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Andrey Stoyanov
York University

Nikolay Zubanov
University of Konstanz and IZA

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ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Skill Complementarity in Production Technology: New Empirical Evidence and Implications

Matched worker-firm data from Danish manufacturing reveal that 1) industries differ in within-firm worker skill dispersion, and 2) the correlation between within-firm skill dispersion and productivity is positive in industries with higher average skill dispersion. We argue that these patterns are a manifestation of technological differences across industries: firms in the "skill complementarity" industries profit from hiring workers of similar skill level, whereas firms in the "skill substitutability" industries benefit from hiring workers of different skill levels. An empirical method we devise produces a robust classification of industries into the distinct complementarity and substitutability groups. Our study unveils hitherto unnoticed technological heterogeneity between industries within the same economy, and demonstrates its importance. Specifically, we show through simulations on a simple general equilibrium model that failing to take technological heterogeneity into account results in large prediction errors.

JEL Classification: D24, D58, J2

Keywords: skill dispersion, complementarity, production technology, firm productivity

Corresponding author:
Nikolay Zubanov
Department of Economics
University of Konstanz
Universitätsstrasse 10
78464 Konstanz
Germany

E-mail: nick.zubanov@uni-konstanz.de

1 Introduction

It is now well known that worker wages differ within firms, even controlling for observed worker characteristics (Lazear and Shaw, 2009; Skans, Edin and Holmund, 2009), and that inter-firm differences in within-firm wage dispersion (WFWD) are persistent (Iranzo, Schivardi and Tosetti, 2008). As wages are fundamentally determined by skill level, why do firms systematically differ in the skill mix of the workers they employ? Empirical studies on the relationship between WFWD and firm performance report diverging results. Some studies find a positive link (Iranzo, Schivardi and Tosetti, 2008; Lee, Lev and Yeo, 2008; Lallemand, Plasman and Rycx, 2009; Arranz-Aperte, 2014), others negative (Grund and Westergaard-Nielsen, 2008), yet other studies find a curvilinear relationship (Mahy, Rycx and Volral, 2011*b*) or non-robust, weak or no significant relationship at all (Hunnes, 2009; Liu, Tsou and Wang, 2010), and some find that the WFWD-performance link is moderated by firms' personnel policies and institutional environment (Jirjahn and Kraft, 2007; Mahy, Rycx and Volral, 2011*a*).

In this paper, we propose that the performance effects of worker skill dispersion are indeed heterogeneous and, in particular, depend on the production technology a firm operates. We present empirical evidence supporting this proposition and illustrate its economic implications with policy simulations. Our study is motivated by observing differences in WFWD between industries in the Danish manufacturing sector over the period 1995-2007. In some industries, such as transportation equipment, office machinery and chemical products, the industry-average WFWD conditional on age, experience, education and occupation is relatively small, about a third of the average wage. In others, such as publishing and printing or apparel, the industry average WFWD is close to half of the average wage. Overall, a simple analysis of variance reveals that industry-level factors account for 37% of the observed variation in WFWD.

We argue that one reason for the variation in WFWD by industry is technological differences in terms of the degree of complementarity between contributions of workers of different skill levels. Our argument draws on the concepts of complementarity and substitutability (cf. Milgrom and Roberts, 1990, p. 516): two production inputs are complements/substitutes/neutral to each other if the marginal product of one increases/decreases/stays constant with the level of the other. Holding the average skill level constant, the marginal product of a higher-skill worker is impaired by the lower skill of the other workers in the same firm if the production technology features skill complementarity. Conversely, in a firm operating under skill substitutability, the marginal product of labor of high-skill workers decreases with the skill level of the other workers. Therefore, holding the total labor costs fixed, firms operating in "complementarity" industries would gain from employing workers of similar skill level, to whom they would pay similar wages, whereas firms in the "substitutability" industries would profit from skill differences between the workers. Differences in WFWD by industry would then reflect the optimal staffing choices in terms of workforce skill composition given the prevailing production technology.

Consistently with the above argument, we observe in our data a positive correlation between WFWD and total factor productivity (TFP) in industries with relatively high average WFWD (Figure 1). We obtain the same pattern when we use other wage-based measures of skill, described in Section 2.2, and also when we augment our data with measures of complementarity computed from employee surveys (Section 2.2.2). Generally, industries with relatively low complementarity scores have higher average within-firm skill dispersion and a more strongly positive correlation between skill dispersion and TFP.

[Figure 1 here.]

Inter-industry differences in the degree of skill complementarity were first documented by Bombardini, Gallipoli and Pupato (2012), and the findings above are consistent with the presence of such differences. Yet, little is known about which industries belong in the "complementarity" or "substitutability" groups, since there is no natural threshold in any empirical measure of skill complementarity that separates complementarity from substitutability. It turns out that knowing if a technology features complementarity or substitutability is more important than the degree of it, since the consequences for labor demand, wages and firm personnel policies depend on the sign of complementarity much more than on its degree. We therefore attempt to classify industries into the complementarity and substitutability groups using a specially designed procedure we describe in detail in Section 3.1.

The application of our classification procedure to the data (Section 3.3) reveals two distinct groups of industries, one featuring complementarity and the other substitutability between workers of different skill levels. Examples of the complementarity industries are chemicals and rubber and plastics. Foundries and transport equipment are examples of the substitutability industries. Our classification results – most importantly, the complementarity/substitutability industry groupings – are robust to the choice of empirical specification in terms of measures of skill and skill complementarity, as well as estimation technique. Also, consistent with the definition of complementarity/substitutability and our preliminary evidence (Figure 1), the correlation between skill dispersion and firm TFP is positive in the substitutability group and is negative in the complementarity group.

The coexistence within the same economy of two industry groups, radically different in the workforce skill composition their production technologies optimally require, has important implications. First, inasmuch as a firm's workforce skill distribution matters beyond the average, choosing the right skill mix is important for gaining and sustaining competitive advantage. Consequently, personnel management policies may also be affected by the extent of complementarity. Our results may thus be helpful in explaining why some firms prefer to hire similarly skilled workers, while others do not (the point also made by Prat (2002)), and why firms in some industries train workers rather selectively, whereas others spread their training budgets more evenly across their workforce (Konings and Vanormelingen, 2015).

Second, complementarity shapes productivity differences between industries, under a given distribution of skill within the labor force, and consequently affects resource allocation domestically as well as international trade flows. For instance, Grossman and Maggi (2000) theory predicts that countries with more homogenous ability distribution will export more goods produced by technologies featuring stronger complementarity, a prediction empirically confirmed by Bombardini, Gallipoli and Pupato (2012). Turning to inter-sectoral productivity differences, Wingender (2015) argues that the relatively high elasticity of substitution between high- and low-skilled workers in agriculture leads to an overrepresentation of skilled workers in non-agriculture, and is behind the large agricultural productivity gap in developing countries, where skilled labor is in limited supply.

While not the first to find differences in the degree of complementarity between industries (the first, to our knowledge, are Bombardini, Gallipoli and Pupato (2012)), our study is the first attempt to classify manufacturing industries into the distinct complementarity and substitutability groups using individual worker and firm data. Iranzo, Schivardi and Tosetti (2008), who used matched worker-firm data similar to ours, and whose empirical approach we take as the starting point, estimated a single complementarity parameter for all industries, thereby assuming all industries to be technologically similar. As we show in this paper, one consequence of this assumption are potentially large prediction errors of the models simulating the economic outcomes of policies or natural events (for example, migration) that affect workforce skill distribution.

To illustrate how large these errors could be, we devise in Section 4 a stylized general equilibrium model of an economy with perfectly competitive labor and product markets, and two types of labor, A (low skill level) and B (high skill level), employed in two sectors, one featuring skill complementarity, the other substitutability. Under this setting – later referred to as the "true model" – we simulate the effects of an exogenous ten-percent increase in the supply of one type of labor on the wages of both types and on labor productivity in each sector. For comparison, we perform the same simulations under the (incorrect) assumption that the two sectors are identical in terms of skill complementarity – later referred to the "false model".

The true model correctly predicts a decrease in wages of the relatively abundant type and an increase in wages of the relatively scarce type. It also predicts that labor productivity will grow in the sector that benefits from changes in workforce diversity, and will decrease in the other sector – again, an intuitively appealing prediction. Yet, depending on the assumed degree of complementarity, common across the two sectors, the false model predicts milder or sharper wage and labor productivity effects than does the true model, with the prediction error of up to 2 percentage points. Generally, the false model produces inaccurate predictions for the effects of changes in workforce composition on labor market outcomes, such as wages and skill premium, with errors commensurate to the magnitude of the correctly estimated effects for a wide range of underlying parameter values. With these illustrations, and informed by our empirical results, we call for taking technological heterogeneity between industries fully into account in policy analysis.

In addition to the labor and trade literatures cited above, our study also speaks to the large literature on workforce diversity (e.g., Shore et al., 2011; Kahane, Longley and Simmons, 2013; Parrotta, Pozzoli and Pytlikova, 2014). We complement the existing research, much of which focusses on diversity in nominal characteristics, such as age, ethnicity, education, or professional background, by examining the effects of diversity in skill levels. Our findings reveal the importance of production technology in the "business case for diversity" (Smedley, 2014), a currently under-researched issue. Our empirical framework can be employed to capture the relationship between firm performance and diversity in terms of other, not necessarily cardinally measurable, characteristics (e.g., gender), thus further contributing to this thriving research area.

2 Data and first results

As we reported in the introduction, industries differ in WFWD and the correlation between firm productivity and WFWD tends to be positive in high-WFWD industries. In this section, we describe our data and measures, and demonstrate that the patterns observed for WFWD hold for other measures of skill dispersion and are further supported by independently obtained measures of skill complementarity/substitutability.

2.1 Data description

We combine matched firm-worker data from Danish manufacturing over the period 1995-2007, compiled by Statistics Denmark, with worker survey data provided by the U.S. Occupational Information Network (O*NET). We limit the scope of our study to manufacturing because it is hard to measure capital input, and hence productivity, in the service sector.

The firm data are a panel of all active manufacturing firms in Denmark. It contains records of total sales, worker headcount, costs of labor and intermediate inputs, capital stock, investment, and three-digit NACE industry classification code. Panel A of Table 1 shows descriptive statistics for the sample of firms in our study. The average firm sells 43.6 million Danish Kroner worth of output (approx. $6.7m) and employs 37 workers. These high average values are influenced by the presence of very large firms, though; the median firm's sales are the more modest 5.5 million Danish Kroner (just over $0.8m), generated by 9 workers.

