds of an industry having either positive or negative physical random effects. Unionisation, on the other hand, greatly reduces the chances of a negative correlation between employee physical control and wages, which suggests unions work as a safeguard that avoids the decline in wages of workers that perform and control mainly physical or tangible activities.

This final section served to further explore the relation between employee control, Impact and wages focusing on technological change, mirrored by the change in the occupational composition of employment by industry, and institutional characteristics. Although preliminary the results challenge the main interpretation of the relation between work content and pay. Unionisation avoids negative wage *premia* from physical control and professional associations are associated to higher odds of a positive effect of abstract control on wages. Moreover, the capacity to impact production and profits seems to have a collective effect with workers in industries where the average Impact is higher enjoying grater wage gains from both abstract and physical control.

The growth rates of physical and abstract control prove largely irrelevant to explain the great heterogeneity in the way employee control relates to wages. Finally, higher wage dispersion within industry is related to increased wages for workers with high abstract control and a penalty for those that hold great control over physical activities.

Discussion

This article presented a critical view on some of the recent literature relating wages and wage inequality to technical progress. The arguments put forward question the traditional interpretation of O*NET work activities as a measure of task intensity and the empirical analysis displays a significant degree of heterogeneity between industries in the returns to employee control that challenges the established results of positive returns to abstract or cognitive work and negative ones to physical, tangible or manual, including routine, activities. Neither does this heterogeneity has an intuitive pattern as seen in figure 5. Although there is a negative relation between abstract and physical employee control

several service industries present positive returns to physical control and as many manufacturing and infrastructure industries are characterized by wage *premia* related to control over abstract activities.

On the positive side the article proposes a novel interpretation to O*NET work activities as a measures of employee control over work. Inspired by Braverman (1998) and the importance of the separation between intellectual and physical work in the division of labour we build two measures of abstract and physical control which rely on O*NET work activities exclusively and encompass a greater number of those in contrast to previous measures obtained from the same dataset. Moreover, work context variables allow us to compute a measure of employee capacity to Impact firm's production and profits.

With the aid of a simple bargaining model we argued that employee control adds to the bargaining power of workers and has a negative relation to impact which is used to a greater extent in industries where control over work is not sufficient to increase wages, a relation that is corroborated by the estimated random effects of our multilevel models. Finally, multinomial logit models at the industry level provide further evidence against technology, proxied by the change in the occupational composition of employment, as the main factor behind wage returns to employee control. Industry average employee Impact and institutional characteristics such as professional associations for abstract and unionisation for physical seem to improve the odds of positive, or at least avoid negative, random effects estimates for the relation between employee control and wages.

The article adds to a recent literature questioning the merits routine and non-routine task measures as an explanation to job polarization (Barany and Siegel, 2017; Schmitt et al. 2013), but with focus on wages and their relation to work content and technology. Even though none of the empirical evidence above is a direct measure of bargaining power, we believe it is enough to consider our interpretation as a valid alternative for future research.

In particular, a relevant next step would relate this measures of employee control directly to collective bargaining agreements and their outcomes. A cross-country comparison would be equally fruitful to find out whether measures of employee control vary with specific labour market institutions such as the predominant level of collective bargaining and the presence of work councils. Unfortunately the lack of detailed cross-country survey on work characteristics like the O*NET, to the best of our knowledge, still pose a substantial challenge for researchers.

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Appendix A - Wage Bargaining

This appendix describes the steps taken to obtain equations (1) to (10) that describe the wage bargaining model. The profit rate as a function of wages in the two occupations is obtain from the distribution of the value of production (y) between wages and profits. Dividing the first equation below by y and using the definition of labour a capital to output ratios gives the relation between wages and profits per unit of output.

$$y = w_1 L_1 + w_2 L_2 + \pi \frac{K}{h(\cdot)}$$
$$1 = \frac{w_1}{a_1} + \frac{w_2}{a_2} + \frac{\pi}{bh(\cdot)}$$
$$\pi = b(1 - \frac{w_1}{a_1} - \frac{w_2}{a_2})h(\cdot)$$

The actual profit rate (π) may also be expressed as the product of r, the profit rate that would obtained if workers had no control, and employees' control function $h(\cdot)$.

$$\pi = rh(\cdot)$$
$$r = b(1 - \frac{w_1}{a_1} - \frac{w_2}{a_2})$$

Wage Bargaining

$$\max_{\{w_1, w_2\}} : S = (w_1 - v_1)^\beta (w_2 - v_2)^\gamma (r.(w_1 - e_1 w_1^A)^\alpha (w_2 - e_2 w_2^A)^{1-\alpha})^\delta$$

The first order condition with respect to w_1 may be rearranged as (A.1).

