

Stijepic, Damir

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Workplace Heterogeneity and the Returns to Versatility

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Workplace Heterogeneity and the Returns to Versatility[☆]

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Damir Stijepic

Johannes Gutenberg University, Mainz

Abstract

In the present paper, I develop an on-the-job search model in which workers face both frictional and structural impediments to sorting. There are two key model predictions. First, versatility enhances the worker's ability to sort into the most productive firms since a mismatch between the job requirements and the worker's skill set is less likely to occur. Second, the larger the productivity differentials between the firms, the larger the returns to sorting and, hence, versatility. I test the latter hypothesis by exploiting industry variation in sales-per-worker dispersion across employers in the United States in 2007. An increase in the sales-per-worker standard deviation by ten log-points is, indeed, estimated to raise the above-median versatile worker's relative wage by 11 to 21 log-points. I also provide supportive evidence from Germany.

Keywords: versatility, workplace heterogeneity, multidimensionality of skills, search and matching, sorting, inter-firm mobility, firm productivity dispersion, wage inequality, skill premium

JEL: J00, I26, J31, J24

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Email address: mail@damir.stijepic.com (Damir Stijepic)

1. Introduction

Wage inequality has risen in many countries over the last decades. Many countries have also experienced a simultaneous surge in the productivity dispersion across employers. Dunne et al. (2004) find that the between-plant wage and productivity dispersion substantially increased in U.S. manufacturing from 1975 to 1992 and that “virtually the entire increase in overall dispersion in hourly wages for U.S. manufacturing workers from 1975 to 1992 is accounted for by the between-plant components” (Dunne et al., 2004, pg. 399). Barth et al. (2014) and Faggio et al. (2010) document similar patterns in other U.S. industries and in several European countries, respectively. Furthermore, recent studies, which fit linear models with additive person and plant fixed effects à la Abowd et al. (1999), find that a substantial share of the increase in the wage gap between higher- and lower-educated workers is attributable to a widening in the average plant wage premia received by differently educated groups, i.e., increasing plant heterogeneity and rising assortativeness between high-wage workers and high-wage plants (see, e.g., Card et al., 2013).

Yet, little is known about the underlying mechanisms. In the present paper, I shed light on the link between the productivity dispersion across employers and the skill premium by providing a new perspective that explicitly takes into account the multidimensionality of skills. Specifically, I explore how the productivity dispersion across employers affects the returns to a worker’s versatility in the sense of being able to perform various different tasks or activities—eventually even across occupations.

In a first theoretical contribution, I develop a parsimonious on-the-job search model that features both frictional and structural impediments to sorting. By establishing a positive relation between the versatility wage premium and the productivity dispersion across employers, I then provide the motivation for the empirical study.¹ The key idea is that, in an environment where jobs differ in requirements, versatility enhances an individual’s ability to sort into the most productive firms since efficient reallocations are less likely to be hindered by unmet job re-

¹See Stijepic (2015e) for a quantitative analysis based on a richer model. Stijepic (2015a) develops a heterogeneous firm model of intra-industry trade with limited inter-firm mobility of workers in order to study the impact of trade liberalization on wage inequality. He finds that trade liberalization (i) amplifies the disparities in profitability between the small and large firms, (ii) raises the within-group wage inequality, and (iii) increases the wage differentials between worker groups who differ in inter-firm mobility.

quirements. The returns to sorting and, hence, versatility are larger, the more pronounced the productivity differentials between the firms. Intuitively, if firms are similar in productivity, the returns from switching firms are low. However, if the disparities between firms are substantial, so will be the returns. The wage differential between the versatile and non-versatile individuals is amplified as the productivity dispersion across firms rises.

In order to test the empirical content of the model’s prediction, I rely on the *1979 National Longitudinal Survey of Youth (NLSY)*. The *NLSY* is unique in the sense that it comprises a nationally representative sample of young people to whom the *Armed Services Vocational Aptitude Battery (ASVAB)* was administered. This set of standardized tests assesses the respondents’ knowledge and skill in several areas and allows me to construct a novel measure of a worker’s versatility. By exploiting variations in plant productivity dispersion across eight broadly defined U.S. industries in 2007, I find that an increase in the sales-per-worker standard deviation by ten log-points is, indeed, estimated to raise the above-median versatile worker’s relative wage by 11 to 21 log-points.

The present paper complements existing models of matching and sorting in the labor market. Specifically, it is related to the strand of literature that stresses the importance for workers of occupational matching (e.g, Groes et al., 2015; Kambourov and Manovskii, 2009), firm matching (e.g, Bagger and Lentz, 2014; Burdett and Mortensen, 1998; Jovanovic, 1979), or both occupational and firm matching (e.g, Kramarz et al., 2014; McCall, 1990). However, this strand of literature does not address the concept of versatility in the sense of being able to perform a wider range of tasks or activities, and how productivity dispersion across employers affects the skill premium.

My framework is most closely related to Charlot et al.’s (2005) search and matching model, in which individuals’ skills vary in both “adaptability” and “intensity.”² However, my approach differs in two key aspects. Most importantly, I allow for heterogeneity in productivity among firms. Furthermore, the worker’s versatility affects both the effective job-finding rate and the separation rate into unemployment. The latter separation rate plays a crucial role in explaining the differences between the worker groups in the ability to sort into the preferred

²Lise and Postel-Vinay (2014) construct a structural model of on-the-job search in which workers differ in skills along several dimensions and sort themselves into jobs with heterogeneous skill requirements along those same dimensions. Sanders and Taber (2012) review the literature on firm-specific human capital, industry- and occupation-specific human capital, and task-specific human capital.

firms (see Stijepic, 2015b).

This paper is structured as follows. In Section 2, I introduce the on-the-job search model that features both frictional and structural impediments to sorting. In order to motivate the empirical analysis, I establish a positive relation between the versatility wage premium and the productivity dispersion across employers within this framework in Section 3. I provide evidence in support of a positive relation between the versatility premium and the productivity dispersion across employers from the United States in Section 4 and from Germany in Section 5. Section 6 draws some concluding remarks.

2. Framework and Equilibrium Characterization

In this section, I develop a parsimonious on-the-job search model in order to motivate the present paper's empirical contribution. The key characteristic of the model is that it features both frictional and structural impediments to sorting. Burdett and Mortensen (1998) and Bontemps et al. (2000) provide a detailed exposition of the canonical on-the-job search model.

2.1. Framework

Consider a random on-the-job search model with continuous ex-ante firm heterogeneity à la Burdett and Mortensen (1998). Let p denote a firm's productivity, which I assume to be Pareto distributed in the economy, i.e., $\Gamma_{p_0}(p) = 1 - (p_0/p)^z$ for $z > 2$, $p_0 > 0$, and $p \geq p_0$. Firms post job offers that are associated with fixed wage contracts, w . Both unemployed and employed workers are contacted by firms according to a Poisson process at rate $\tilde{\lambda} > 0$. A worker is either employed or unemployed. In the former case, the worker receives the wage offered by the respective firm; in the latter case, I normalize the flow income enjoyed by the worker to zero. Both workers and firms are risk neutral. Without loss of generality, let the measures of the sets of workers and firms equal unity.

I extend the Burdett and Mortensen (1998) framework by assuming that jobs differ in task requirements and that the jobs' task requirements may change over time. Specifically, there is a continuum of tasks in the economy. The task associated with a job is randomly and uniformly reassigned according to a Poisson process at rate $\tilde{\delta} > 0$. The share of the tasks the workers are able to perform is denoted by $\alpha \in (0, 1)$, where I assume that the tasks that the workers are able to perform are uniformly distributed. The only matches formed are those in which the worker is able to fulfill the task required by the respective job. Similarly, if the task required by the job changes and the worker is not able to fulfill the new task,

the match is dissolved. The resulting model is isomorphic in terms of worker flows to the canonical on-the-job search model, where the worker's offer-arrival rate, λ , and the job-destruction rate, δ , are given by $\lambda = \alpha \tilde{\lambda}$ and $\delta = (1 - \alpha) \tilde{\delta}$, respectively. Let κ denote the ratio of the effective job-finding rate, λ , to the separation rate into unemployment, δ , i.e., $\kappa = \lambda/\delta$.