[Table 1 here.]

The worker data come from the Integrated Database for Labor Market Research (IDA), and are matched with the firms where workers were employed in each year. The IDA data contain annual records of wage and other income, years of experience, and demographic information: age, gender, education, measured by the highest attained degree (high school, college, university), occupation level (low-, mid-, high-level, and managers) and ISCO-08 occupation code. Overall, we have records of 3,382,486 workers employed in 36,523 firms in 23 two-digit (101 three-digit) NACE Revision 1 industry groups. Descriptive statistics in panel B of Table 1 show that the average worker is about 40 years old and earns 281,500 DKK per year ($43,000) with 9.4 years of experience. 70% of the workforce are male, 67% have a college degree or higher, and most (90%) have non-managerial positions in their firms.

We link the firm-worker data described above with the O*NET data by industry. The O*NET data are used to calculate industry-specific measures of complementarity/substitutability following the method developed by Bombardini, Gallipoli and Pupato (2012) which we describe in more detail in Section 2.2.2.

2.2 Measures

2.2.1 Individual skill level and within-firm skill dispersion

Following Iranzo, Schivardi and Tosetti (2008), we proxy skill with wages and construct four measures, each capturing a particular component of individual wage. We estimate these components from the wage regression with worker, firm and year fixed effects, all observable worker characteristics,[1] firm size (in log headcount) and the interactions between worker characteristics and firm size:

$$\log \text{wage}_{it} = \text{worker FE}_i + \text{firm FE}_{J(i,t)} + \text{year FE}_t + \text{worker chars}_{it}\beta_w + \\ + \text{firm chars}_{J(i,t)}\beta_f + \text{worker*firm chars}_{it} + \text{error}_{it}, \tag{1}$$

where i and t are worker and year counters, and $J(i,t)$ is the is the ID of the firm that employed worker i in year t. We use the method developed by Abowd and Kramarz (1999) to estimate the above equation.

Our measures of skill come from equation (1) and are as follows: *skill1*= worker FE_i; *skill2*= worker FE_i + worker $\text{chars}_{it}\beta_w$; *skill3*= $\log \text{wage}_{it}$ − firm $\text{FE}_{J(i,t)}$; *skill4*= $\log \text{wage}_{it}$. *skill1* reflects the wage component due to the worker's pure skill independent of the firm, time period or time-varying observable characteristics. *skill2* is more inclusive: it incorporates all worker characteristics but not their interactions with firm size. This is because the return to the same level of skill may differ with firm size: workers at the top of the hierarchy will be paid not only for their own skill but also for the effect they cause on the productivity of their subordinates (Rosen, 1982). *skill3* and *skill4* are progressively more inclusive. For each of the above measures, $skill1 - skill4$, we calculate the corresponding measure of within-firm skill dispersion in each firm-year cell, $wsd1 - wsd4$. For example, $wsd4$, the within-firm skill dispersion corresponding to *skill4* is the WFWD we used to produce Figure 1 in the introduction.

Descriptive statistics on our measures of skill dispersion (Panel A of Table 1) show differences in worker skill levels even when workers are employed by the same firm. While these differences go down when we control for worker observables, they do not disappear: the average of $wsd1$ is 0.41 vs. 0.53 of $wsd4$, the WFWD. We also observe a wide distribution of firms in terms of within-firm skill dispersion, with the log interquartile range of the order of 0.2 to 0.4, depending on the measure. A large part of the variation in within-firm skill dispersion by firm is in fact the variation by industry: the interquartile range of the distribution of within-firm skill dispersion averaged at the industry level is 0.2-0.3 (Panel C of Table 1), comparable to the interquartile range calculated at the firm level. In fact, an analysis of variance carried out on our measures of within-firm skill dispersion shows that industry-level factors account for 25-40% of their variation.

2.2.2 Complementarity/Substitutability

Following Bombardini, Gallipoli and Pupato (2012), we compute measures of skill complementarity/substitutability for each industry using data from the Occupational Information Network (O*NET). The O*NET database con-

[1] The worker characteristics included in the wage equation are: education and occupation level dummies, and polynomials of age and experience.

tains descriptions of 965 occupations in the Standard Occupational Classification (SOC). For each occupation, there are multiple "descriptors" – survey questions sent to randomly selected employees in that occupation to evaluate the importance of various aspects of their job. We calculate measures of complementarity based on the following four descriptors, each rated by every employee on a 1-5 Likert scale in the original surveys: 1) *teamwork*: how important are interactions that require you to work with a group or team to perform your job? 2) *impact*: how do decisions of one employee impact the results of co-workers, clients or the firm? 3) *communication*: how important is communicating with supervisors, peers or subordinates to the performance of your current job? 4) *contact*: how much contact with others is required to perform your current job? Higher descriptor ratings are suggestive of stronger skill complementarity. The industry-level measures of skill complementarity are computed by averaging individual survey responses on each descriptor by occupation, and then by calculating the weighted median for each industry with industry-specific occupational headcounts used as weights. We use the concordance table from Statistics Canada to match NAICS industry codes used in O*NET with the NACE industry codes in the firm-worker data.

Panel C of Table 1 reports descriptive statistics on the complementarity measures *teamwork-contact*. The averages tend to be high (an upwards of 3.4 on a 1-5 scale), but there is some variation by industry. The complementarity measures are negatively correlated with the measures of skill dispersion *wsd1-wsd4*, which is consistent with the optimally lower skill dispersion under more strong complementarity. They are also positively correlated with each other, suggesting that they may be different measures of the same underlying construct (skill complementarity). In fact, principal component analysis (PCA) on *teamwork-contact* reveals the presence of one component that explains 86% of the total variance in them. All four measures load on this component with approximately equal weights. We therefore construct an additional measure of complementarity, labelled PCA, as the PCA-weighted average of *teamwork-contact*.

2.2.3 Firm productivity

We calculate firm productivity as the total factor productivity term (TFP) in the Cobb-Douglas production function equation with log gross output as the dependent variable and logs of capital, labor and intermediate inputs as the regressors, which is the standard approach in the empirical literature. Our estimation procedure controls for input endogeneity, in particular, for nonrandom selection of workers into firms, by using Olley and Pakes (1996) control function-based estimator. However, we obtain qualitatively similar results for TFP estimated with ordinary least squares or for simple value added.

2.3 First results

Figure 2 plots averages of the within-firm skill dispersion measure $wsd1$ (dispersion in the worker fixed effects from wage regression (1), right vertical axis) and its correlations with firm TFP (left vertical axis) for each quartile of the skill complementarity measure PCA (the PCA-weighted average of the four complementarity measures, horizontal axis). Within-firm skill dispersion, $wsd1$, decreases with the quartile of PCA, suggesting that both these measures are linked to skill complementarity. There is a positive and statistically significant correlation between $wsd1$ and TFP in the industries in the first and second quartile of PCA, where skill dispersion is relatively high. The correlation between $wsd1$ and TFP in the industries in the two upper quartiles is weaker and insignificant. The differences in the correlations between skill dispersion and TFP by quartile of PCA are statistically significant. The patterns depicted in Figure 2 are not unique to this particular combination of measures; they hold for other measures of skill dispersion and complementarity. In sum, our proposition that the pattern of correlation between skill dispersion and TFP owes itself to the presence of technological differences between industries in terms of skill complementarity, receives further empirical support.

[Figure 2 here.]

What the results in Figure 2 do not reveal, however, is whether there is a complementarity/substitutability divide between the industries in our sample, or whether all industries feature skill complementarity (or substitutability) of varying degrees. As we demonstrate in Section 4, knowing this is important for understanding the consequences of shocks to skill distribution. Therefore, we next attempt to classify industries into the complementarity and substitutability groups and test whether our data support such classification.

3 The skill complementarity and substitutability industries

3.1 Analytical framework

To capture the link between worker skill mix and firm productivity, we model the gross output of firm i in year t as a Cobb-Douglas function of capital and materials, K_{it}, M_{it}, as well as labor input, $\widetilde{L}_{it}$, expressed in "efficiency units":

$$Y_{it} = A_{it} K_{it}^{\alpha_K} M_{it}^{\alpha_M} \widetilde{L}_{it}^{\alpha_N}, \tag{2}$$

where A_{it} is TFP. We follow Iranzo, Schivardi and Tosetti (2008) in letting $\widetilde{L}_{it}$ depend not only on the worker headcount, N_{it}, but also on individual skill levels of every worker, s_{lit}, and their composition:

$$\widetilde{L}_{it} = N_{it} \left[\frac{1}{N_{it}} \sum_{l=1}^{N_{it}} s_{lit}^{\rho} \right]^{\frac{1}{\rho}} \tag{3}$$

The parameter ρ measures the degree of complementarity/substitutability between skill levels of different workers: $\rho < 1$ implies complementarity, $\rho > 1$ substitutability in the sense of Milgrom and Roberts (1990)'s definition.[2] When $\rho = 1$, worker skill levels do not affect each other's productivity, so the effective labor input reduces to headcount times the average of the individual skill levels, $\widetilde{L}_{it} = N_{it} \cdot \bar{s}_{it}$.