$$\frac{\partial S}{\partial w_1} : \frac{\beta}{\delta} \frac{\pi}{(w_1 - e_1 w_1^A)} = \frac{b}{a_1}(w_1 - e_1 w_1^A)^\alpha (w_2 - e_2 w_2^A)^{1-\alpha} - r\alpha (w_1 - e_1 w_1^A)^{\alpha-1}(w_2 - e_2 w_2^A)^{1-\alpha}$$
$$\frac{\beta}{\delta}r = \frac{b}{a_1}(w_1 - e_1 w_1^A) - r\alpha$$
$$\frac{r}{\delta} = \frac{b(w_1 - e_1 w_1^A)}{a_1(\beta + \alpha\delta)} \tag{A.1}$$

And that with respect to w_2 as (A.2).

$$\frac{\partial S}{\partial w_2} : \frac{\gamma}{\delta} \frac{\pi}{(w_2 - e_2 w_2^A)} = \frac{b}{a_2}(w_1 - e_1 w_1^A)^\alpha (w_2 - e_2 w_2^A)^{1-\alpha} - r(1-\alpha)(w_1 - e_1 w_1^A)^\alpha (w_2 - e_2 w_2^A)^{-\alpha}$$

$$\frac{\gamma}{\delta} r = \frac{b}{a_2}(w_2 - e_2 w_2^A) - r(1-\alpha)$$

$$\frac{r}{\delta} = \frac{b(w_2 - e_2 w_2^A)}{a_2(\gamma + (1-\alpha)\delta)} \tag{A.2}$$

Combining (A.1) and (A.2) yields the relation between the bargained wages in occupations one and two (A.3).

$$\frac{b(w_1 - e_1 w_1^A)}{a_1(\beta + \alpha\delta)} = \frac{b(w_2 - e_2 w_2^A)}{a_2(\gamma + (1-\alpha)\delta)}$$

$$\frac{w_2}{a_2} = \frac{(w_1 - e_1 w_1^A)}{a_1} \frac{(\gamma + (1-\alpha)\delta)}{(\beta + \alpha\delta)} + \frac{e_2 w_2^A}{a_2} \tag{A.3}$$

Substituting (A.3) back in the first order condition (A.1) we find the expression for the bargained wage in occupation 1 (8).

$$\frac{b}{\delta}\left[1 - \frac{w_1}{a_1} - \frac{(w_1 - e_1 w_1^A)}{a_1}\frac{(\gamma + (1-\alpha)\delta)}{(\beta + \alpha\delta)} - \frac{e_2 w_2^A}{a_2}\right] = \frac{b(w_1 - e_1 w_1^A)}{a_1(\beta + \alpha\delta)}$$

$$\frac{w_1}{a_1}\left[\frac{1}{\delta} + \frac{1}{\delta}\frac{(\gamma + (1-\alpha)\delta)}{(\beta + \alpha\delta)} + \frac{1}{a_1(\beta + \alpha\delta)}\right] = \frac{1}{\delta} + \frac{e_1 w_1^A}{a_1}\left[\frac{1}{\delta}\frac{a_2(\gamma + (1-\alpha)\delta)}{(\beta + \alpha\delta)} + \frac{1}{(\beta + \alpha\delta)}\right] - \frac{e_2 w_2^A}{a_2}$$

$$\frac{w_1}{a_1}\left[\frac{1 + \delta}{\delta(\beta + \alpha\delta)}\right] = \frac{1}{\delta} + \frac{e_1 w_1^A}{a_1}\left[\frac{\delta + \gamma + (1-\alpha)\delta}{\delta(\beta + \alpha\delta)}\right] - \frac{e_2 w_2^A}{a_2}$$

$$w_1 = \frac{a_1(\beta + \alpha\delta)}{1 + \delta} + \frac{e_1 w_1^A(\delta + \gamma + (1-\alpha)\delta)}{1 + \delta} - e_2 w_2^A \frac{a_1}{a_2}\frac{(\beta + \alpha\delta)}{1 + \delta}$$

The expression for w_1 may now be substituted back into A.3, which gives us w_2 (9).

$$\frac{w_2}{a_2} = \left[\frac{a_1(\beta + \alpha\delta)}{1 + \delta} + \frac{e_1 w_1^A(\delta + \gamma + (1-\alpha)\delta)}{1 + \delta} - e_2 w_2^A \frac{a_1}{a_2}\frac{(\beta + \alpha\delta)}{1 + \delta}\right]\left(\frac{(\gamma + (1-\alpha)\delta)}{(\beta + \alpha\delta)}\right) + \frac{e_2 w_2^A}{a_2} - e_1 w_1^A \frac{a_2(\gamma + (1-\alpha)\delta)}{a_1(\beta + \alpha\delta)}$$

$$w_2 = \frac{a_2(\gamma + (1-\alpha)\delta)}{1 + \delta} + \frac{e_2 w_2^A(\delta + \beta + \alpha\delta)}{1 + \delta} - e_1 w_1^A \frac{a_2}{a_1}\frac{(\gamma + (1-\alpha)\delta)}{(1 + \delta)}$$