The ratio of the effective job-finding rate to the separation rate into unemployment, κ , is a key parameter in the Burdett and Mortensen (1998) framework. A higher κ induces first-order stochastic dominance in the distribution of workers over firms. In other words, the higher this ratio, the larger the share of workers employed at the productive firms. Intuitively, separations into unemployment represent negative mobility shocks. The more pronounced the shocks, the less likely are individuals to sort into a specific firm. Therefore, the job-finding rate is to be scaled by the separation rate into unemployment in order to obtain an adequate measure of the workers' ability to reallocate across firms. Interestingly, the literature typically finds a positive correlation between the ratio of the job-finding rate to the separation rate into unemployment, κ , and educational attainment (see Stijepic, 2015a,b).

The present paper's microfoundation for the transition parameters is in line with the findings of Stijepic (2015b). Relying on the *1996 Panel of the Survey of Income and Program Participation*, Stijepic (2015b) estimates that above-median versatile individuals, proxied by the number of different courses attended in high school, are 1.6 times more likely to separate to another employer than into unemployment relative to below-median versatile individuals.³ The effect is similar in magnitude to that of a college degree on a high school dropout's risk ratio. Finally, Stijepic (2015b) also finds a positive correlation between versatility and the standard measures of education.

2.1.1. Workers

Workers' optimal behavior is as follows. When information about job opportunities with suitable task requirements arises, employed workers quit their current job and move to the new one, provided that the new wage offer exceeds the current one. Given a flow income of zero, unemployed workers accept any positive wage offer.

Following Burdett and Mortensen (1998), I confine the analysis to the steady

³The risk ratio of an employer–employer transition to a separation into unemployment is an ordinal transformation of the ratio of the job-finding rate to the separation rate into unemployment, κ . See Stijepic (2015b) for further details.

state equilibrium. Let u denote the equilibrium measure of the set of unemployed workers, $F(w)$ the equilibrium proportion of firms offering a wage no greater than w , henceforth referred to as the wage offer distribution, and $G(w)$ the equilibrium proportion of workers receiving a wage no greater than w , henceforth referred to as the cross-sectional wage distribution. In the steady state, the flow of workers into employment, λu , equals the flow into unemployment, $\delta(1 - u)$. Therefore, the steady state measure of the unemployed workers is $u = 1/(1 + \kappa)$. In the steady state, the flow of unemployed workers into firms offering a wage no greater than w , $\lambda F(w)u$, equals the flow of employed workers into unemployment, $\delta G(w)(1 - u)$, and into higher paid jobs, $\lambda(1 - F(w))G(w)(1 - u)$. Therefore, the steady state cross-sectional wage distribution is $G(w) = F(w)/(1 + \kappa(1 - F(w)))$.⁴

2.1.2. Firms

A firm with a workforce of mass l and offering a wage w loses workers when they separate into unemployment, δl , or are poached by other firms that offer higher wages, $\lambda(1 - F(w))l$. The firm attracts workers who are unemployed, λu , or poaches workers from firms that offer lower wages, $\lambda G(w)(1 - u)$. Hence, the firm's steady state workforce is $l(w) = \kappa(1 + \kappa(1 - F(w)))^{-2}$.

Following Burdett and Mortensen (1998), I assume that firms maximize their steady state profits:

$$\pi(p) \equiv \max_w \{(p - w)l(w)\} \quad (1)$$

The firm's optimization problem consists in the trade-off that is induced by the ambivalent effect of the offered wage on the profits. On the one hand, a higher wage decreases the profits per worker. On the other hand, a higher posted wage allows the firm to attract and to retain more workers.

2.2. Equilibrium Characterization

Firms of equal productivity choose the same wage strategy in equilibrium. Hence, there is no wage dispersion among equally productive firms. Intuitively, a continuous productivity distribution leaves no room for wage dispersion among equally productive firms. In the case of a discrete productivity distribution, firms of the same productivity typically do not choose the same wage posting strategy. Furthermore, more productive firms offer higher wages in equilibrium. Intuitively, more productive firms enjoy higher marginal revenues for a given posted

⁴Alternatively, one may derive the law of motion for the cross-sectional job distribution by the Fokker-Planck formalism (see, e.g., Stijepic, 2015c; Bayer and Wälde, 2010).

wage. Hence, they find it optimal to offer wages that exceed those posted by less productive firms in order to attract and to retain more workers. Formally, there exists a non-decreasing equilibrium wage offer function, denoted by $w(p)$, so that $F(w(p)) = \Gamma_{p_0}(p)$.⁵

In the remainder of this section, I derive the workers' average wage, \bar{w} . The first-order condition with respect to the posted wage, w , for the firm's maximization problem, as described by Equation (1), is $(p - w)dl/dw(w) = l(w)$. Exploiting the equilibrium relation $F(w(p)) = \Gamma_{p_0}(p)$, one obtains

$$\frac{2\kappa\gamma_{p_0}(p)(p - w(p))}{1 + \kappa(1 - \Gamma_{p_0}(p))} = \frac{dw}{dp}(p), \quad (2)$$

where $\gamma_{p_0}(p)$ denotes the density that is associated with the productivity distribution, $\Gamma_{p_0}(p)$. This is a linear differential equation. With the boundary condition $w(p_0) = 0$, it admits the solution

$$w(\Gamma) = 2p_0\kappa(1 + \kappa(1 - \Gamma))^2 \int_0^\Gamma \frac{(1 - x)^{-1/z}}{(1 + \kappa(1 - x))^3} dx, \quad (3)$$

where I use a change of variables formula in order to rewrite wages in terms of the firms' productivity rank, Γ .⁶ It follows for the workers' average wage

$$\bar{w} = \int_0^1 w(\Gamma) dG(\Gamma) = 2p_0\kappa(1 + \kappa) \int_0^1 \frac{(1 - x)^{1-1/z}}{(1 + \kappa(1 - x))^3} dx. \quad (4)$$

3. Qualitative Analysis

In this section, I compare the economic outcomes of a high-versatility worker group to those of a low-versatility worker group, subscripted by H and L , respectively. The two groups differ only in the share of the tasks that they are able to perform, i.e., $\alpha_H > \alpha_L$. The key implication is that $\kappa_H > \kappa_L$. In the following analysis, I focus on the mechanisms that generate the versatility wage premium, and the impact of the productivity dispersion across employers on that wage premium.

⁵See Bontemps et al. (2000) for a formal proof.

⁶It is optimal for the least productive active firm to offer a wage of zero. Otherwise, the firm could decrease its wage offer without reducing its steady state workforce, and, hence, increase its profits (see, e.g., Bontemps et al., 2000).

3.1. The Versatility Wage Premium

In order to shed light on the mechanisms that generate the versatility wage premium, I study the two counterfactual wage premia $\bar{w}_{HH}/\bar{w}_{LH}$ and $\bar{w}_{HH}/\bar{w}_{HL}$, where $\bar{w}_{ij} = \int_0^1 w_i(\Gamma) dG_j(\Gamma)$ for $i, j \in \{L, H\}$. Note that \bar{w}_{HH} and \bar{w}_{LL} are simply the high- and low-versatility workers' average wages, i.e., \bar{w}_H and \bar{w}_L , respectively.

The first counterfactual wage premium $\bar{w}_{HH}/\bar{w}_{LH}$ imposes the same distribution over firms on both worker groups, i.e., the average wage of the high-versatility workers is measured relative to the average wage of the low-versatility workers that would have arisen if the low-versatility workers were matched with firms as the high-versatility workers. Therefore, the difference in the average wage between the two groups would then be solely due to differences in the wage offer function between the two groups. Henceforth, I refer to this counterfactual wage premium as the appropriation wage premium.

The second counterfactual skill premium $\bar{w}_{HH}/\bar{w}_{HL}$ imposes the same wage within firms on both worker groups, i.e., the high-versatility workers' average wage is measured relative to the low-versatility workers' average wage that would have arisen if the low-versatility workers were paid the same wage as the high-versatility workers in each firm. Therefore, the difference in the average wage would then be solely determined by differences in the distribution over firms. Henceforth, I refer to this counterfactual wage premium as the allocation wage premium.

Proposition 1 (Allocation Premium). *In the steady state, the average wage of the high-versatility group exceeds that of the low-versatility group even conditional on the firms' wage offers, i.e., the allocation wage premium, $\bar{w}_{HH}/\bar{w}_{HL}$, is positive.*

PROOF. A higher κ induces first-order stochastic dominance in the steady state equilibrium distribution of workers over the firm-productivity classes, $G(\Gamma) = \Gamma/(1 + \kappa(1 - \Gamma))$. Since the posted wage is increasing in the firm's productivity, Proposition 1 follows. \square

The ratio of the effective job-finding rate to the separation rate into unemployment, κ , plays a key role in determining the distribution of workers over firms. A higher κ induces first-order stochastic dominance in the distribution of workers over the firm-productivity classes. This is associated, ceteris paribus, with a higher average match productivity. The allocation of resources across economic activities is an important determinant of aggregate productivity. Hsieh and Klenow (2009)

analyze the resource allocation across firms in a cross-country study. They argue that aggregate productivity could rise by as much as 50 percent in China and 60 percent in India if resources were as efficiently allocated in those countries as in the United States. Lentz and Mortensen (2008) estimate a Schumpeterian growth model using Danish data. They find that more than one-half of the aggregate growth is accounted for by the resource reallocation from less to more productive firms.