The efficiency term in equation (3) can be approximated with its second-order Taylor series expansion around

[2] Recalling the definition of complementarity/substitutability, worker skills are complements/substitutes to each other if the marginal product of a worker i's skill increases/decreases with the skill level of another worker j. The cross derivative of effective labor input with respect to s_{lit}, s_{ljt} is $\frac{\partial^2 \widetilde{L}_{it}}{\partial s_{lit} \partial s_{ljt}} \propto (1-\rho)$, and is positive when $\rho < 1$ and negative when $\rho > 1$.

the average skill level $\bar{s}_{it}$:

$$\left[\frac{1}{N_{it}}\sum_{l=1}^{N_{it}} s_{lit}^{\rho}\right]^{\frac{1}{\rho}} \approx \bar{s}_{it} + \frac{1}{2}(\rho-1)\frac{\sigma_{it}^2}{\bar{s}_{it}}, \tag{4}$$

where σ_{it}^2 is skill dispersion. The above result is instructive and implies that, holding the headcount and the average skill level constant, skill dispersion reduces the efficiency of labor input when production technology features skill complementarity ($\rho < 1$) and enhances it under skill substitutability. Substituting the approximation in (4) into (3) and (2) and taking logs of all factor inputs, we obtain an estimable equation that links worker skill distribution, expressed in terms of the average skill and its dispersion, with firm performance:

$$y_{it} = \alpha_K k_{it} + \alpha_N n_{it} + \alpha_M m_{it} + a_{it} + \alpha_N \ln\left(\bar{s}_{it} + \frac{1}{2}(\rho-1)\frac{\sigma_{it}^2}{\bar{s}_{it}}\right) \tag{5}$$

3.2 Estimation procedure

The key parameter in equation (5) is ρ. Industries with $\rho < 1$ will be in the complementarity group, and those with $\rho > 1$ in the substitutability group. One approach to studying technological differences between industries in terms of skill complementarity could be to estimate a separate ρ for each industry. There are two problems with this approach, however. First, some industries do not have sufficiently large number of observations to reliably estimate a nonlinear equation such as (5). Second, the estimates of ρ are sensitive to the scale in which skill is measured: raising everyone's wage by the same amount would increase $\bar{s}_{it}$ but would leave σ_{it}^2 unchanged, whereas multiplying everyone's wage by the same amount would increase σ_{it}^2 by a larger factor than $\bar{s}_{it}$.

The approach we take instead is to classify every industry into one of the two groups, each with a separate ρ, and is based on the threshold regression method developed by Hansen (1999). Rewrite equation (5) as a threshold regression:

$$y_{it} = \begin{cases} X_{it}'\alpha + \alpha_N \ln\left(\bar{s}_{it} + \frac{1}{2}(\rho_H - 1)\frac{\sigma_{it}^2}{\bar{s}_{it}}\right) + \varepsilon_{it}, & \text{if } z_{it} \le \gamma \\ X_{it}'\alpha + \alpha_N \ln\left(\bar{s}_{it} + \frac{1}{2}(\rho_L - 1)\frac{\sigma_{it}^2}{\bar{s}_{it}}\right) + \varepsilon_{it}, & \text{if } z_{it} > \gamma \end{cases} \tag{6}$$

where X_{it} is the vector of factor inputs, α is the vector of input factor elasticities, ε_{it} is the error term containing TFP and noise, z_{it} is the threshold variable (in our application, a measure of skill complementarity), and $\gamma \in [\underline{\gamma}, \bar{\gamma}]$ is the threshold parameter estimated from the data. Specification (6) allows industry groups with the measures of complementarity below and above γ to have different complementarity parameters, ρ_H and ρ_L. Given the preliminary evidence, reported earlier in the introduction and Section 2.3, we expect to find $\rho_L < \rho_H$. Furthermore, we may observe $\rho_L < 1 < \rho_H$ if the industries below and above the threshold not simply differ in the degree of skill substitutability ($1 < \rho_L < \rho_H$) or complementarity ($\rho_L < \rho_H < 1$) but belong to the distinct complementarity ($\rho_L < 1$) and substitutability ($\rho_H > 1$) groups.

The procedure of estimating the parameters of (6), $\hat{\alpha}, \hat{\alpha}_N, \hat{\rho}_H, \hat{\rho}_L, \hat{\gamma}$, amounts to ranging industries in terms of the threshold variable z and then performing a grid search over all distinct values $\underline{\gamma} < ... < \hat{\gamma}_i < ... < \bar{\gamma}$ that z takes on our sample, to find the threshold value $\hat{z} = \hat{\gamma}$ that minimizes the residual sum of squares in (6). To have sufficient observations to estimate both parts of (6), we restrict the search range $[\underline{\gamma}, \bar{\gamma}]$ so as to have at least two industries with at least 500 observations above and below each possible value of $\hat{\gamma}$.[3] We estimate (6) at each iteration of the grid search using two estimators: NLLS and NLLS-OP. The first is a standard nonlinear least squares estimator. NLLS-OP is a NLLS enhanced with an Olley and Pakes (1996) (OP)-style procedure that deals with potential factor input endogeneity (more productive firms employing larger quantities, or better quality, of factor inputs) by expressing firm TFP as a function of observables. As in the standard OP estimator, we augment the production function in (6) with the *control function* of observables and their interactions to capture the unobserved firm productivity. Hence, NLLS-OP estimates are robust to possibly nonrandom sorting of workers into firms.

Testing for technological heterogeneity in terms of the degree of skill complementarity/substitutability amounts to testing the hypothesis $H_0 : \rho_L = \rho_H$. According to Hansen (1999), the likelihood ratio test statistic for the above hypothesis has a non-standard distribution; therefore, we obtain its distribution and the p-value for H_0 through bootstrap.

3.3 Results

Figure 3 illustrates the application of our estimation procedure, described in the previous section, to a particular specification, that is, a combination of the measures of skill dispersion and skill complementarity, and the estimator. Specifically, the results in Figure 3 are obtained from applying the NLLS (panel A) and NLLS-OP (panel B) estimators to equation (6) where skill dispersion is measured with $wsd1$ (the dispersion of the worker fixed effects from the wage equation (1) computed for each firm-year cell, Section 2.2.1) and the skill complementarity measure used to define the threshold variable z is PCA (Section 2.2.2).

Every dot on each graph in Figure 3 represents a particular industry. The horizontal axis on each graph plots each industry's measure of complementarity, which is the threshold value γ in equation (6). On each panel, the vertical axis of the lower graph plots the sum of squared residuals from estimating equation (6) for each threshold value. The vertical axis of the middle graph plots the estimated complementarity parameter ρ_L for the industries with the complementarity measure above a given threshold γ, and the same of the upper graph plots the complementarity parameter ρ_H for the industries whose measure of complementarity is below the given γ. The red vertical line points to the threshold value $\hat{\gamma}$ that minimizes the residual sum of squares, and the corresponding values of the skill complementarity parameters ρ_L, ρ_H in the industries whose measure of complementarity is above and below $\hat{\gamma}$.

We see that there is a clear minimum of the residual sum of squares criterion at $\hat{\gamma}$ just below 4, and this threshold is the same for both estimators, NLLS and NLLS-OP. The estimated complementarity parameter ρ_H for the industries below $\hat{\gamma}$ is about 3.75, well in excess of 1, implying that the industries where skill complementarity is relatively less important are those where production technology features skill substitutability. The remaining industries, where skill complementarity is relatively more important, feature strong skill complementarity with ρ_L about -1.5. The estimates of ρ_L and ρ_H are on the opposite sides from 1, and are significantly

[3] That is, we run $I - 4 = 46$ regressions where $I = 50$ is the number of industries with at least 500 observations in our sample. The estimates from the regression that gives the minimal residual sum of squares are taken as the basis for classification.

different from each other (the bootstrapped $p-$value of the test statistic for $H_0 : \rho_L = \rho_H$ is below 0.01), implying that the industries in our sample significantly differ in their production technology, falling into either the skill complementarity or substitutability group.[4]

[Figure 3 here.]

We now summarize our results by specification. We have a total of 40 specifications, each of which is a particular combination of five measures of complementarity, four measures of skill dispersion, and two estimators.[5] Table 2 presents, for each specification, estimates of ρ_L and ρ_H, $p-$values of the test statistic for $H_0 : \rho_L = \rho_H$, and information on the relative size of the substitutability group of industries (the complementarity group is the rest). ρ_H and ρ_L are always on the opposite sides from 1, and the difference between ρ_H and ρ_L is statistically significant at conventional levels in most of the specifications.

[Table 2 here.]

While the complementarity and substitutability industry groups are large in terms of output, employment, and the number of firms in every specification, their relative size varies by specification. We therefore probe into the robustness of the composition of the complementarity and substitutability groups to different specifications. We begin by computing, for each industry, the percentage of specifications that classify it into the complementarity group, henceforth denoted as c. Table 3 summarizes the results. A total of 13 industries are always in either in the complementarity ($c = 1$) or substitutability ($c = 0$) group. 30 industries, or 60% of the total, are classified as either complementarity (15 industries) or substitutability (15 industries) in at least 70% of specifications ($c \leq 0.3$ or $c \geq 0.7$). These 30 industries together represent three-quarters of total output and 70% of total employment. The complementarity and substitutability groups are equally large, except that the average firm size in the complementarity groups is larger than in the substitutability group (there are 26% of all firms in the complementarity group, and 35% in the substitutability group). The 20 industries that are not consistently classified into either group ($0.3 < c < 0.7$, the middle column of Table 3) account for a quarter of total output and 30% of total employment, and are populated by smaller firms (39% of the firm count).

[Table 3 here.]

There are three possible sources of variation of a given industry's classification status by specification: the measure of skill dispersion, the estimator, and the measure of complementarity. Examining the importance of these sources, we find that the first two do not matter; in other words, an industry's classification status is robust to the choice of a measure of skill dispersion or an estimator. It is less robust to the measure

[4]Figures A1 and A2 in the Appendix replicate Figure 3 by showing the same results with individual components of the PCA measure of skill complementarity (Figure A1) and other measures of skill dispersion (Figure A2).

[5]There are fewer industries in our estimation sample than the total number of industries in the original data. This reduction is due to the restrictions required by our estimation procedure (Section 3.2).

of complementarity: for example, an industry will be classified into the complementarity group 78% of the time by the specifications with complementarity measure *communication*, and 18% of the time with *team*. Holding the measure of complementarity fixed, we find that industries with relatively high or low values of the complementarity measure are classified more consistently than those in the middle. Thus, Table 3 shows that the average PCA-based measure of skill complementarity for the industries with a $c \leq 0.3$ (the bottom tercile) is 3.62, for those with a $c \geq 0.7$ (the upper tercile) it is 4.01, and for those in the middle, with $0.3 < c < 0.7$, where classification is less consistent, it is 3.88. This difference is statistically significant and is consistent with our other findings, since industries in the middle are likely to feature less strong skill complementarity or substitutability than those at the extremes, and are therefore more likely to be misclassified. Indeed, estimating the production function (5) separately on each tercile of c gives a ρ of 2.3 to 5.7 (depending on the measure of skill dispersion) for the first tercile, -0.19 to 0.9 for the middle, and -3.89 to -1.74 for the upper tercile.