Market Wages

As mentioned before, the market wages are found based on the assumption that the alternative wage for a worker in occupation, say, one is equal to the bargained wage for the same occupation as all firms are identical. Then equations (8) and (9) may be rearranged as the system below. We apply Cramer's rule to get the market wages.

$$\boldsymbol{Ax = b}$$

$$\left[\begin{array}{cc} a_{11} & a_{12} \\ a_{21} & a_{22} \end{array}\right]\left[\begin{array}{c} w_1 \\ w_2 \end{array}\right] = \left[\begin{array}{c} b_1 \\ b_2 \end{array}\right]$$

$$\begin{bmatrix} 1 + \delta - e_1(\delta + \gamma + (1-\alpha)\delta) & \frac{a_1}{a_2}e_2(\beta + \alpha\delta) \\ \frac{a_2}{a_1}e_1(\gamma + (1-\alpha)\delta) & 1 + \delta - e_2(\delta + \beta + \alpha\delta) \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} a_1(\beta + \alpha\delta) \\ a_2(\gamma + (1-\alpha)\delta) \end{bmatrix}$$

The equations below give the numerator of equation (10).

$$\begin{vmatrix} b_1 & a_{12} \\ b_2 & a_{22} \end{vmatrix} = a_1(\beta + \alpha\delta)\left[1 + \delta - e_2(\delta + \beta + \alpha\delta)\right] - \frac{a_1}{a_2}e_2(\beta + \alpha\delta)a_2(\gamma + (1-\alpha)\delta)$$

$$= a_1(\beta + \alpha\delta)\left[1 + \delta - e_2(1 - \beta - \gamma + \gamma + \beta + \delta - \alpha\delta + \alpha\delta)\right]$$

$$= a_1(\beta + \alpha\delta)(1 + \delta)(1 - e_2)$$

And the numerator of equation (11).

$$\begin{vmatrix} a_{11} & b_1 \\ a_{21} & b_2 \end{vmatrix} = \left[1 + \delta - e_1(\delta + \gamma + (1-\alpha)\delta)\right]a_2(\gamma + (1-\alpha)\delta) - a_1(\beta + \alpha\delta)\frac{a_2}{a_1}e_1(\gamma + (1-\alpha)\delta)$$

$$= a_2(\gamma + (1-\alpha)\delta)\left[1 + \delta - e_1(1 - \beta - \gamma + \gamma + \beta + \delta - \alpha\delta + \alpha\delta)\right]$$

$$= a_2(\gamma + (1-\alpha)\delta)(1 + \delta)(1 - e_1)$$

After some algebraic manipulations on the determinant we find the denominator of equations (10) and (11).

$$\begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix} = \left[1 + \delta - e_1(\delta + \gamma + (1-\alpha)\delta)\right]\left[1 + \delta - e_2(\delta + \beta + \alpha\delta)\right] - \frac{a_1}{a_2}e_2(\beta + \alpha\delta)\frac{a_2}{a_1}e_1(\gamma + (1-\alpha)\delta)$$

$$= 1 + \delta - e_2\delta - e_2(\beta + \alpha\delta) + \delta + \delta^2 - e_2\delta^2 - e_2\delta(\beta + \alpha\delta) - e_1\delta - e_1\delta^2 + e_1e_2\delta^2 + e_1e_2\delta(\beta + \alpha\delta) - e_1(\gamma + (1-\alpha)\delta) - \ldots$$

$$\ldots - e_1\delta(\gamma + (1-\alpha)\delta) + e_1e_2\delta(\gamma + (1-\alpha)\delta) + e_1e_2(\beta + \alpha\delta)(\gamma + (1-\alpha)\delta) - e_1e_2(\beta + \alpha\delta)(\gamma + (1-\alpha)\delta)$$

$$= (1 + \delta) - e_1\delta(1 + \delta) - e_2\delta(1 + \delta) + \delta(1 + \delta) - e_1(\gamma + (1-\alpha)\delta)(1 + \delta) - e_2(\beta + \alpha\delta)(1 + \delta) + e_1e_2\delta(1 + \delta)$$

$$= (1 + \delta)\left[1 + \delta - e_1\delta - e_2\delta - e_1(\gamma + (1-\alpha)\delta) - e_2(\beta + \alpha\delta) + e_1e_2\delta\right]$$

$$= (1 + \delta)\left[(1 - e_1)(1 + \delta(1 - e_2)) + (e_1 - e_2)(\gamma + \alpha\delta)\right]$$

Using the fact that $\gamma = 1 - \beta - \delta$, it is shown that the denominator of (11) is equal to the one in (10).

$$(1 + \delta)\left[1 - e_1 + \delta(1 - e_1)(1 - e_2) + e_1 - e_2 + (e_2 - e_1)(\beta + (1-\alpha)\delta)\right]$$

$$(1 + \delta)\left[(1 - e_2)(1 + \delta(1 - e_1)) + (e_2 - e_2)(\beta + (1-\alpha)\delta)\right]$$

Finally, we get the expressions, (10) and (11), for the market wages in the two occupations.