Provided that wages depend positively on the match productivity, a higher ratio of the effective job-finding rate to the separation rate into unemployment, κ , induces also higher wages by increasing the average match productivity. This impact of sorting on wages is prominently analyzed within the Abowd et al. (1999) framework with additive employee and employer wage fixed effects.⁷ For instance, Card et al. (2015) find that the under-representation of women at firms that offer higher wage premiums for both gender groups explains about 15 percent of the overall 23 log-point gender wage gap in Portugal.

Proposition 2 (Appropriation Premium). *In the steady state, the average wage of the high-versatility group exceeds that of the low-versatility group even conditional on the workers' distribution over firms, i.e., the appropriation wage premium, $\bar{w}_{HH}/\bar{w}_{LH}$, is positive.*

PROOF. In order to prove Proposition 2, I show that $w_H(\Gamma) \geq w_L(\Gamma)$ for all $\Gamma \in [0, 1]$ and for some Γ with strict inequality. By Equation (3), the differential equation for the wage as a function of a firm's productivity rank is

$$\frac{dw}{d\Gamma}(\Gamma) = \frac{2\kappa}{1 + \kappa(1 - \Gamma)} \left(p_0(1 - \Gamma)^{-1/z} - w(\Gamma) \right). \quad (5)$$

If $w_H(\Gamma) = w_L(\Gamma) < p_0(1 - \Gamma)^{-1/z}$, then $dw_H/d\Gamma(\Gamma) > dw_L/d\Gamma(\Gamma)$ since $\kappa_H > \kappa_L$. Note that $w_H(0) = w_L(0) = 0$. \square

The high-versatility and the low-versatility workers are equally productive at a given firm. Hence, the differences in wages within firms solely reflect the differences in the rent shares that the workers are able to appropriate. Following Burdett and Mortensen (1998), I do not assume the workers' rent share to be an exogenous constant, but motivate it by the workers' search for better jobs while

⁷Eeckhout and Kircher (2011) discuss the methodological challenges of identifying assortative matching in the data.

employed. Indeed, Cahuc et al. (2006) estimate the workers' exogenous rent share to be only modest or not significant at all, once it is accounted for between-firm competition resulting from on-the-job search. Differences between worker groups in their employers' monopsonistic power play a potentially important role in explaining relative wages. For instance, Ransom and Oaxaca (2010) estimate labor supply elasticities at the firm level in the U.S. retail grocery industry. They find that the difference in the supply elasticity between women and men explains well the lower relative pay of women.⁸

Proposition 3 (Versatility Premium). *In the steady state, the average wage of the high-versatility group exceeds that of the low-versatility group, i.e., the versatility wage premium, \bar{w}_H/\bar{w}_L , is positive.*

PROOF. Proposition 3 follows from the proofs of Propositions 1 and 2. \square

In conclusion, versatility increases the workers average wage by enhancing their ability to allocate to the most productive firms, and by reducing the employers' monopsonistic power. Figure 1 provides numerical illustrations for this section's main results. I set the shape parameter of the Pareto distribution, z , to three, which implies a coefficient of variation of the productivity distribution of 0.5. The scale parameter, p_0 , is normalized to one. Note that Cahuc et al. (2006) estimate the ratio of the job-finding rate to the separation rate into unemployment, κ , to be 1.02 and 3.95 among the lowest and the highest of the four skill groups in French manufacturing, respectively.

The left-hand side of Figure 1 illustrates the relation between the worker's rent share, $\bar{w}/\int_{p_0}^{\infty} p dG(p)$, and the ratio of the job-finding rate to the separation rate into unemployment, κ . The higher is κ , the larger is the share of the average match surplus that the workers are able to appropriate. The relation is highly concave and essentially flat for high values of κ . The right-hand side of Figure 1 depicts the versatility and the counterfactual wage premia in percentage points relative to the reference group with a κ of one. All of the premia are increasing in the ratio of the job-finding rate to the separation rate into unemployment, κ .

3.2. The Impact of the Productivity Dispersion across Firms

In this section, I analyze the effect of a mean-preserving firm-productivity spread on the versatility wage premium. Let the mean-preserving spread of the

⁸See Manning (2003) for a detailed exposition of the dynamic monopsony model.

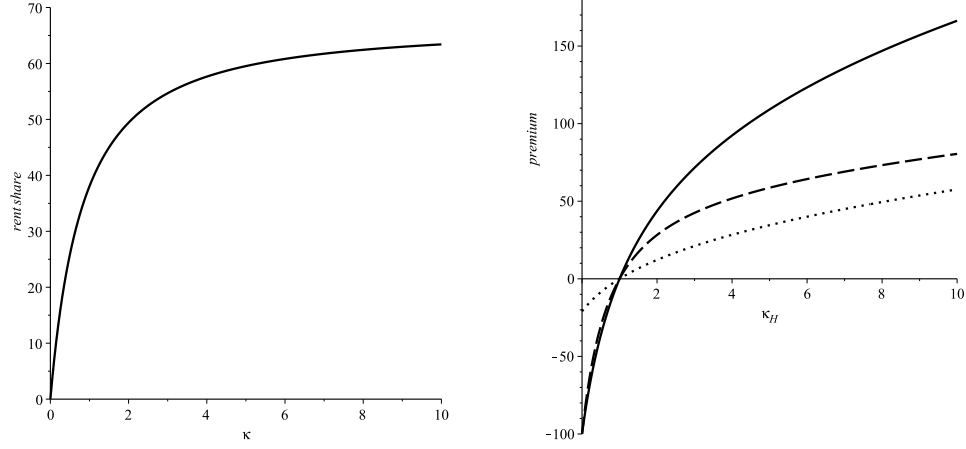


Figure 1: The left-hand side depicts the workers' rent share ($\bar{w}/\int_{p_0}^{\infty} p dG(p)$) in percentage points against the ratio of the job-finding rate to the separation rate into unemployment, κ . The right-hand side depicts the versatility wage premium (w_H/w_L , solid line), the allocation wage premium (w_H/w_{HL} , dotted line), and the appropriation wage premium (w_H/w_{LH} , dashed line) in percentage points against the high-versatility workers' ratio of the job-finding rate to the separation rate into unemployment, κ_H , where the low-versatility workers' κ_L is set to one. The shape, z , and the scale, p_0 , parameters of the productivity distribution are set to three and one, respectively.

productivity distribution $\Gamma_{p_0}(\cdot)$ be denoted by $\Gamma_{p_0^*}^*(\cdot)$. Specifically, I assume the firm-productivities above the threshold $p_x \in (p_0, \infty)$ to increase by a factor of $P_x > 1$. I then rescale the firm-productivities by p_0/p_0^* , where the parameter p_0^* is implicitly defined by $\int_{p_0^*}^{\infty} p d\Gamma_{p_0^*}^*(p) = \int_{p_0}^{\infty} p d\Gamma_{p_0}(p)$, so that the mean firm-productivity is unaltered. Hence,

$$\Gamma_{p_0^*}^*(p) = \begin{cases} 1 - \left(\frac{p_0^*}{p/P_x}\right)^z & \text{if } p > P_x p_x \\ 1 - \left(\frac{p_0^*}{p_x}\right)^z & \text{if } P_x p_x \geq p > p_x \\ 1 - \left(\frac{p_0^*}{p}\right)^z & \text{if } p_x \geq p \geq p_0^* \\ 0 & \text{otherwise} \end{cases}.$$

All variables under the mean-preserving productivity spread, $\Gamma_{p_0^*}^*(\cdot)$, are denoted by an asterisk.