Examples of industries consistently classified into the complementarity group are manufacture of chemical products (NACE3 codes 201-205), rubber (221) and plastics (222). Industries such as manufacture of metals (NACE3 codes 241-246) and other transport equipment (300) are consistently in the skill substitutability group. It is worth noting, however, that in this study we cannot go deep into technological specificities of the industries in our data that may explain their position in our classification. We simply document the evidence for the existence of technological heterogeneity between industries in terms of skill complementarity, exploring its implications in the next section.

In addition to the results reported above, as a further robustness check, we relax the restriction implied by equation (6) of factor input elasticities being the same for both industry groups and reestimate (6) allowing α, α_N to vary across the groups. Figure A3 in the Appendix matches Figure 3 above in all specifications, except that it is based on the unrestricted version of (6) that allows all input elasticities to vary by industry group. Although the results in Figure A3 differ from those in Figure 3 in terms of the threshold value $\hat{\gamma}$ and the magnitudes of ρ_L, ρ_H, there are still two distinct industry groups, one of which is the complementarity group ($\rho_L < 1$) and the other substitutability ($\rho_H > 1$). Table A1 in the Appendix replicates the results reported in Table 2 for the unrestricted version of (6), showing that the differences between the groups in terms of the degree of skill complementarity are significant in most of the specifications. The overall conclusion from the results of this and other robustness checks performed earlier is that our main results are robust a variety of possible empirical model specifications, including the various measures of skill dispersion and skill complementarity, restricted or unrestricted regression equations, and NLLS or NLLS-OP estimators.

4 Why, and how, technological heterogeneity matters

We have shown empirically that firms' workforce skill composition and their productivity are linked positively or negatively depending on whether their production technology features skill complementarity or substitutability. Variations in production technology, which we have also documented, affect labor demand. As labor demand meets supply and its skill composition, the equilibrium distribution of wages by skill level is realized. Changes in the underlying skill composition will affect the wage distribution through changes in labor demand across all skill levels, caused in part by skill complementarity or substitutability. In this section, we simulate scenarios like this using a simple general equilibrium model with two types of labor employed in two industry sectors, one featuring skill complementarity the other substitutability, to show the importance of this heterogeneity in shaping model predictions.

4.1 The model

Consider an economy with two perfectly competitive industry sectors, indexed by $i = 1, 2$, with linear demand functions:

$$Q_i = a_i - b_i p_i \tag{7}$$

where Q_i is the quantity of good i consumed, and $a_i > 0$ and $b_i > 0$ are the demand function parameters.

The output Y_i in each sector is produced by combining two types of labor, A and B, using a production technology similar to (2) and (3):

$$Y_i = L_i \widehat{L}_i \tag{8}$$

where $L_i = \left(L_i^A + L_i^B\right)$ is the total employment in sector i, L_i^k is the amount of type-k labor used in sector i, $\widehat{L}_i = \left[\theta_i^A (s_A)^{\rho_i} + \theta_i^B (s_B)^{\rho_i}\right]^{\frac{1}{\rho_i}}$ is the labor efficiency term, $\theta_i^k = \frac{L_i^k}{L_i}$ is the share of type-k labor in total employment, ρ_i is the parameter that captures the degree of complementarity between the two types of labor in sector i, and $s_k > 0$ are the type-specific labor productivity parameters. Note that the total factor productivity in each sector is fixed to one, so that industries differ only in the degree of complementarity between the two types of labor, captured by parameters ρ_i, and in the demand conditions, a_i, b_i. Each type of labor is supplied inelastically: there are $\overline{L}_A$ and $\overline{L}_B$ units of each type, and full employment.

Firms within each sector are symmetric. Given the production technologies defined above, firm j operating in industry i chooses the level of employment for each type of labor in order to maximize its profit function

$$\pi_{ij} = p_i Y_i - w_A L_{ij}^A - w_B L_{ij}^B$$

where p_i is the market price of a good produced by sector i, and w_k is the wage rate earned by workers of type k.

Taking the first-order conditions of the profit function with respect to L_{ij}^A and L_{ij}^B and summing across all firms within an industry, we obtain the demand functions for each type of labor in each sector:

$$\frac{p_i Y_i}{L_i}\left[1 + \theta_i^n \frac{1}{\rho_i} \frac{L_i}{\widehat{L}_i} \left[(s_k)^{\rho_i} - (s_n)^{\rho_i}\right]\right] = w_k, \ n \neq k \tag{9}$$

The marginal production costs in sector i are then equal to

$$mc_i = \frac{w_A L_i^A + w_B L_i^B}{Y_i} \tag{10}$$

The equilibrium in this simple model is defined as a set of resource allocations $\{L_i^k\}$, market prices $\{p_i\}$, wages for each type of labor $\{w_k\}$, output levels by sector $\{Y_i\}$, and consumption of each good $\{Q_i\}$ such that, given production technologies and market demand functions:

i) the labor markets clear

$$L_1^A + L_2^A = \overline{L}_A \quad (11)$$
$$L_1^B + L_2^B = \overline{L}_B,$$

ii) the goods markets clear

$$Y_i = Q_i, \quad (12)$$

iii) firms maximize profits

$$p_i = mc_i. \quad (13)$$

Equilibrium conditions (7), (9), (11), (13), and (12) provide a system of twelve equations with twelve unknowns, p_i, w_k, Y_i, Q_i, L_i^A, L_i^B.

4.2 Simulation scenarios and results

We employ the model described above to simulate two scenarios: i) a 10% increase in the low-skill type A labor, and ii) a 10% increase in the high-skill type B labor, everything else being the same. Both can be thought of as mimicking changes in workforce composition caused by immigration of low- or high-skill workers. The outcomes we focus on are: changes in nominal wages of both types, w_A, w_B, skill premium, w_B/w_A, and labor efficiency (the term $\widehat{L}_i = \left[\theta_i^A (s_A)^{\rho_i} + \theta_i^B (s_B)^{\rho_i}\right]^{\frac{1}{\rho_i}}$ in equation (8)) in each sector.

We set the initial labor endowments at $\overline{L}_A = \overline{L}_B = 100$, and labor productivity parameters at $s_A = 0.1$ and $s_B = 0.2$, that is, both types are equally prevalent but type B workers are twice as productive as type A. We assume the demand conditions in both sectors to be identical, setting $a_i = 100$ and $b_i = 1$. Informed by our empirical results (Table 2) we set $\rho_1 = -1$ and $\rho_2 = 3$, that is, sectors 1 and 2 represent industries with skill complementarity and substitutability, respectively.

The above setting corresponds to what we refer to as the "true model". For comparison, we perform the same computations with the "false model", which is the same as the true model in all respects except that the false model assumes the degree of complementarity to be the same in both sectors, that is, $\rho_1 = \rho_2 = \rho \in [-1, 3]$. One may think of the false model as being informed by an empirical model like the one we estimated earlier except that that model would ignore technological heterogeneity between the industries, estimating instead a single ρ economy-wide. As we do not wish to focus on any specific ρ in the false model, we run it for a range of values of ρ between -1 and 3, within which range an estimate of ρ would likely be found empirically.

[Figures 4 and 5 here.]

Figures 4 and 5 plot simulation results from the true and false models for the two scenarios we consider. Starting with the first scenario, a 10% increase in the low-skill type A labor (Figure 4), the true model predicts a decrease in the wages of the now more abundant type A labor (-1.4%) and a smaller (+0.02%) increase in the wages of type B labor (panel A), resulting in the increase in the skill premium of 1.6% (panel C), all of which effects are highly plausible. The true model also predicts an increase (+2%, panel D) in labor efficiency in the skill complementarity sector 1, and a decrease (-1.5%) in the substitutability sector 2 ($\rho_2 = 3$). The equilibrium effects in the second scenario (Figure 5) are almost a mirror image of the first. In the true model, a 10% increase in the high-skill type B labor results in a decrease (-2.7%, panel A) in its wages, and a very small increase in wages of type A labor. The skill premium goes down by nearly 3%. Sector 2 enjoys a 3% labor efficiency increase, whereas labor efficiency in sector 1 goes down by nearly 4%.

The predictions generated by the false model are different from, and sometimes starkly contrast with, the above. Depending on the assumed value of ρ, the increase in supply of each labor type causes its wages to increase (under low values of ρ) or decrease (high ρ). These dynamics make logical sense assuming the economy is technologically homogenous, as is the case in the false model, and could be borne out by data from such an economy (if it existed). Under skill complementarity, all firms in this economy would try to hire homogenous labor, which would boost demand for the more prevalent type of labor, A or B, depending on the scenario. Conversely, skill substitutability favors the scarcer type of labor. Under skill neutrality ($\rho = 1$), firms are indifferent about which combination of labor types to hire; thus, the false model correctly predicts no effect on the skill premium (panel C of Figures 4 and 5).

Their internal validity notwithstanding, the predictions from the false model are inaccurate, with errors comparable in magnitude with the effect size for a large part of the range of ρ's (panel B), and misleading. In particular, the false model grossly underestimates the effect on the skill premium in the first scenario, and overestimates in the second, and fails to capture changes in productivity between the sectors caused by changes in workforce composition. The false model generates wrong predictions because it does not fully take into account the interplay between the productivity effects of average skill level and skill dispersion. While the effect of changes in $\bar{s}$ is the same in all sectors, the effects of changes in skill dispersion, which are also present in both scenarios we consider, are sector-specific because they depend on the degree of skill complementarity ρ. Their sector specificity generates comparative advantage for type A labor in the skill complementarity sector 1, and for type B labor in the skill substitutability sector 2. The comparative advantage of both types of labor in specific sectors provides a margin of adjustment of the economy to changes in workforce composition, whereby workers of different types sort into the sectors where they are relatively productive. This sorting generates uneven distribution of worker types between the sectors in the true model, whereas the false model predicts an equal distribution of labor types between the sectors.

Overall, our simulations demonstrate the importance of taking cross-industry differences in production technologies into account. Assuming away the variation in the degree of skill complementarity between sectors could lead to erroneous predictions of labor market reactions to economic shocks. In particular, ignoring technological heterogeneity leads to substantially over-estimated elasticity of wage to changes in labor supply and, consequently, wrong predictions for the effects on skill premium and wage inequality.