$$w_1 = \frac{\begin{vmatrix} b_1 & a_{12} \\ b_2 & a_{22} \end{vmatrix}}{\begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix}} = \frac{a_1(\beta + \alpha\delta)(1 - e_2)}{(1 - e_2)(1 + \delta(1 - e_1)) + (e_2 - e_1)(\beta + (1-\alpha)\delta)}$$

$$w_2 = \frac{\begin{vmatrix} a_{11} & b_1 \\ a_{21} & b_2 \end{vmatrix}}{\begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix}} = \frac{a_2(\gamma + (1-\alpha)\delta)(1 - e_1)}{(1 - e_1)(1 + \delta(1 - e_2)) + (e_1 - e_2)(\gamma + \alpha\delta)}$$

Value of the impact function $h(w_1, w_2, e_1, e_2, w_1^A, w_2^A)$

Since the impact function is strictly increasing on the bargained wages, in order to asses its maximum value we repeat the bargaining procedure subject to the highest possible value for the sum of the wages in the two occupations. Therefore, using equation (4) the maximum sum of wages per value of a unit of output is given when the profit rate (r) is equal to zero.

$$w_2 = a_2(1 - \frac{w_1}{a_1}) \tag{A.4}$$

Then, using the expression above and the fact that $r = 0$ the Nash bargaining is now give by:

$$\max_{\{w_1\}}: S = (w_1 - e_1 w_1^A)^\beta (a_2(1 - \frac{w_1}{a_1}) - e_2 w_2^A)^\gamma$$

The expressions for the bargained wage in occupation 1 may be obtained from the first order condition while w_2 is found substituting w_1 in equation (A.4).

$$w_1 = \frac{\beta}{\beta + \gamma} a_1 + \frac{\gamma}{\beta + \gamma} e_1 w_1^A - \frac{\beta}{\beta + \gamma} \frac{a_1}{a_2} e_2 w_2^A$$

$$w_2 = \frac{\gamma}{\beta + \gamma} a_2 + \frac{\beta}{\beta + \gamma} e_2 w_2^A - \frac{\gamma}{\beta + \gamma} \frac{a_2}{a_1} e_1 w_1^A$$

Once again the bargained wages in all identical firms will be equal ($w_1 = w_1^A$ and $w_2 = w_2^A$) and the two equations above may be rearranged as a system.

$$\begin{bmatrix} \beta + \gamma(1 - e_1) & \beta e_2 \frac{a_1}{a_2} \\ \gamma e_1 \frac{a_2}{a_1} & \gamma + \beta(1 - e_2) \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} \beta a_1 \\ \gamma a_2 \end{bmatrix}$$

The final market wages are obtained solving the three following expressions.

$$\begin{vmatrix} b_1 & a_{12} \\ b_2 & a_{22} \end{vmatrix} = \beta a_1(1 - e_2)(\beta + \gamma)$$

$$\begin{vmatrix} a_{11} & b_1 \\ a_{21} & b_2 \end{vmatrix} = \gamma a_2(1 - e_1)(\beta + \gamma)$$

$$\begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix} = (\beta + \gamma)[\beta(1 - e_2) + \gamma(1 - e_1)]$$

Hence, the market wages in the two occupations when profits are zero are:

$$w_1 = \frac{\beta a_1(1 - e_2)}{\beta(1 - e_2) + \gamma(1 - e_1)]}$$

$$w_2 = \frac{\gamma a_2(1 - e_1)}{\beta(1 - e_2) + \gamma(1 - e_1)]}$$

We may now substitute the wages in the equations above into the impact function.

$$h(w_1, w_2, e_1, e_2, w_1^A, w_2^A) = \left(\frac{\beta a_1(1 - e_2)(1 - e_1)}{\beta(1 - e_2) + \gamma(1 - e_1)]} \right)^\alpha \left(\frac{\gamma a_2(1 - e_1)(1 - e_2)}{\beta(1 - e_2) + \gamma(1 - e_1)]} \right)^{1-\alpha}$$

$$h(w_1, w_2, e_1, e_2, w_1^A, w_2^A) = (\beta a_1)^\alpha (\gamma a_2)^{1-\alpha} \frac{(1 - e_1)(1 - e_2)}{\beta(1 - e_2) + \gamma(1 - e_1)]} < 1$$

$$(\beta a_1)^\alpha (\gamma a_2)^{1-\alpha} < \frac{\beta(1 - e_2) + \gamma(1 - e_1)]}{(1 - e_1)(1 - e_2)}$$

Now, the last expression above may be studied under some simplifying assumptions. If for instance the capacity to impact profits is equal in the two occupations ($\alpha = 0.5$) the maximum value for $h(\cdot)$ is achieved when the two arguments of the function are equal. Hence, assuming that $a_1 = a_2 = a$, $\beta = \gamma$ and $e_1 = e_2 = e$, the previous inequality reduces to:

$$a < \frac{2}{(1-e)}$$

Hence, in this balanced case the impact function $h(\cdot)$ would only exceed one for very high output to labour ratios, particularly if the employment rate is high. For example, if $e = 0.9$, the output to labour ratio necessary such that $h(\cdot) > 1$ must exceed 20.