The equilibrium wage offer function under the mean-preserving productivity spread is

$$w(\Gamma) = 2p_0^* \kappa (1 + \kappa(1 - \Gamma))^2 \int_0^\Gamma \frac{P(x)(1 - x)^{-1/z}}{(1 + \kappa(1 - x))^3} dx, \quad (6)$$

where $P(x) = P_x$ if $x \geq \Gamma_{p_0^*}^*(p_x)$ and 1 otherwise. Therefore, the average wages and counterfactual average wages are

$$\begin{aligned}\bar{w}_{ij}^* &= 2p_0^*\kappa_i(1 + \kappa_j) \int_0^1 \frac{(1-x)^{-1/z}\varphi(x, i, j)}{(1 + \kappa_i(1-x))^3} dx \\ &\quad + (P_x - 1)2p_0^*\kappa_i(1 + \kappa_j) \int_{\Gamma_x}^1 \frac{(1-x)^{-1/z}\varphi(x, i, j)}{(1 + \kappa_i(1-x))^3} dx,\end{aligned}$$

for $i, j \in \{L, H\}$, where $\Gamma_x = \Gamma_{p_0^*}^*(p_x)$ and $\varphi(x, i, j) = \int_x^1 (1 + \kappa_i(1-y))^2 / (1 + \kappa_j(1-y))^2 dy$. The first term on the right-hand side is simply $(p_0^*/p_0)\bar{w}_{ij}$. Let the second term be denoted by $(p_0^*/p_0)(P_x - 1)\bar{w}'_{ij}$.

In order to shed light on the mechanisms that generate the positive relation between the productivity dispersion across employers and the versatility wage premium, I first study the impact of a mean-preserving productivity spread on the appropriation premium, $\bar{w}_{HH}/\bar{w}_{LH}$, and the allocation premium, $\bar{w}_{HH}/\bar{w}_{HL}$.

Proposition 4 (Allocation Premium and Productivity Dispersion). *The allocation wage premium under the mean-preserving firm-productivity spread, $\bar{w}_{HH}^*/\bar{w}_{HL}^*$, exceeds that under the initial firm-productivity distribution, $\bar{w}_{HH}/\bar{w}_{HL}$, in the steady state.*

PROOF. Proposition 4 claims, equivalently, $\bar{w}'_{HH}/\bar{w}_{HH} > \bar{w}'_{HL}/\bar{w}_{HL}$. This inequality is implied by

$$\begin{aligned}&\int_{\Gamma_x}^1 \frac{(1-x)^{-1/z}\varphi(x, H, H)}{(1 + \kappa_H(1-x))^3} dx \Bigg/ \int_0^1 \frac{(1-x)^{-1/z}\varphi(x, H, H)}{(1 + \kappa_H(1-x))^3} dx \\ &> \int_{\Gamma_x}^1 \frac{(1-x)^{-1/z}\varphi(x, H, L)}{(1 + \kappa_H(1-x))^3} dx \Bigg/ \int_0^1 \frac{(1-x)^{-1/z}\varphi(x, H, L)}{(1 + \kappa_H(1-x))^3} dx\end{aligned}$$

where the inequality follows from $\kappa_H > \kappa_L$ since $\alpha_H > \alpha_L$. \square

Proposition 4 states that if both the high-versatility and the low-versatility workers would be offered the same wage within each firm, the high-versatility workers' relative wage would, nevertheless, increase as the productivity dispersion across firms rises. Intuitively, the rising productivity gap between the low- and high-productivity firms amplifies the wage disparities between those firms. Since high-versatility workers, due to their higher κ , represent a disproportionately large share of the workforce at the high-productivity firms, their relative wage rises.

This sorting effect is also prominently analyzed within the Abowd et al. (1999) framework. For instance, Card et al. (2013) fit linear models with additive person and establishment fixed effects for West Germany for the years 1985–2009. They find that two-thirds of the increase in the wage gap between lower- and higher-educated workers are attributable to a widening in the average establishment wage premia received by differently educated groups.

Proposition 5 (Appropriation Premium and Productivity Dispersion). *The appropriation wage premium under the mean-preserving firm-productivity spread, $\bar{w}_{HH}^*/\bar{w}_{LH}^*$, exceeds that under the initial firm-productivity distribution, $\bar{w}_{HH}/\bar{w}_{LH}$, in the steady state.*

PROOF. Proposition 5 claims, equivalently, $\bar{w}'_{HH}/\bar{w}_{HH} > \bar{w}'_{LH}/\bar{w}_{LH}$. This inequality is implied by

$$\begin{aligned} \int_{\Gamma_x} \frac{(1-x)^{-1/z} \varphi(x, H, H)}{(1 + \kappa_H(1-x))^3} dx & \Bigg/ \int_0^1 \frac{(1-x)^{-1/z} \varphi(x, H, H)}{(1 + \kappa_H(1-x))^3} dx \\ & > \int_{\Gamma_x} \frac{(1-x)^{-1/z} \varphi(x, L, H)}{(1 + \kappa_L(1-x))^3} dx & \Bigg/ \int_0^1 \frac{(1-x)^{-1/z} \varphi(x, L, H)}{(1 + \kappa_L(1-x))^3} dx, \end{aligned}$$

where the inequality follows from $\kappa_H > \kappa_L$ since $\alpha_H > \alpha_L$. \square

Proposition 5 states that if the high-versatility and the low-versatility workers would be matched with the firms exactly in the same way, the high-versatility workers' relative wage would still rise as the productivity dispersion across firms increases. The intuition is as follows. First, note that κ is the average number of outside contracts per employment spell. The more firms are expected to interact during an employment spell, the lower is the employers' monopsonistic power. Hence, the higher is the rent share that the workers are able to appropriate. Second, the workers' outside option, i.e., the flow income of zero while unemployed, is an important determinant of the wages at the low-productivity firms. However, it is predominantly κ , i.e., the fierceness of the between-firm competition, that determines the wages at the high-productivity firms. Therefore, a high κ , as induced by a high versatility, is crucial in order to appropriate some of the additional relative match surplus at the firms with the relative productivity gains.⁹

⁹Stijepic (2015d) documents the comovement of the skill premium with the differential

The following proposition is the present paper's main theoretical contribution. It establishes the positive relation between the productivity dispersion across firms and the versatility wage premium.

Proposition 6 (Versatility Premium and Productivity Dispersion). *The versatility wage premium under the mean-preserving firm-productivity spread, \bar{w}_H^*/\bar{w}_L^* , exceeds that under the initial firm-productivity distribution, \bar{w}_H/\bar{w}_L , in the steady state.*

PROOF. Proposition 6 claims $\bar{w}_H^*/\bar{w}_L^* > \bar{w}_H/\bar{w}_L$, which is equivalent to $\bar{w}'_{HH}/\bar{w}_{HH} > \bar{w}'_{LL}/\bar{w}_{LL}$. The latter inequality is implied by

$$\begin{aligned} \int_{\Gamma_x}^1 \frac{(1-x)^{1-1/z}}{(1+\kappa_H(1-x))^3} dx & \Bigg/ \int_0^1 \frac{(1-x)^{1-1/z}}{(1+\kappa_H(1-x))^3} dx \\ & > \int_{\Gamma_x}^1 \frac{(1-x)^{1-1/z}}{(1+\kappa_L(1-x))^3} dx \Bigg/ \int_0^1 \frac{(1-x)^{1-1/z}}{(1+\kappa_L(1-x))^3} dx, \end{aligned}$$

where the inequality follows from $\kappa_H > \kappa_L$ since $\alpha_H > \alpha_L$. \square

In conclusion, the versatility wage premium increases in the productivity dispersion across firms since the high-versatility workers represent a disproportionately large share at the firms with the relative productivity gains, and since the high-versatility workers are able to appropriate a higher share of the additional relative match surplus at those firms. Figure 2 provides numerical illustrations of the effect of the mean-preserving productivity spread on the worker groups' labor market outcomes. I set the firm-productivity threshold, p_x , to 1.5, so that 30 percent of the firms would experience relative productivity gains under the initial productivity distribution. Broadly in line with the estimates of Cahuc et al. (2006), the low-versatility and the high-versatility workers' ratios of the job-finding rate to the separation rate into unemployment, κ_L and κ_H , are one and four, respectively. Consistent with the first numerical exercise, I set the shape, z , and the scale, p_0 , parameters of the productivity distribution to three and one, respectively.

employer-size wage premium between high- and low-skill workers in U.S. manufacturing during the postwar era. Most notably, the surge in the skill premium in the 1980s and 1990s coincides with the surge in the differential size premium. This suggests that differences between small and large employers play a potentially important role in explaining the recent increases in wage inequality.