5 Conclusion

This study was motivated by observing large and persistent differences in within-firm wage dispersion across manufacturing industries in Denmark that formed a pattern consistent with "skill complementarity" and "skill substitutability" industry sectors coexisting with each other. Theoretically, firms in the former benefit from employing similarly skilled workers, while firms in the latter thrive on skill diversity. Hence industries where skill complementarity is more important would have more compressed wage distributions within firms.

We find robust empirical support for this intuition. Industries with higher measures of skill complementarity tend to have lower average within-firm skill dispersion, and more negative correlation between skill dispersion and productivity. Structural estimation results show significant difference in the degree of skill complementarity (ρ) between industries. Industries in the skill complementarity group ($\rho < 1$) tend to have higher skill complementarity measures than those in the skill substitutability group ($\rho > 1$). Industries consistently placed in either complementarity or substitutability group together count for about three-quarters of the Danish manufacturing sector's total output and employment.

Our results speak to the literatures on several topics in labor and trade. The main message of our study, however, is a call for taking inter-industry technological differences fully into account when modelling labor market effects of changes in workforce composition. As we show with simple examples, ignoring this heterogeneity may produce wrong predictions. Allowing for technological heterogeneity seems to be straightforward, at least in simple general equilibrium models akin to the one we used, and amounts to adding extra equilibrium conditions to identify sector-specific outcomes. We hope our work will motivate further exploration of the consequences of technological heterogeneity in the context of other economic models, as well as empirically.

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Table 1. Summary statistics.

		Mean (1)	Std. dev. (2)	q25 (3)	q50 (4)	q75 (5)	N (6)
				Panel A: Firm-level data			
Annual sales		43.6	386.7	2.3	5.6	17.2	154648
Labor costs		7.4	51.1	0.4	1.3	3.9	154668
Intermediate inputs		21.6	236.6	0.8	2.1	7.1	154578
Capital stock		11.4	137.9	0.4	1.2	3.9	152301
Number of workers		36.8	200.3	4.0	9.0	23.0	154668
Measures of skill dispersion	skill1	0.41	0.28	0.28	0.37	0.47	125596
	skill2	0.43	0.32	0.25	0.37	0.52	125596
	skill3	0.51	0.38	0.28	0.43	0.64	125596
	skill4	0.53	0.39	0.29	0.45	0.67	127254
Log TFP measures	OP	3.34	0.33	3.17	3.31	3.46	151504
	OLS	3.65	0.34	3.49	3.63	3.79	151504
	VA per worker	3.16	0.55	5.89	6.17	6.46	153572
				Panel B: Worker-level data			
Annual income		281.5	158.8	209.9	263.9	331.0	4086727
Experience		9.44	0.98	9.09	9.72	10.11	4086727
Age		39.57	11.00	31	39	48	4086727
1 if Male		0.70	0.46	0	1	1	4086727
1 if max. education level is:	High School	0.33	0.47	0	0	1	4086727
	College	0.53	0.50	0	1	1	4086727
	University	0.15	0.35	0	0	0	4086727
1 if occupational level is:	Low	0.19	0.39	0	0	0	4086727
	Mid	0.58	0.49	0	1	1	4086727
	High	0.13	0.33	0	0	0	4086727
	Manager	0.10	0.30	0	0	0	4086727
				Panel C: Industry-level data			
Measures of skill dispersion	skill1	0.42	0.29	0.29	0.37	0.47	19688
	skill2	0.44	0.30	0.27	0.38	0.53	19688
	skill3	0.53	0.36	0.33	0.46	0.63	19688
	skill4	0.55	0.37	0.35	0.49	0.66	19688
Measures of skill complementarity	Teamwork	3.98	0.14	3.91	4.03	4.10	22849
	Contact	4.20	0.21	4.16	4.23	4.35	22849
	Communication	3.62	0.28	3.60	3.61	3.77	22849
	Impact	3.47	0.12	3.46	3.49	3.51	22849

Notes: In Panel A, sales, labor costs, intermediate inputs and capital are measured in millions of Danish Krone. In Panel B, labor income is measured in thousands Danish Krone. Skill1 is measured as worker fixed effect from log wage equation. Skill2 is worker fixed effects and observables (net of occupation effects) from log wage equation. Skill3 is log wage net of firm fixed effect from log wage equation. Skill 4 is the log wage.

Table 2. Estimation results by specification.

Measure of skill complementarity	Measure of skill dispersion	ρ_H	ρ_L	p-value for $\rho_H = \rho_L$	Shares of industries with skill substitutability in the total		
					Output	Employment	# of firms
Panel A: estimation results for NLLS							
PCA	skill1	8.26	-0.45	0.00	0.728	0.700	0.678
	skill2	2.30	-5.21	0.00	0.728	0.700	0.678
	skill3	1.93	-2.24	0.02	0.728	0.700	0.678
	skill4	2.06	-0.97	0.17	0.728	0.700	0.678
Impact	skill1	3.99	-2.54	0.00	0.221	0.172	0.107
	skill2	9.16	-8.39	0.00	0.221	0.172	0.107
	skill3	6.88	-2.42	0.00	0.221	0.172	0.107
	skill4	7.01	-3.20	0.00	0.221	0.172	0.107
Teamwork	skill1	8.71	-0.78	0.00	0.754	0.739	0.731
	skill2	8.88	-5.47	0.00	0.754	0.739	0.731
	skill3	11.21	-2.20	0.00	0.754	0.739	0.731
	skill4	5.52	-0.97	0.00	0.754	0.739	0.731
Contact	skill1	6.52	-0.74	0.00	0.508	0.549	0.581
	skill2	14.96	-5.36	0.00	0.508	0.549	0.581
	skill3	9.37	-2.30	0.00	0.508	0.549	0.581
	skill4	9.82	-3.13	0.00	0.508	0.549	0.581
Communication	skill1	3.79	-2.63	0.00	0.204	0.151	0.090
	skill2	8.57	-8.08	0.00	0.204	0.151	0.090
	skill3	6.42	-2.39	0.00	0.204	0.151	0.090
	skill4	6.63	-3.08	0.00	0.204	0.151	0.090
Panel B: estimation results for NLLS with control function							
PCA	skill1	1.39	-0.43	0.00	0.491	0.405	0.285
	skill2	1.85	-5.77	0.00	0.491	0.405	0.285
	skill3	1.59	-1.99	0.07	0.491	0.405	0.285
	skill4	1.22	-2.64	0.04	0.491	0.405	0.285
Impact	skill1	1.39	0.19	0.33	0.367	0.260	0.155
	skill2	1.87	-4.50	0.00	0.367	0.260	0.155
	skill3	1.50	-1.63	0.03	0.367	0.260	0.155
	skill4	1.20	-2.41	0.08	0.367	0.260	0.155
Teamwork	skill1	1.97	0.12	0.11	0.754	0.739	0.731
	skill2	4.08	-3.45	0.00	0.754	0.739	0.731
	skill3	3.12	-1.44	0.00	0.754	0.739	0.731
	skill4	2.74	-0.56	0.00	0.754	0.739	0.731
Contact	skill1	1.44	0.18	0.06	0.723	0.694	0.671
	skill2	2.78	-3.58	0.00	0.723	0.694	0.671
	skill3	2.03	-1.71	0.00	0.723	0.694	0.671
	skill4	1.75	-0.75	0.09	0.723	0.694	0.671
Communication	skill1	1.55	-0.58	0.06	0.204	0.151	0.090
	skill2	2.57	-5.50	0.00	0.204	0.151	0.090
	skill3	1.88	-1.75	0.00	0.204	0.151	0.090
	skill4	1.55	-2.52	0.00	0.204	0.151	0.090

Notes: Each line in the table presents the threshold regression estimation results for different measures of complementarity, skill dispersion, and econometric estimators. The first column describes the measure of skill complementarity used in the estimation, with PCA standing for the aggregate measure obtained by grouping all four measures into one using a principal component analysis (PCA). The second column describes the measure of skill dispersion: skill1 is measured as worker fixed effect from log wage equation; skill2 is worker fixed effects and observables (net of occupation effects) from log wage equation; skill3 is log wage net of firm fixed effect from log wage equation; skill 4 is the log wage. The p-value for the test of $\rho_H = \rho_L$ is obtained through bootstrap using 100 repetitions.

Table 3. Estimation results by robustness of classification.

	Frequency of being classified into the complementarity group (% out of 40 specifications)		
	0-30%	30-70%	70-100%
	(1)	(2)	(3)
Number of industries	15	20	15
Share of industries in total			
output	38.7	24.1	37.2
employment	33.3	30.4	36.3
number of firms	26.0	39.2	34.7
Average measure of complementarity			
PCA	3.62	3.88	4.01
Impact	3.36	3.49	3.64
Teamwork	3.83	4.06	4.09
Communication	3.36	3.69	4.01
Contact	3.95	4.29	4.30
Complementarity parameter (ρ) estimates by measure of skill dispersion			
skill1	2.30	0.90	-1.74
skill2	5.71	-0.19	-3.89
skill3	2.75	0.26	-2.85
skill4	2.73	0.34	-2.68

Notes: Each column shows a selection of summary statistics and estimation results for industry groups that were classified into the complementarity group in 0-30% (column 1), 30-70% (column 2) and 70-100% (column 3) of specifications. For example, the 15 industries in column 1, which are rarely or never classified into the complementarity group, have relatively low scores on the complementarity measures and relatively high, well above 1, estimates of the complementarity parameter ρ.

Figure 1: Correlation between firm productivity (TFP) and within-firm wage dispersion (WFWD) by industry.

This Figure plots on the horizontal axis the average within-firm wage dispersion (WFWD) in each industry, and the correlation between WFWD and firm productivity (TFP) estimated on the data from the respective industry. Each pair of observations is represented by a circle whose radius is proportional to the size of the industry in terms of its share in total output.