In the case of equilibrium wages presented in the model positive profits imply lower wages and a lower value for the impact function. Therefore, an even higher value of the output to labour ratio would be necessary for the impact function to exceed unit. Let us reassess the simple balanced case in which output to labour ratios, the weights of the Nash product and employment rates are equal in the two occupations using the market wages defined in equations (10) and (11), and using the fact that the denominator in the two equations are equal.

$$h(w_1, w_2, e_1, e_2, w_1^A, w_2^A) = \left(\frac{a_1(\beta + \alpha\delta)(1-e_2)(1-e_1)}{(1-e_1)(1+\delta(1-e_2)) + (e_1-e_2)(\gamma+\alpha\delta)} \right)^{\alpha} \left(\frac{a_2(\gamma + (1-\alpha)\delta)(1-e_1)(1-e_2)}{(1-e_1)(1+\delta(1-e_2)) + (e_1-e_2)(\gamma+\alpha\delta)} \right)^{1-\alpha}$$

If $e_1 = e_2 = e$:

$$h(w_1, w_2, e_1, e_2, w_1^A, w_2^A) = (a_1(\beta + \alpha\delta))^{\alpha} (a_2(\gamma + (1-\alpha)\delta))^{1-\alpha} \frac{(1-e)^2}{(1-e)(1+\delta(1-e))}$$

Now, once again is $\alpha = 0.5$ the impact function will assume its maximum value when its two arguments are equal, hence, $\beta = \gamma$ and $a_1 = a_2 = a$.

$$h(w_1, w_2, e_1, e_2, w_1^A, w_2^A) = \frac{a(\beta + \frac{\delta}{2})(1-e)}{(1+\delta(1-e))} < 1$$

$$h(w_1, w_2, e_1, e_2, w_1^A, w_2^A) = a < \left(\frac{1}{1-e} + \delta \right) \frac{2}{2\beta + \delta}$$

Now using the fact that if $\beta = \gamma$, then $\delta = 1 - 2\beta$ we obtain:

$$a < 2 \left(\frac{1}{1-e} + \delta \right)$$

Therefore, in order to the impact function to be greater than one in market equilibrium an even higher output to labour ratio would be necessary. Apart from the very simplified case analysed above it is also unlikely that the function would assume high values as it would require either a high output to labour ratio or a very high unemployment ratio.

The effect of Y on wages

As mentioned on the main text, each occupations' employment rate may be expressed in terms or total output. Starting from equations (10) and (11), let us assume that the employment rates in both occupations are an increasing function of total output: $e_1(Y)$, $e_1^{'} > 0$ and $e_2(Y)$, $e_2^{'} > 0$. The effect of an output increase in wages will then be given by the derivatives below.

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$$\frac{\partial w_1}{\partial Y} = \frac{0 - [-e_1^{'}\delta - e_1^{'}(\beta + (1-\alpha)\delta) + e_2^{'}(\beta + (1-\alpha)\delta)]}{[(1 + \delta(1 - e_1)) + (e_2 - e_1)(\beta + (1-\alpha)\delta)]^2} > 0$$
$$= e_1^{'}(\beta + (2-\alpha)\delta) - e_2^{'}(\beta + (1-\alpha)\delta) > 0$$
$$= \frac{e_1^{'}}{e_2^{'}} > \frac{(\beta + (1-\alpha)\delta)}{(\beta + (2-\alpha)\delta)}$$

As for w_2 we have.

$$\frac{\partial w_1}{\partial Y} = \frac{0 - [-e_2^{'}\delta - e_2^{'}(\gamma + \alpha\delta) + e_1^{'}(\gamma + \alpha\delta)]}{[(1 + \delta(1 - e_2)) + (e_1 - e_2)(\gamma + \alpha\delta)]^2} > 0$$
$$= e_2^{'}(\gamma + (1+\alpha)\delta) - e_1^{'}(\gamma + \alpha\delta) > 0$$
$$= \frac{e_1^{'}}{e_2^{'}} < \frac{(\gamma + (1+\alpha)\delta)}{(\gamma + \alpha\delta)}$$

Hence, in order for both wages to be increasing in total output it is necessary that:

$$\frac{(\beta + (1-\alpha)\delta)}{(\beta + (2-\alpha)\delta)} < \frac{e_1^{'}}{e_2^{'}} < \frac{(\gamma + (1+\alpha)\delta)}{(\gamma + \alpha\delta)}$$

The interval in which both wages grow as a function of output is, therefore, increasing on the employer's bargaining power (δ). If, for example, the employment rate increase due to an output expansion in occupation one is much larger than in occupation two ($e_1^{'} >> e_2^{'}$) it is more likely that only w_1 will rise while w_2 could fall once Y increases. The underlying logic behind this movements is that a much stronger growth in e_1 with respect to e_2 also increases the outside option in occupation one, inducing employers to negotiate higher wages these employees in order to avoid their direct impact on profits.