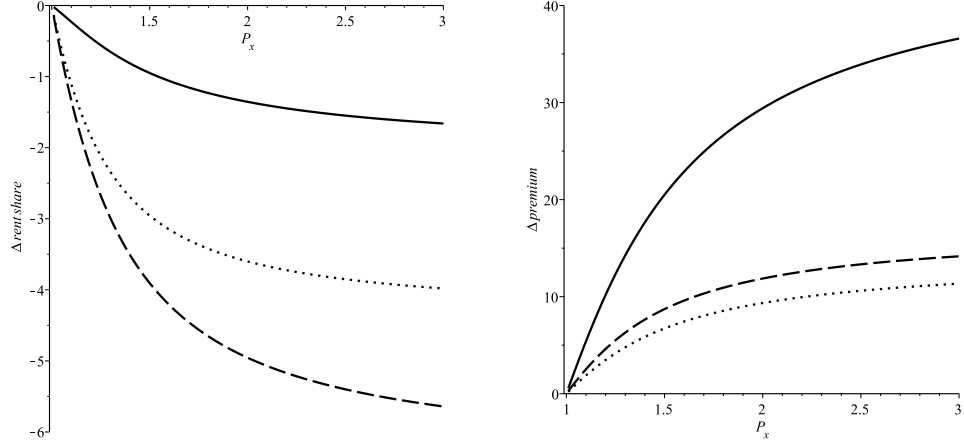


Figure 2: The left-hand side depicts the high-versatility workers' percentage-point change in the rent share of the average match surplus ($\bar{w}_H^*/\int_{p_0^*}^{\infty} p dG_H^*(p) - \bar{w}_H/\int_{p_0}^{\infty} p dG_H(p)$, dotted line), the low-versatility workers' change in the rent share under the high-versatility workers' distribution over firms ($\bar{w}_{LH}^*/\int_{p_0^*}^{\infty} p dG_H^*(p) - \bar{w}_{LH}/\int_{p_0}^{\infty} p dG_H(p)$, dashed line), and the difference between these rent share changes of the high-versatility and the low-versatility workers (solid line) against the relative productivity gains, P_x . The right-hand side depicts the percentage-point change in the versatility wage premium ($w_H^*/w_L^* - w_H/w_L$, solid line), the allocation wage premium ($w_H^*/w_{HL}^* - w_H/w_{HL}$, dotted line), and the appropriation wage premium ($w_H^*/w_{LH}^* - w_H/w_{LH}$, dashed line) against the relative productivity gains, P_x . The low-versatility and the high-versatility workers' ratios of the job-finding rate to the separation rate into unemployment, κ_L and κ_H , are one and four, respectively. The productivity threshold, p_x , is 1.5. The shape, z , and the scale, p_0 , parameters of the productivity distribution are set to three and one, respectively.

The left-hand side of Figure 2 illustrates the relation between the workers' rent share and the relative productivity gains under the mean-preserving productivity spread, P_x . Both the high-versatility workers' rent share, $\bar{w}_H^*/\int_{p_0^*}^{\infty} p dG_H^*(p)$, and the low-versatility workers' rent share under the high-versatility workers' distribution over firms, $\bar{w}_{LH}^*/\int_{p_0^*}^{\infty} p dG_H^*(p)$, are smaller in the steady state equilibrium with the mean-preserving productivity spread than in the steady state equilibrium with the initial productivity distribution. However, the decrease in the low-versatility workers' rent share is more pronounced. The right-hand side of Figure 2 depicts the percentage-point change in the versatility and the counterfactual wage premia against the relative productivity gains under the mean-preserving firm-productivity spread, P_x . All of the premia are increasing in the relative productivity gains, P_x .

4. Evidence from the United States

The subsequent analysis is based on a subsample of the *1979 National Longitudinal Survey of Youth*. The statistics on the productivity dispersion across establishments within industries are from the *Economic Census*. A description of the data sets and the sample selection is in Section 4.1. I introduce the standard variables in Section 4.2 and the versatility measure in Section 4.3. Summary statistics are in Section 4.4. Further details are in Appendix A.

4.1. Data Sets

1979 National Longitudinal Survey of Youth follows a sample of the American youth born in 1957–64. The first round of interviews was in 1979 when the survey participants were of ages 14–22. By the year 2012, 25 interview rounds had been completed. The *National Longitudinal Survey of Youth* is unique in the sense that it comprises a nationally representative sample of young people to whom the *Armed Services Vocational Aptitude Battery* was administered. This set of standardized tests assesses the respondents’ knowledge and skill in several areas and allows me to construct a novel measure of a worker’s versatility.

I focus on the participants’ labor markets outcomes in 2007. The sample selection is as follows. First, only respondents who worked full-time, i.e., at least 35 hours per week, and at least 52 weeks in 2007 may enter the final sample. Therefore, I abstract from the peculiarities associated with part-time work or limited labor market attachment. Second, the sample encompasses only white men since non-white individuals’ and women’s opportunities and decisions may be partly influenced by non-market considerations.¹⁰ Third, I only consider individuals born in the United States to improve the quality of the measures of education. Fourth, I exclude respondents if irregularities occurred during the *Armed Services Vocational Aptitude Battery* testing procedure. The final sample encompasses 969 individuals.

The *Economic Census* collects information on the U.S. economy once every five years, combining both administrative records and establishment surveys. The scope of the *Economic Census* has evolved over the years. Since 1992, the industries covered by the program account for more than 98 percent of the gross

¹⁰For instance, firms’ discrimination against specific worker groups due to distaste à la Becker (1971), i.e., a concept of discrimination that is not dictated by profit maximization, is a potential source of differences in labor market outcomes.

domestic product. I use *Economic Census* statistics from 2007 reported by Barth et al. (2014).

4.2. Standard Variables

The hourly wage is defined as the annual wage and salary income divided by the total hours worked in that year. I discard all observations below the 1st percentile and above the 99th percentile. The average hourly wage in the sample amounts to 31.74 US-Dollars.

Respondents are grouped into five education categories according to their educational attainment: individuals who have completed at most the 12th grade and have no high school diploma (*no high school*), high school graduates (*high school*), individuals with some college but either no degree or else an associate degree (*some college*), individuals with a bachelor's degree (*college*), and individuals with a master's, professional school or doctoral degree (*advanced*).

Following Barth et al. (2014), I define eight major industries: (i) mining, construction, utilities, and transport, (ii) manufacturing, (iii) wholesale and retail trade, (iv) information and communication, (v) finance, insurance, and real estate, (vi) business services, (vii) health, education, and social services, and (viii) personal services. I use the standard deviation of the log-sales-per-employee across establishments from 2007, computed by Barth et al. (2014) on the basis of the *Economic Census*, as a measure of the productivity dispersion within industries.

I distinguish four regions of residence: the northeastern, the northern central, the southern, and the western region of the United States. The full set of controls also includes four-digit Census 2003 occupation and industry level fixed effects. Additionally, I group the respondents according to the type of their employer: government, private for profit company, non-profit organization, self employed, and family business.

I also exploit interview questions from various years that provide information on the respondents' attitudes and traits. Since the questions are administered at various survey points, I only have the complete list of variables for 881 individuals who participated in the survey in all the relevant years. In order to infer risk attitudes, the survey participants are asked whether they are generally fully prepared to take risks or whether they try to avoid taking risks. The maximum possible score is ten, indicating the full preparedness to take risks, and the minimum possible score is zero, indicating the unwillingness to take any risks. Trust is measured on the basis of the question of how often you can trust other people. The possible answers range from one, indicating always, to five, indicating never.

The *Rotter Locus of Control Scale* measures the extent to which individuals believe that they have control over their lives through self-motivation or self-determination as opposed to the extent that the environment controls their lives (Rotter, 1966). The maximum possible score is 16, indicating a high external control, while the minimum possible score is four, indicating a high internal control. The *Rosenberg Self-Esteem Scale* describes the degree of approval or disapproval towards oneself (Rosenberg, 1965). The maximum possible score is 30, while the minimum possible score is zero. A higher score designates a higher self-esteem. The *Pearlin Mastery Scale* describes the extent to which individuals perceive themselves in control of the forces that significantly impact their lives (Pearlin et al., 1981). The total score could range from 7 to 28. Higher scores represent greater mastery.

4.3. Versatility

The *Armed Services Vocational Aptitude Battery* was administered to a total of 11,914 *National Longitudinal Survey of Youth* respondents in 1980, representing a completion rate of approximately 94 percent. The testing was conducted according to standard *ASVAB* procedural guidelines. Five to ten persons were tested at more than 400 test sites, including hotels, community centers, and libraries throughout the United States and abroad. The *NLSY* respondents were paid 50 US-Dollars for completing the test in order to compensate them for their time and travel expenses.