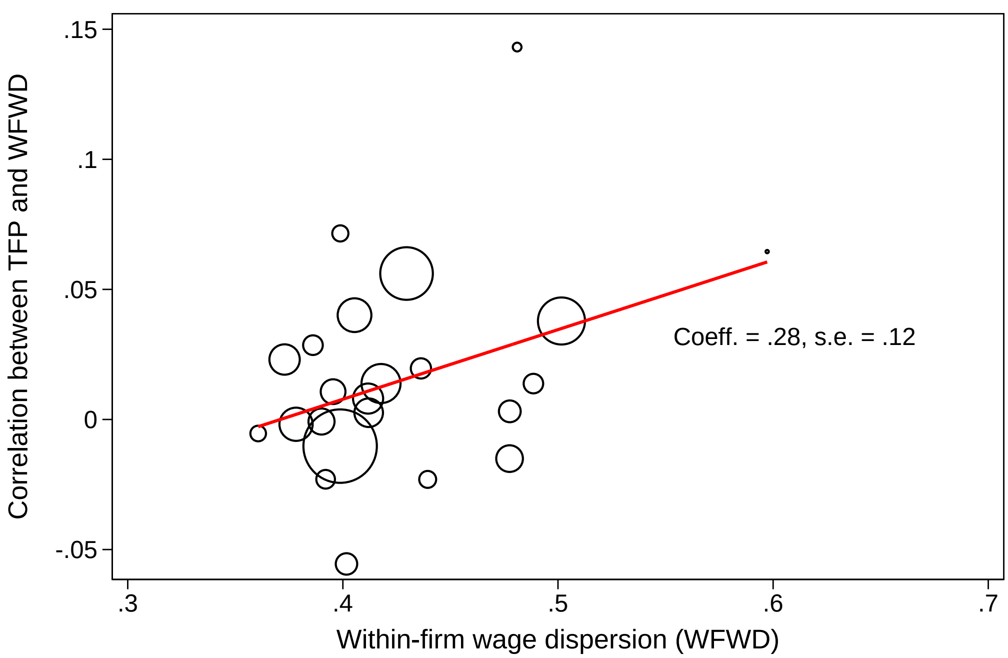

.15
.1
.05
0
-.05
Correlation between TFP and WFWD
.3
.4
.5
.6
.7
Within-firm wage dispersion (WFWD)
Coeff. = .28, s.e. = .12

Figure 2: Correlation between firm productivity (TFP) and within-firm wage dispersion (WFWD), and average WFWD by quartile of skill complementarity measure PCA.

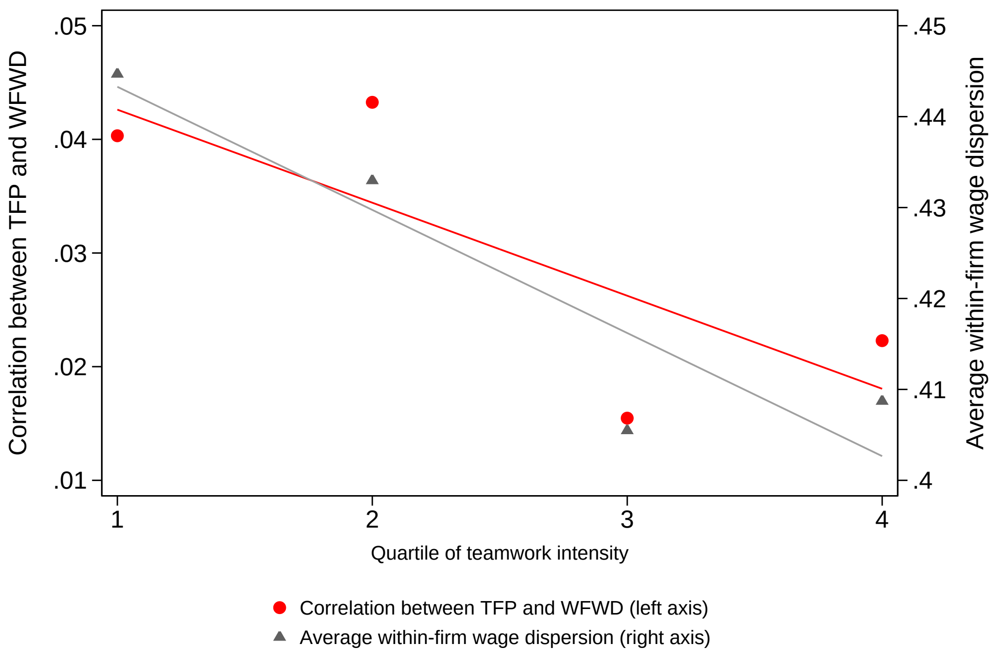
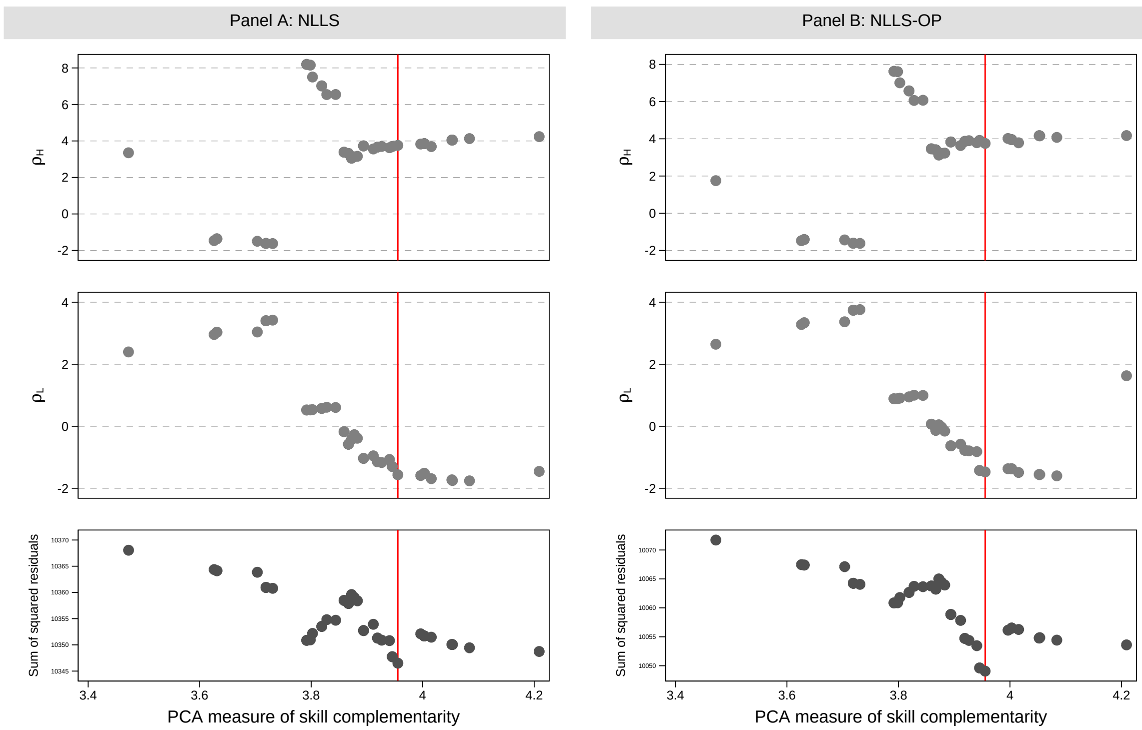
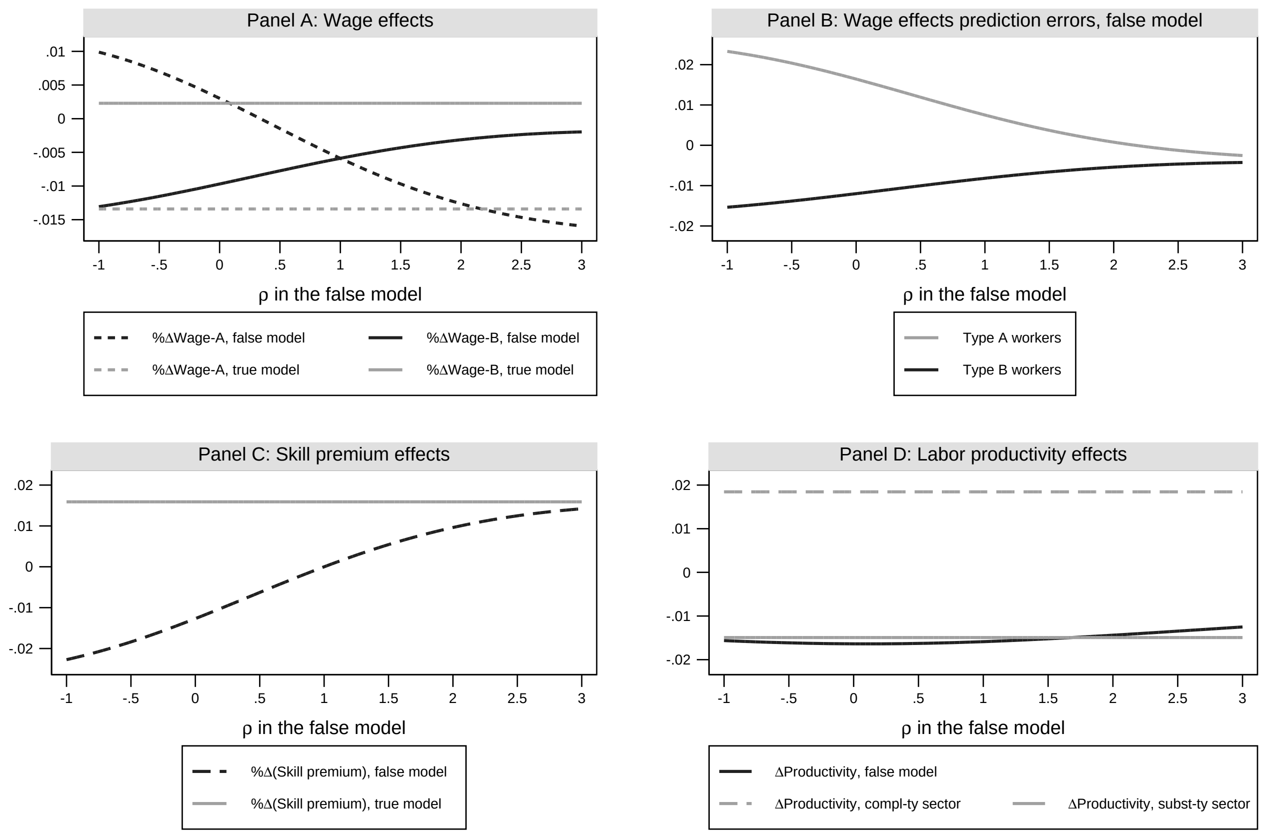


Figure 3: An illustration of the threshold regression estimation procedure applied to estimating differences in skill complementarity between two industry sectors.