Appendix B - Data

This second appendix provides background information on the empirical analyses performed in the article. It includes more detailed information on the O*NET work activities and work context characteristics that compose the employee control and Impact variables as well as descriptive statistics and some information on the residuals of the regressions carried on.

Tables (B.1) and (B.2) give more detailed definitions of the O*NET work activities used to build the two employee control variables.

Table B.1: Description of O*NET work activities in physical employee control

Variable	Description
Monitor Processes, Materials, or Surroundings	Monitoring and reviewing information from materials, events, or the environment, to detect or assess problems.
Inspecting Equipment, Structures, or Material	Inspecting equipment, structures, or materials to identify the cause of errors or other problems or defects.
Operating Vehicles, Mechanized Devices, or Equipment	Running, maneuvering, navigating, or driving vehicles or mechanized equipment, such as forklifts, passenger vehicles, aircraft, or water craft.
Assisting and Caring for Others	Providing personal assistance, medical attention, emotional support, or other personal care to others such as coworkers, customers, or patients
Monitoring and Controlling Resources	Monitoring and controlling resources and overseeing the spending of money.
Controlling Machines and Processes	Using either control mechanisms or direct physical activity to operate machines or processes (not including computers or vehicles).
Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment	Providing documentation, detailed instructions, drawings, or specifications to tell others about how devices, parts, equipment, or structures are to be fabricated, constructed, assembled, modified, maintained, or used.
Repairing and Maintaining Mechanical Equipment	Servicing, repairing, adjusting, and testing machines, devices, moving parts, and equipment that operate primarily on the basis of mechanical (not electronic) principles.
Repairing and Maintaining Electronic Equipment	Servicing, repairing, calibrating, regulating, fine-tuning, or testing machines, devices, and equipment that operate primarily on the basis of electrical or electronic (not mechanical) principles.
Documenting/Recording Information	Entering, transcribing, recording, storing, or maintaining information in written or electronic/magnetic form.
Performing Administrative Activities	Performing day-to-day administrative tasks such as maintaining information files and processing paperwork.
Performing general physical activities	Performing physical activities that require considerable use of your arms and legs and moving your whole body, such as climbing, lifting, balancing, walking, stooping, and handling of materials
Handling and moving objects	Using hands and arms in handling, installing, positioning, and moving materials, and manipulating things.

Table B.2: Description of O*NET work activities in abstract employee control

Variable	Description
Getting Information	Observing, receiving, and otherwise obtaining information from all relevant sources.
Identifying Objects, Actions, and Events	Identifying information by categorizing, estimating, recognizing differences or similarities, and detecting changes in circumstances or events.
Estimating the Quantifiable Characteristics of Products, Events, or Information	Estimating sizes, distances, and quantities; or determining time, costs, resources, or materials needed to perform a work activity.
Judging the Qualities of Things, Services, or People	Assessing the value, importance, or quality of things or people.
Evaluating Information to Determine Compliance with Standards	Using relevant information and individual judgment to determine whether events or processes comply with laws, regulations, or standards.
Analyzing Data or Information	Identifying the underlying principles, reasons, or facts of information by breaking down information or data into separate parts.
Making Decisions and Solving Problems	Analyzing information and evaluating results to choose the best solution and solve problems.
Thinking Creatively	Developing, designing, or creating new applications, ideas, relationships, systems, or products, including artistic contributions.
Interpreting the Meaning of Information for Others	Translating or explaining what information means and how it can be used.
Communicating with Persons Outside Organization	Communicating with persons outside organization, representing the organization to customers, the public, government, and other external sources. This information can be exchanged in person, in writing, or by telephone or e-mail.
Establishing and maintaining interpersonal relationships	Developing constructive and cooperative working relationships with others and maintaining them over time.
Selling or Influencing Others	Convincing others to buy merchandise/goods or to otherwise change their minds or actions.
Resolving Conflicts and Negotiating with Others	Handling complaints, settling disputes, and resolving grievance and conflicts, or otherwise negotiating with others.
Performing for or Working Directly with the Public	Performing for people or dealing directly with the public. This includes serving customers in restaurants and stores, and receiving clients or guests.
Provide Consultation and Advice to Others	Providing guidance and expert advice to management or other groups on technical, systems, or process related topics.

In order to compare the above work activities with the frequencies of the tasks that correspond to them it is necessary to attribute values to the seven frequency categories in the original data. Table (B.3) shows the seven categories, on the left, and their corresponding values in times per year a task is performed. The value for 5-daily is based on 5 work days a week. For 7-hourly or more it is assumed 8 hours of work for 251 days a year and for category 6-several times a day we take half of the highest frequency, hence roughly a task is performed once every two hours of work.