The *ASVAB* consists of a battery of ten tests that measure knowledge and skill in the following areas: (i) general science, (ii) arithmetic reasoning, (iii) word knowledge, (iv) paragraph comprehension, (v) numerical operations, (vi) coding speed, (vii) auto and shop information, (viii) mathematics knowledge, (ix) mechanical comprehension, and (x) electronics information. Each subtest has been fitted separately to an item response curve psychometric model: a three-parameter logistic model for the power subtests and a Poisson model for the speeded subtests. When the logistic model is estimated, it is capable of accounting for the facts that (i) some subjects perform better than others on the items in the subtest, (ii) some items in the subtest are easier than others, (iii) some items measure the underlying ability more precisely than other, and (iv) because the test items are multiple choice, subjects can occasionally answer any item correctly by guessing. In order to recover the respondents underlying ability, the Poisson model is fitted under the two assumptions that (i) the item content within a subtest is homogeneous, and that (ii) a subtest is infinitely long. The final knowledge and skill estimates

have been standardized within each *ASVAB* subtest to weighted population means of zero and standard deviations of one.

In order to construct the versatility measure, I proceed as follows. First, I identify the respondents with above-median scores for each subtest separately. Second, I compute the number of subtests with above-median scores for each respondent. Figure 3 displays the distribution of the respondents' number of subtests with above-median scores. The number of subtests with an above-median score is rather uniformly distributed. Most frequently, survey participants perform above the median in eight subtests, i.e., fourteen percent of the sample. Least frequently, respondents have above-median scores in two subtests, i.e., six percent of the sample. On average, the respondents obtain above-median scores in 5.6 subtests.

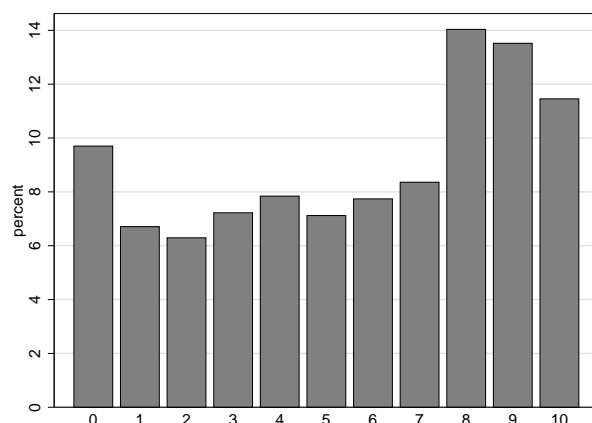


Figure 3: Respondents' number of *ASVAB* subtests with above-median scores. Sample restricted to full-time employed white male workers aged 25-55 and born in the United States. Author's calculations based on the *1979 National Longitudinal Survey of Youth*.

Finally, I identify all respondents who have above-median scores in at least six *ASVAB* subtests as versatile. Therefore, 55.1 percent of individuals are versatile and 44.9 percent are not versatile. In order to take into account further differences in the survey participants' skills, I additionally include each *ASVAB* subtest score of the survey participants in all the subsequent regressions.

4.4. Summary Statistics

Table 1 presents summary statistics for the overall sample and separately by education. The number of subtests in which the respondents have above-median scores is increasing in educational attainment. On the one hand, high school

dropouts perform above the median in only 0.9 subtests. On the other hand, respondents with advanced education have above-median scores in 8.2 subtests. Consequently, the share of versatile individuals is also increasing in educational attainment. None of the high school dropouts have above-median scores in at least six subtests. However, a share of 91 percent of individuals with advanced education obtain above-median scores in at least six subtests.

	<i>Overall</i>	<i>No high school</i>	<i>High school</i>	<i>Some college</i>	<i>College</i>	<i>Advanced</i>
<i>Share (in %)</i>	100	5.47 (0.73)	40.97 (1.58)	16.00 (1.18)	22.50 (1.34)	15.07 (1.15)
<i>Above-median scores</i>	5.61 (0.11)	0.87 (0.18)	4.37 (0.15)	5.66 (0.25)	7.28 (0.16)	8.19 (0.16)
<i>Versatile</i>	55.11 (1.60)	0.00	37.53 (2.43)	53.55 (4.02)	77.52 (2.83)	91.10 (2.37)
<i>Rotter locus of control</i>	8.39 (0.08)	9.75 (0.34)	8.72 (0.12)	8.49 (0.20)	8.00 (0.16)	7.49 (0.19)
<i>Rosenberg self-esteem</i>	22.88 (0.13)	21.19 (0.61)	22.16 (0.19)	23.42 (0.33)	23.32 (0.28)	24.24 (0.31)
<i>Pearlin mastery</i>	22.61 (0.10)	20.67 (0.37)	21.97 (0.14)	22.70 (0.24)	23.43 (0.18)	23.75 (0.25)
<i>Trust attitude</i>	2.70 (0.03)	3.30 (0.14)	2.86 (0.05)	2.72 (0.07)	2.52 (0.05)	2.30 (0.05)
<i>Risk attitude</i>	5.27 (0.08)	4.80 (0.45)	4.85 (0.13)	5.08 (0.20)	6.01 (0.15)	5.64 (0.15)
<i>Hourly wage</i>	31.74 (0.80)	16.22 (1.20)	23.26 (0.70)	26.47 (1.19)	42.39 (2.03)	50.08 (2.86)

Table 1: Various summary statistics for full-time employed white male workers aged 25–55 and born in the United States. Standard errors in parentheses. Author’s calculations based on the 1979 *National Longitudinal Survey of Youth*.

Table 2 displays summary statistics by industry. The sales-per-employee standard deviation substantially varies across industries. Education, health, and social services is the least dispersed industry with a standard deviation of 73 log-points. Finance, insurance, and real estate is the most dispersed industry with a standard deviation of 120 log-points. The share of versatile individuals and the versatility wage premium also substantially vary across industries.

4.5. *Productivity Dispersion and the Returns to Versatility*

In this section, I estimate how the returns to versatility depend on the productivity dispersion across establishments. Specifically, I exploit variations in the standard deviation of log-sales-per-employee across eight major U.S. industries in 2007. I identify respondents as versatile who have above-median scores in at

	Employment share	College share	Versatility share	Hourly wage	College premium	Versatility premium	Sales-per- employee s.d.
<i>Mining, construction, utilities, and transportation</i>	26.01 (1.41)	13.49 (2.16)	38.49 (3.07)	24.23 (0.80)	31.28 (10.04)	13.73 (7.13)	98
<i>Manufacturing</i>	24.97 (1.39)	33.47 (3.04)	56.20 (3.20)	31.20 (1.29)	49.56 (7.07)	34.61 (7.03)	86
<i>Wholesale and retail trade</i>	17.13 (1.21)	33.73 (3.68)	46.39 (3.88)	30.11 (1.95)	61.40 (9.72)	40.64 (9.78)	113
<i>Information and communication</i>	3.30 (0.57)	68.75 (8.32)	87.50 (5.94)	40.45 (5.29)	37.57 (21.73)	-5.10 (31.92)	92
<i>Finance, insurance, and real estate</i>	6.81 (0.81)	72.73 (5.52)	65.15 (5.91)	45.91 (4.59)	60.65 (23.36)	73.68 (21.03)	120
<i>Business services</i>	10.73 (0.99)	58.65 (4.85)	75.00 (4.27)	41.76 (3.18)	75.30 (12.47)	74.33 (14.79)	106
<i>Education, health, and social services</i>	10.22 (0.97)	61.62 (4.91)	71.72 (4.55)	33.36 (3.08)	77.31 (13.50)	59.91 (15.73)	73
<i>Personal services</i>	0.83 (0.29)	12.50 (12.50)	50.00 (18.90)	15.86 (3.27)	-15.71 (64.44)	55.80 (36.27)	77
<i>All industries</i>	100	37.56 (1.56)	55.11 (1.60)	31.74 (0.80)	58.00 (3.98)	42.62 (4.06)	112

Table 2: Various summary statistics by industry for full-time employed white male workers aged 25–55 and born in the United States. Industry employment share in percent of the overall employment. College graduates’ and versatile individuals’ share in percent of the industry employment. College wage premium, versatility wage premium, and sales-per-employee standard deviation in log-points. Standard errors in parentheses. Author’s calculations based on the 1979 *National Longitudinal Survey of Youth*. Sales dispersion statistics from Barth et al. (2014).

least six *ASVAB* subtests. In order to take into account further differences in the survey participants' skills, I additionally control for each *ASVAB* subtest score of the survey participants in all the subsequent regressions.