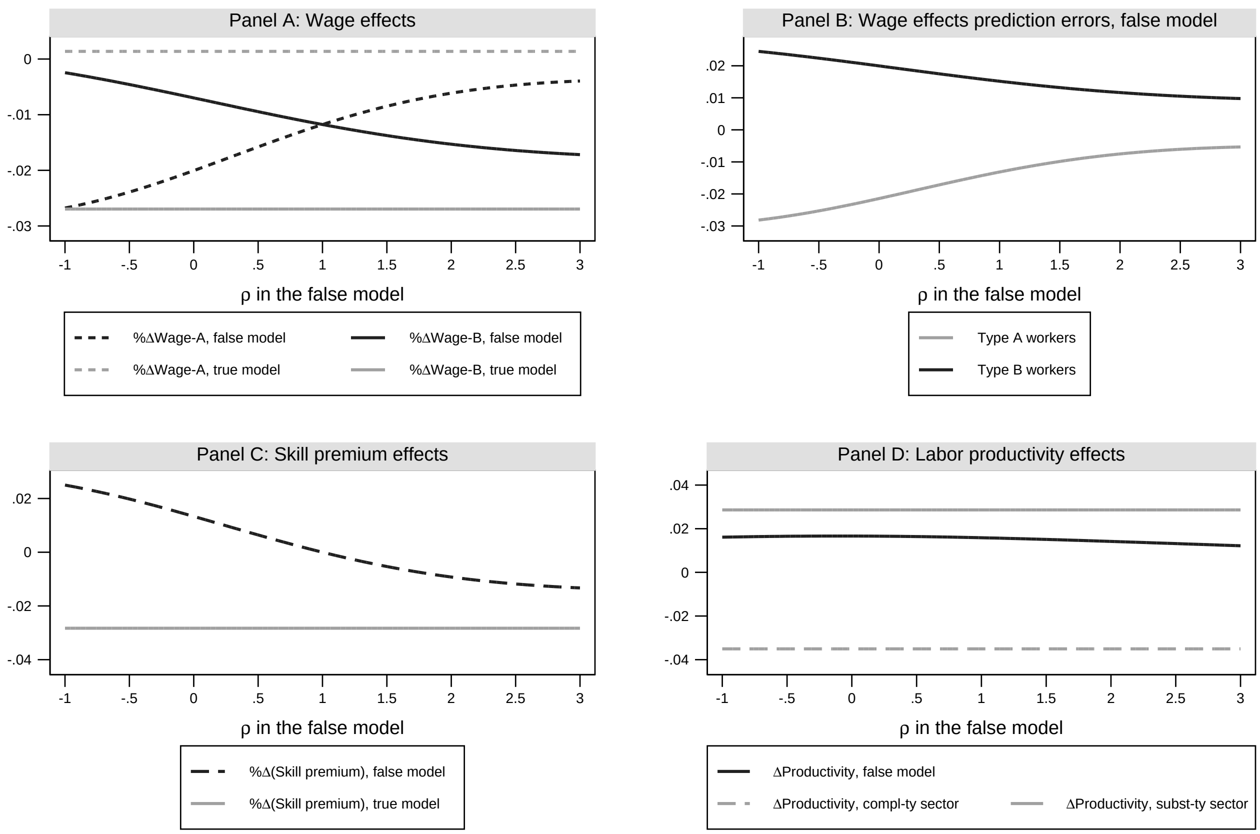
This Figure plots the key results from the threshold regression estimation procedure, described in Section 3.2, for two particular regression specifications characterized by the measure of complementarity (PCA in this case), measure of skill dispersion ($wsd1$), and the regression estimator (NLLS in Panel A, NLLS-OP in Panel B). Every dot on each graph represents a particular industry. The horizontal axis plots each industry's measure of complementarity (PCA), which is the threshold value γ in equation (6). On each panel, the vertical axis of the lower graph plots the sum of squared residuals from estimating equation (6) for each threshold value. The vertical axis of the middle graph plots the estimated complementarity parameter ρ_L for the industries with the complementarity measure above a given threshold γ, and the same of the upper graph plots the complementarity parameter ρ_H for the industries whose measure of complementarity is below the given γ. The red vertical line points to the threshold value $\hat{\gamma}$ that minimizes the residual sum of squares, and the corresponding values of the skill complementarity parameters ρ_L, ρ_H in the industries whose measure of complementarity is above and below $\hat{\gamma}$.

Figure 4: Simulation results from Scenario 1: a 10% increase in the low-skill type A labor, in the true and false models.



The true model has two sectors, Sector 1 with the production technology featuring skill complementarity ($\rho_1 = -1$), and Sector 2 with the production technology featuring skill substitutability ($\rho_2 = 3$). The false model also has two sectors, but both sectors are assumed to have the same production technology with $-1 \leq \rho \leq 3$ depicted on the horizontal axis.

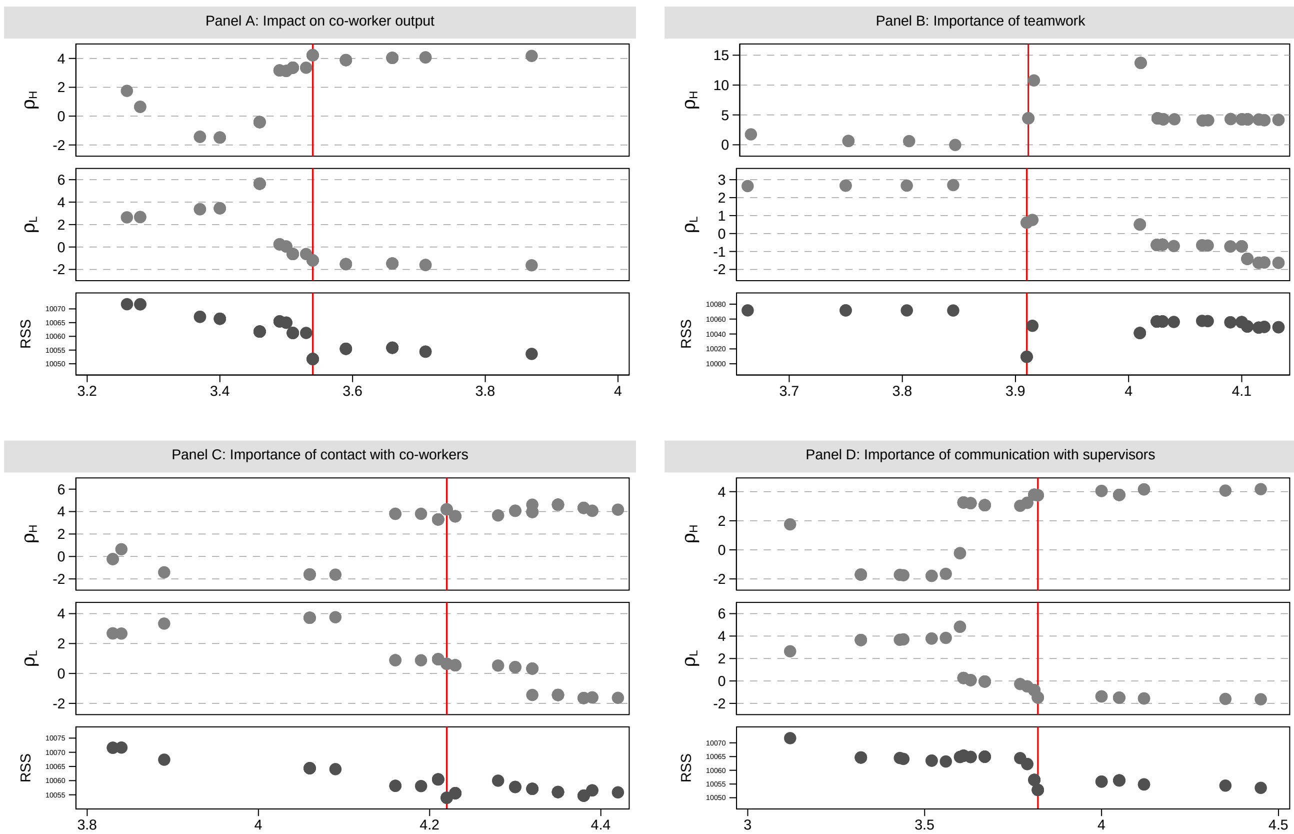
Figure 5: Simulation results from Scenario 2: a 10% increase in the high-skill type B labor, in the true and false models.



The true model has two sectors, Sector 1 with the production technology featuring skill complementarity ($\rho_1 = -1$), and Sector 2 with the production technology featuring skill substitutability ($\rho_2 = 3$). The false model also has two sectors, but both sectors are assumed to have the same production technology with $-1 \leq \rho \leq 3$ depicted on the horizontal axis.