Table B.3: Corresponding value in number of times a year for each task frequency category

	Category	Value
1-	Yearly or less	1
2-	More than early	4
3-	More than monthly	12
4-	More than weekly	48
5-	Daily	251
6-	Several times a day	1004
7-	Hourly or more	2008

The Impact variable is build using work context. In particular, we select characteristics from a specific subset of work context: criticality of position amount of impact the worker has on final products and their outcomes[49], which is part of structural job characteristics. Out of the four variables in this category, reported in table (B.4), two are selected to compose our Impact variable. The other two variables, frequency of decision making and freedom to make decisions, are excluded because they do not asses the actual impact or the consequences of employee's actions but rather the frequency or decisions that *could* affect the firm and are, hence, more related to a measure of discretion than one of impact.

Table B.4: O*NET Work Context characteristics that compose the criticality of position amount of impact the worker has on final products and their outcomes for Impact variable

Variable	Selected	Description
Consequence of error	yes	How serious would the result usually be if the worker made a mistake that was not readily correctable?
Impact of Decisions on Co-workers or Company Results	yes	What results do your decisions usually have on other people or the image or reputation or financial resources of your employer?
Frequency of Decision Making	no	How frequently is the worker required to make decisions that affect other people, the financial resources, and/or the image and reputation of the organization?
Freedom to Make Decisions	no	How much decision making freedom, without supervision, does the job offer?

Table $B.5$ contains the means and standard deviations of the dependent and independent variables used in the regression analyses displayed in table 2., 3. and 4. for the final sample of non-managerial workers.

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[49] 4.C.3.a in the O*NET content reference model.

Table B.5: Descriptive statistics of main variables in tables 2., 3. and 4.

	Mean	S.D.		Mean	S.D.
Real hourly wages	22.72	16.07	Race/ethnicity		
Log real wage hourly wages	2.94	0.57	White	0.68	0.47
Abstract	-0.06	0.97	Black	0.09	0.29
Physical	-0.13	0.90	Hispanic	0.16	0.36
Physical routine	-0.21	0.88	Asian	0.06	0.24
Physical non-routine	-0.10	0.92	Other	0.01	0.10
Impact	-0.15	1.06	Education		
Union	0.08	0.28	Less than high school	0.07	0.26
Female	0.43	0.49	High school	0.31	0.46
Age	40.27	12.22	Some college	0.30	0.46
Potential experience	20.47	12.40	College	0.22	0.41
U.S. citizenship	0.90	0.29	Advanced degree	0.10	0.30

$N = 146,067$ excluding workers in managerial occupations

The next four figures plot the random intercepts and slopes of the multilevel analysis in table (4) and figures (4) and (5). Figures (B.1) and (B.2) are from model (5) while (B.3) and (B.4) correspond to model (6). The random slopes and intercept estimates are shown with their 90% confidence intervals. The grid lines in the normal quantile plots for the level 1 residuals of models (5), left of figure (B.2), and (6), left of figure (B.4), represent the 5, 10, 25, 50, 75, 90 and 95 percentiles. The histograms for the same models, in grey bars, are shown together with a line that plots a normal distribution.

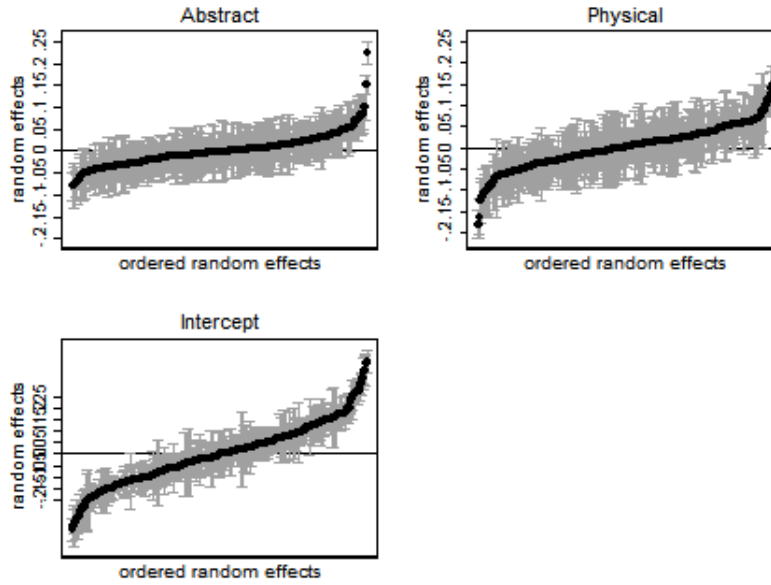Figure B.1: Estimated random effects for model 5 (table 4)