Table 3 displays the ordinary least squares estimates of the effect of the displayed control variables on the logarithm of the hourly wage. The first specification in Table 3 includes the versatility indicator variable, its interaction with the industry standard deviation of log-sales-per-employee, the industry standard deviation of log-sales-per-employee, the indicator variables for the education groups, and the *ASVAB* subtest scores and their interactions with the industry standard deviation of log-sales-per-employee. The interaction between the versatility indicator variable and the industry sales dispersion is estimated to be positive. An increase in the standard deviation of log-sales-per-employee by ten log-points is associated with an increase in the versatility wage premium by 12 log-points in the sample. The relation is statistically significant at the five percent level.

Since the proposed measure of versatility is highly correlated with educational attainment, I additionally include the interactions of the education indicator variables with the industry standard deviation of log-sales-per-employee in the second specification. I obtain quantitatively similar and statistically significant estimates for the positive relation between the versatility wage premium and the industry standard deviation of log-sales-per-employee. Furthermore, the estimates do not suggest a clear and significant relation between the returns to educational attainment and the industry sales dispersion.

In the third specification, I also control for career choices by including four-digit Census 2003 industry and occupation level fixed effects, indicator variables for the five worker types, and region of residence indicator variables. In the fourth specification, I additionally include the interaction terms of the *ASVAB* subtest scores, and interact the interaction terms of *ASVAB* subtest scores with the industry standard deviation of log-sales-per-employee, in order to account for skill complementarity. In the fifth specification, I finally also control for the respondents' attitudes and traits as described in Section 4.2. Since the economics literature suggests a prominent role for risk and trust attitudes, I generate indicator variables for each of the eleven risk and five trust categories. All the measures of the respondents' attitudes and traits are also interacted with the industry standard deviation of log-sales-per-employee. The relation between the versatility wage premium and the industry standard deviation of log-sales-per-employee is consistently estimated to be positive. Furthermore, the estimates are statistically significant at least at the five percent level in all the specifications.

	(1)	(2)	(3)	(4)	(5)
<i>Versatility</i>	-1.175** (0.486)	-1.150** (0.487)	-1.154** (0.585)	-1.773** (0.703)	-2.065** (0.797)
<i>Versatility and sales dispersion interacted</i>	1.178** (0.493)	1.147** (0.494)	1.198** (0.589)	1.876*** (0.710)	2.137*** (0.803)
<i>Education</i>					
No high school	-0.163* (0.092)	-0.722 (0.780)	-1.174 (1.117)	-0.709 (1.270)	-1.672 (1.409)
Some college	0.053 (0.057)	-0.111 (0.444)	0.009 (0.575)	-0.110 (0.649)	0.493 (0.728)
College	0.368*** (0.060)	0.151 (0.444)	0.372 (0.600)	0.292 (0.691)	0.302 (0.769)
Advanced	0.489*** (0.070)	-0.158 (0.480)	0.131 (0.711)	0.149 (0.811)	0.649 (0.903)
<i>Education and sales dispersion interacted</i>					
No high school	—	0.574 (0.798)	0.934 (1.132)	0.494 (1.281)	1.721 (1.418)
Some college	—	0.168 (0.456)	-0.021 (0.583)	0.078 (0.658)	-0.558 (0.741)
College	—	0.227 (0.446)	-0.162 (0.594)	-0.070 (0.682)	-0.145 (0.766)
Advanced	—	0.685 (0.499)	0.176 (0.717)	0.169 (0.812)	-0.385 (0.905)
<i>Sales dispersion</i>	0.082 (0.254)	-0.139 (0.338)	—	—	—
<i>Attitudes and traits, and interactions with sales dispersion</i>	—	—	—	—	x
<i>Interacted ASVAB subtest scores, and interactions with sales dispersion</i>	—	—	—	x	x
<i>Industry, occupation, worker type, and region</i>	—	—	x	x	x
<i>ASVAB subtest scores, and interactions with sales dispersion</i>	x	x	x	x	x
<i>R-squared</i>	0.256	0.258	0.645	0.711	0.781
<i>Observations</i>	969	969	969	969	881

Table 3: Ordinary least squares regressions of the logarithm of the hourly wage on the displayed variables for full-time employed white male workers aged 25–55 and born in the United States. Standard errors in parentheses. Statistical significance at the 10, 5, and 1 percent level denoted by *, **, and ***, respectively. Author's calculations based on the 1979 *National Longitudinal Survey of Youth*. Sales dispersion statistics from Barth et al. (2014).

5. Evidence from Germany

An important question is whether the positive correlation between the productivity dispersion across employers and the versatility wage premium is specific to

the United States or whether it is a feature of modern market economies in general. In order to address this question, I exploit industry variation in labor-productivity dispersion across establishments in Germany in 2012. Well in line with my findings for the U.S. economy, I document that an increase in the labor-productivity standard deviation across establishments by ten log-points is associated with an increase in the above-median versatile worker's relative wage by 8 to 14 log-points in Germany.

I describe the data sets in Section 5.1, the standard variables in Section 5.2, and the versatility measure in Section 5.3. The estimates of the effect of the labor-productivity dispersion across establishments on the versatility wage premium are in Section 5.4. Further details are in Appendix A.

5.1. Data Sets

The following empirical analysis is based on the *Programme for the International Assessment of Adult Competencies (PIAAC)*, a large-scale initiative of the *Organization for Economic Cooperation and Development (OECD)* that aims at assessing key adult competencies. The data collection for the first round of the *PIAAC* was carried out in 24 countries, including Germany in 2011–2012. The competencies of the adult population ages 16–65 in the domains literacy, numeracy, and problem solving in technology-rich environments were assessed. This cognitive assessment was supplemented with a questionnaire that collected a wide variety of background information, including those related to demographic, social, educational, and economic variables. The interviews generally took place at the respondents' homes. Respondents first answered questions from the background questionnaire, and then worked on the cognitive assessment.¹¹

Similar to my sample restrictions for the *National Longitudinal Survey of Youth*, I only consider full-time employed male workers aged 25–55 and born in Germany. Furthermore, I exclude respondents if irregularities occurred during the assessment of their competencies in the domains literacy, numeracy, or problem solving in technology-rich environments. The final sample encompasses 771 individuals.

In order to compute industry statistics, e.g., the productivity dispersion across establishments, I make use of the *Linked Employer–Employee Data from the Institute for Employment Research (LIAB)*.¹² The data set also contains information

¹¹For further information on the *Programme for the International Assessment of Adult Competencies (PIAAC)* see the OECD (2013, forthcoming) technical report.

¹²This study uses the cross-sectional model of the linked employer–employee data (*LIAB* ver-

from the *IAB Establishment Panel*, which is a representative employer survey of individual establishments in Germany. Near to 16,000 establishments from all branches of the economy and of all sizes are surveyed annually and nationwide from the end of June until October. Specifically, I exploit the retrospective questions on the establishments' activities in 2012 from the 2013 questionnaire.

5.2. Standard Variables

The average hourly wage including bonuses is 19.25 Euro in the sample. Respondents are grouped into six education categories according to their educational attainment: (i) at most lower secondary education, (ii) upper secondary education, (iii) post-secondary but not tertiary education, (iv) tertiary education with a professional degree, (v) tertiary education with a bachelor's degree, and (vi) tertiary education with a master's or research degree. The full set of controls includes four-digit *International Standard Classification of Occupations (ISCO)* level fixed effects, and 41 industry level fixed effects as defined in the 2013 *IAB Establishment Panel* questionnaire.¹³ Additionally, I group the respondents according to the type of their employer: government, private for profit company, non-profit organization, self employed, and family business. I distinguish four regions of residence: the northwestern, the western central, the southern, and the eastern region of Germany. Since the sample covers several cohorts, I also control for age by a third-order polynomial.

In the following regressions, I exploit variations in labor-productivity dispersion across 14 major industries as defined in the 2013 *IAB Establishment Panel* questionnaire: (i) agriculture, forestry, and fishing, (ii) mining and quarrying, (iii) energy and water supply, waste management, and remediation activities, (iv) manufacturing, (v) construction, (vi) trade, (vii) transportation and storage, (viii) information and communication, (ix) accommodation and food service activities, (x) financial and insurance activities, (xi) professional, scientific, and commercial services, (xii) education services, (xiii) human health and social work activities, and (xiv) other services. I measure an establishment's labor-productivity by its log-value-added-per-worker.

sion 2, years 1993–2010) from the Institute for Employment Research. Data access was provided via on-site use at the Research Data Centre of the German Federal Employment Agency at the Institute for Employment Research and subsequently via remote data access. Heining et al. (2013) give a detailed description of the data set.