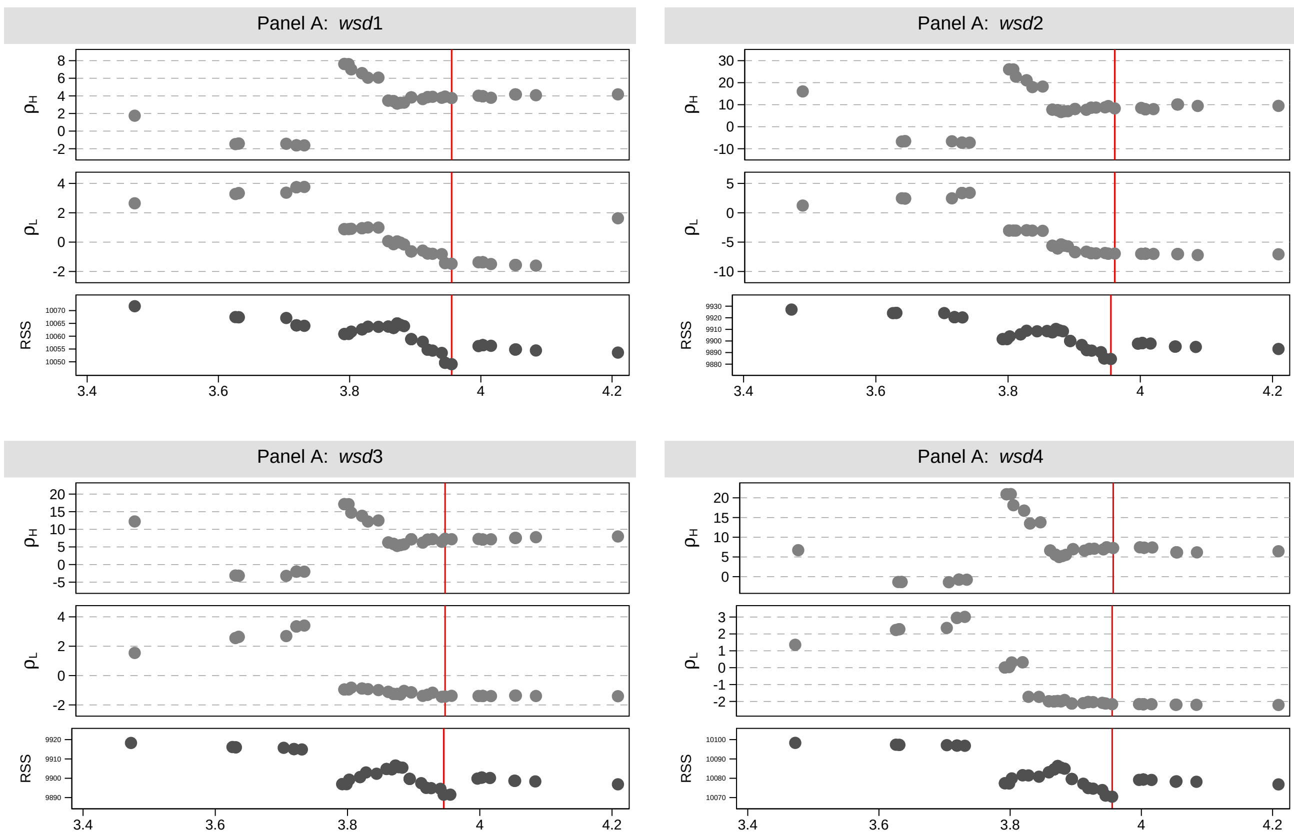
Appendix: Additional Figures and Tables

Figure A1: Figure 3 replicated for different measures of skill complementarity.



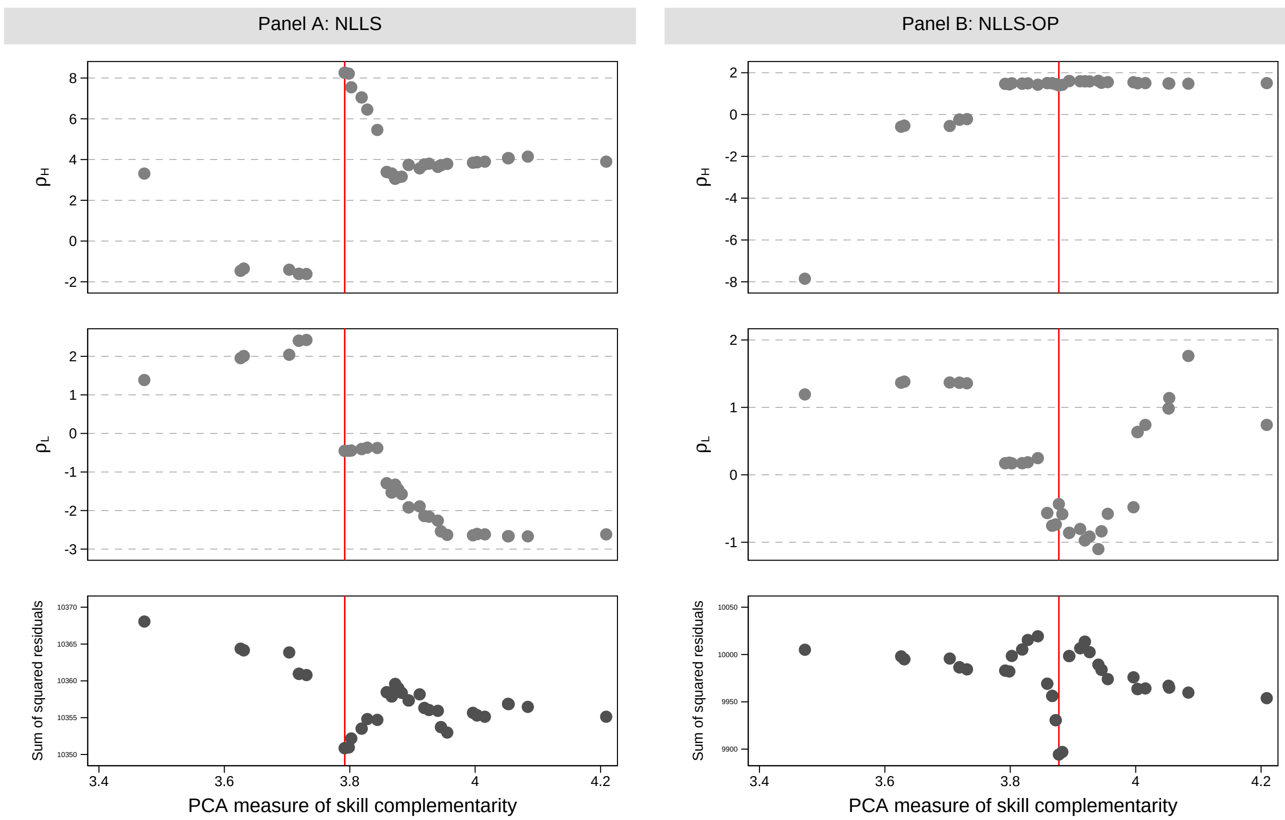
This Figure replicates the results plotted in Panel B (NLLS-OP estimator) of Figure 3 for different measures of skill complementarity described in detail in Section 2.2.2.

Figure A2: Figure 3 replicated for different measures of within-firm skill dispersion.



This Figure replicates the results plotted in Panel B (NLLS-OP estimator) of Figure 3 for different measures of within-firm skill dispersion described in detail in Section 2.2.1. all of which are based on the estimates from the individual wage equation (1).

Figure A3: Figure 3 replicated for the unrestricted version of equation (6).



This Figure replicates Figure 3 in all specifications except that it is based on the unrestricted version of equation (6). That is, it plots the residual sums of squares and estimated skill complementarity parameters ρ_H, ρ_L for all potential threshold values based on PCA measure of skill complementarity from the unrestricted version of equation (6) which allows all factor input elasticities, α, α_N, to vary by subsample above and below the threshold.

Table A1. Estimation results by specification in the unrestricted version of equation (6).

Measure of skill complementarity	Measure of skill dispersion	ρ_H	ρ_L	p-value for $\rho_H = \rho_L$	Shares of industries with skill substitutability in the total: Output	Employment	# of firms
Panel A: estimation results for NLLS							
PCA	skill1	3.76	-1.56	0.00	0.204	0.151	0.09
	skill2	7.69	-7.08	0.00	0.204	0.151	0.09
	skill3	5.78	-1.42	0.00	0.204	0.151	0.09
	skill4	6.47	-2.20	0.00	0.204	0.151	0.09
Impact	skill1	3.97	-1.57	0.00	0.221	0.172	0.107
	skill2	8.43	-7.15	0.00	0.221	0.172	0.107
	skill3	6.88	-1.43	0.00	0.221	0.172	0.107
	skill4	7.03	-2.23	0.00	0.221	0.172	0.107
Teamwork	skill1	8.31	0.19	0.00	0.754	0.739	0.731
	skill2	9.34	-4.51	0.00	0.754	0.739	0.731
	skill3	9.43	-1.29	0.00	0.754	0.739	0.731
	skill4	3.83	-0.15	0.04	0.754	0.739	0.731
Contact	skill1	6.29	0.23	0.00	0.508	0.549	0.581
	skill2	8.02	-4.52	0.00	0.508	0.549	0.581
	skill3	7.84	-1.32	0.00	0.508	0.549	0.581
	skill4	8.39	-2.03	0.00	0.508	0.549	0.581
Communication	skill1	3.75	-1.56	0.00	0.204	0.151	0.09
	skill2	7.69	-7.08	0.00	0.204	0.151	0.09
	skill3	5.78	-1.43	0.00	0.204	0.151	0.09
	skill4	6.47	-2.20	0.00	0.204	0.151	0.09
Panel B: estimation results for NLLS with control function							
PCA	skill1	3.76	-1.47	0.13	0.204	0.151	0.09
	skill2	8.31	-6.94	0.00	0.204	0.151	0.09
	skill3	7.19	-1.38	0.00	0.224	0.173	0.115
	skill4	7.27	-2.16	0.00	0.204	0.151	0.09
Impact	skill1	4.23	-1.19	0.06	0.221	0.172	0.107
	skill2	9.19	-7.21	0.00	0.221	0.172	0.107
	skill3	7.72	-1.29	0.00	0.221	0.172	0.107
	skill4	7.50	-2.15	0.00	0.221	0.172	0.107
Teamwork	skill1	4.44	0.61	0.03	0.754	0.739	0.731
	skill2	5.91	-3.55	0.00	0.754	0.739	0.731
	skill3	4.04	-1.08	0.00	0.754	0.739	0.731
	skill4	4.82	0.40	0.00	0.754	0.739	0.731
Contact	skill1	4.20	0.65	0.05	0.508	0.549	0.581
	skill2	6.50	-3.45	0.00	0.508	0.549	0.581
	skill3	5.84	-0.96	0.00	0.508	0.549	0.581
	skill4	5.59	-1.95	0.00	0.508	0.549	0.581
Communication	skill1	3.76	-1.47	0.08	0.204	0.151	0.09
	skill2	8.32	-6.94	0.00	0.204	0.151	0.09
	skill3	7.19	-1.38	0.00	0.204	0.151	0.09
	skill4	7.73	-2.16	0.00	0.204	0.151	0.09

Notes: Each line in the table presents the threshold regression estimation results for different measures of complementarity, skill dispersion, and econometric estimators based on the unrestricted version of equation (6) which allows factor input elasticities to vary by subsample below and above each value of the threshold variable. The first column describes the measure of skill complementarity used in the estimation, with PCA standing for the aggregate measure obtained by grouping all four measures into one using a principal component analysis (PCA). The second column describes the measure of skill dispersion: skill1 is measured as worker fixed effect from log wage equation; skill2 is worker fixed effects and observables (net of occupation effects) from log wage equation; skill3 is log wage net of firm fixed effect from log wage equation; skill 4 is the log wage. The p-value for the test of $\rho_H = \rho_L$ is obtained through bootstrap using 100 repetitions.