Figure B.2: Normal quantile plot and histogram of model (5) residuals (table 4)
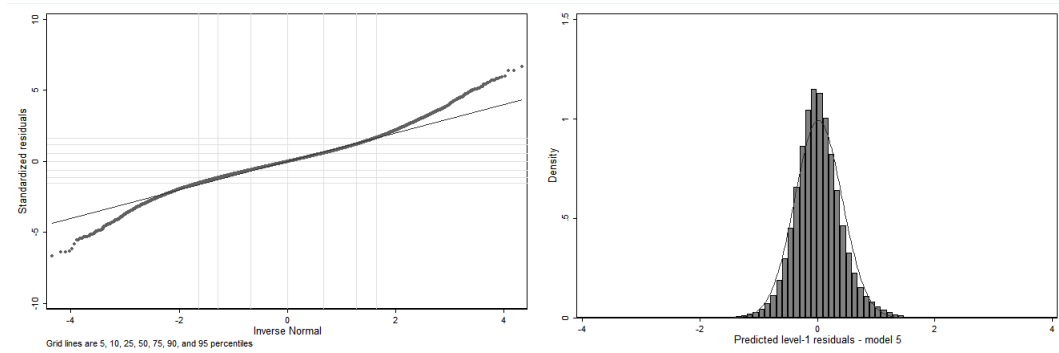

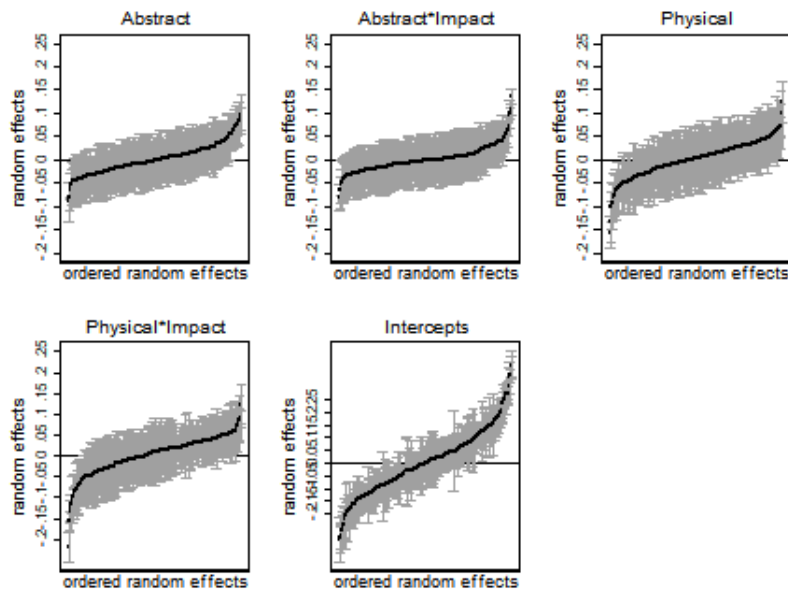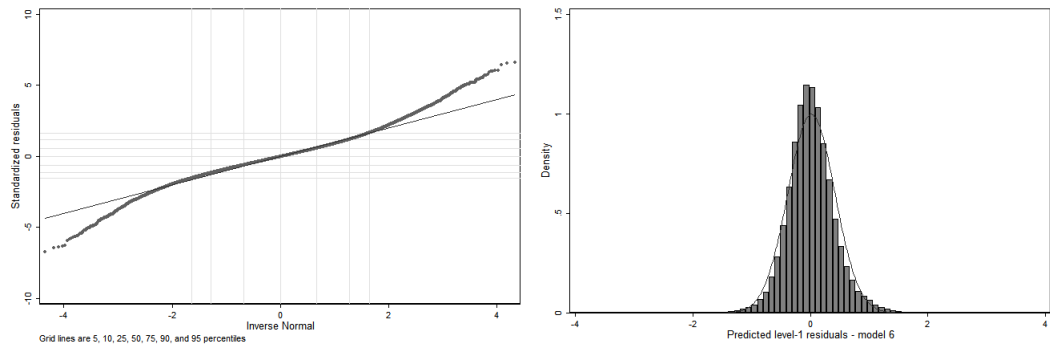Figure B.3: Estimated random effects for model 6 (table 4).

Figure B.4: Normal quantile plot and histogram of model (6) residuals (table 4)

The final table of the appendix (B.6) contains the descriptive statistics for the industry level variables in the multinomial logit regressions.

Table B.6: Descriptive statistics of multinomial logit variables

	Mean	S.D.		Mean	S.D.
Abstract r.e.	0.00	0.04	Union	0.08	0.10
Discrete abstract r.e.	1	0.48	Δunion	-0.01	0.06
Physical r.e.	0.00	0.05	Professional associations	6.06	3.02
Discrete physical r.e.	0.97	0.59	Δprofessional associations	0.44	0.76
Physical	-0.11	0.45	Industry mean wages	24.44	7.73
Δphysical	-0.02	0.07	Δindustry mean wages	0.08	0.19
Abstract	-0.02	0.49	Industry wage dispersion	15.15	6.18
Δabstract	0.01	0.09	Δindustry wage dispersion	0.18	0.44
Impact	-0.17	0.38			
Δimpact	0.01	0.07			

$N = 249 \; industries$