¹³I do not obtain consistently statistically significant estimates if I include four-digit *International Standard Industrial Classification (ISIC)* level fixed effects.

5.3. Versatility

For literacy and numeracy, an adaptive algorithm was implemented to select item sets, i.e., task difficulty was adapted to the information derived from the background questionnaire and the performance in previous parts of the computer branch. The assessment design for the problem solving in technology-rich environments was not adaptive. Using item response theory scaling and latent regression models, a set of plausible values for literacy, numeracy, and problem solving in technology-rich environments was produced.¹⁴

I identify respondents as versatile if they have above-median scores in all three domains, i.e., literacy, numeracy and problem solving in technology-rich environments. Therefore, 42.9 percent of respondents are versatile, and 57.1 percent are not versatile. I do not obtain consistently statistically significant estimates if I also categorize respondents with above-median scores in only two domains as versatile. From the model perspective, this is perhaps not too surprising. All three domains represent basic skills. Individuals with below-median skills already in one domain are unlikely to be versatile in the sense of being able to perform various different tasks or activities.

In contrast to the data on the United States, the skills are not assessed at the beginning of the survey participants' working lives, but at the same point in time at which the labor market outcomes are also measured. Therefore, reverse causality is a more prominent issue for the analysis with the German data, since the individuals' labor market biographies might also have an impact on their skills.

5.4. Productivity Dispersion and the Returns to Versatility

Table 4 displays ordinary least squares estimates of the effect of the displayed variables on the logarithm of the hourly wage. The first specification in Table 4 includes the versatility indicator variable, its interaction with the industry standard deviation of log-value-added-per-worker, the industry standard deviation of log-value-added-per-worker, the indicator variables for the education groups, the *PIAAC* basic skill scores and their interactions with the industry standard deviation of log-value-added-per-worker, and a third-order polynomial in age. The interaction term between the versatility indicator variable and the industry productivity dispersion is estimated to be positive. An increase in the standard deviation of value-added-per-worker by ten log-points is associated with an increase

¹⁴In order to consistently employ the same methodology, I use the averages over all generated plausible values in each domain in the subsequent analysis.

in the versatility wage premium by eight log-points. The relation is statistically significant at the ten percent level.

	(1)	(2)	(3)	(4)	(5)
<i>Versatility</i>	-0.644 (0.409)	-0.718* (0.423)	-1.133*** (0.398)	-2.363 (3.107)	-2.508 (3.176)
<i>Versatility and industry characteristics interacted</i>					
Productivity dispersion	0.833* (0.491)	0.916* (0.506)	1.404*** (0.476)	1.345** (0.659)	1.269* (0.670)
Productivity	—	—	—	0.125 (0.341)	0.129 (0.349)
Investment activity	—	—	—	-0.165 (0.885)	-0.017 (0.902)
Innovation activity	—	—	—	0.522 (0.765)	0.660 (0.807)
R&D activity	—	—	—	-1.478 (1.428)	-1.190 (1.477)
R&D employment share	—	—	—	2.163 (9.088)	0.210 (9.399)
<i>Education interacted with all industry characteristics</i>	—	—	—	—	x
<i>PIAAC basic skills scores interacted with all industry characteristics</i>	—	—	—	x	x
<i>Industry, occupation, worker type, and region</i>	—	—	x	x	x
<i>Education interacted with productivity dispersion</i>	—	x	x	x	x
<i>PIAAC basic skills scores, and interactions with productivity dispersion</i>	x	x	x	x	x
<i>Education, and a third-order polynomial in age</i>	x	x	x	x	x
<i>R-squared</i>	0.370	0.375	0.738	0.754	0.771
<i>Observations</i>	771	771	771	771	771

Table 4: Ordinary least squares regressions of the logarithm of the hourly wage on the displayed variables for full-time employed male workers aged 25–55 and born in Germany. Standard errors in parentheses. Statistical significance at the 10, 5, and 1 percent level denoted by *, **, and ***, respectively. Author's calculations based on the *Programme for the International Assessment of Adult Competencies* and the *Linked Employer–Employee Data from the Institute for Employment Research*.

In the second specification, I also interact the educational attainment measures with the industry standard deviation of log-value-added-per-worker. In the third specification, I also control for career choices by including industry and occupation level fixed effects, indicator variables for the five worker types, and region

of residence indicator variables. In all the specifications, the relation between the versatility wage premium and the industry standard deviation of log-value-added-per-employee is consistently estimated to be positive and statistically significant.

In the fourth and fifth specifications, I also consider other industry characteristics than exclusively the standard deviation of log-value-added-per-worker. Specifically, I also take into account the average value-added-per-worker across the establishments within the industry, the share of investing establishments, the share of innovating establishments, the share of establishments with research and development activities, and the average establishment share of full-time employees in research and development activities. In the fourth specification, I only interact these industry characteristics with the versatility indicator variable. In the fifth specification, I additionally interact these industry characteristics with the educational attainment indicator variables. The relation between the versatility wage premium and the industry standard deviation of log-value-added-per-employee is consistently estimated to be positive and statistically significant.

Finally, note that I do not obtain consistently statistically significant estimates for the relation between the versatility wage premium and the industry standard deviation of log-value-added-per-employee if I additionally include the interaction terms of the *PIAAC* basic skill scores, and interact the interaction terms with the industry standard deviation of log-value-added-per-employee as in specification four of Table 3.

6. Conclusion

For the United States, I document that (i) workers' versatility is positively correlated with their educational attainment and that (ii) the versatility wage premium is more pronounced in industries with a higher log-sales-per-worker dispersion across establishments. An increase in the standard deviation of sales-per-worker by ten log-points is estimated to raise the above-median versatile workers' relative wage by 11 to 21 log-points. I also provide supportive evidence from Germany.

The findings are consistent with a model that features both frictional and structural impediments to sorting. In an environment where jobs differ in requirements, versatility enhances an individual's ability to allocate to the most productive firms since efficient reallocations are less likely to be hindered by unmet job requirements. Furthermore, the returns to sorting into the most productive firms and, hence, versatility are larger the more pronounced the productivity-differentials between the firms. Intuitively, if firms are similar in productivity, the returns from sorting into more productive firms are low. However, if the disparities between

firms are substantial, so will be the returns. The wage differential between the versatile and non-versatile individuals is amplified.

In view of the surge in the productivity dispersion within industries and the positive correlation between educational attainment and versatility, the present paper's findings suggest a potentially prominent role for versatility in explaining the rise in the college wage premium in the United States between the 1970s and 1990s. All in all, it is potentially not the specialization into particularly productive specific tasks or activities that allowed college graduates to obtain relative wage raises, but rather the ability to perform various tasks and activities—eventually even across occupations.

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Appendix A. Data Appendix—For Online Publication

In this appendix, I provide further information on the data sets and I also present some auxiliary empirical results.

Appendix A.1. Evidence from the United States—Data and Auxiliary Results

Following Barth et al. (2014), I define eight broad industry categories based on the major industries of the 2003 *Census Industry Classification System*—the recodes are in parentheses: (i) mining, construction, utilities, and transport (2,3,6), (ii) manufacturing (4), (iii) wholesale and retail trade (5 (including eating and drinking places 8689–8690)), (iv) information and communication (7), (v) finance, insurance, and real estate (8), (vi) business services (9, 11 (excluding 8680–8690, 12 (excluding 8880–9090)), (vii) health, education, and social services (10), and (viii) personal services (12 (8880–9090)).

In order to assess the impact of single industries on the present paper’s main findings, I reestimate the fourth specification from Table 3, but exclude one of the eight industries in turn. I choose the fourth specification from Table 3 for the sensitivity analysis, since this specification yields the most significant estimate for the relation between the versatility wage premium and the industry sales dispersion on the full sample. Table A.5 presents the regression results. The interaction term between the versatility indicator variable and the industry sales dispersion is always estimated to be positive. All estimates are significant at least at the ten percent level.

Since none of the respondents without a high school diploma is categorized as versatile, I repeat the regression without this subgroup. The qualitative results are unaltered. See Table A.6. As an alternative measure of versatility, I identify all respondents with above-first-quartile scores in all ten *ASVAB* subtests as versatile. Hence, 46.2 percent of the respondents are versatile, and 53.8 percent are categorized as not versatile. Once more, I obtain positive coefficient estimates for the interaction term between the versatility indicator variable and the industry sales dispersion. Except for the first two specifications, the estimates remain statistically significant at least at the ten percent level. See Table A.7.

As yet another alternative measure of versatility, I use the number of above-median *ASVAB* subtests in a linear specification. While the point estimates remain positive, I do not find statistically significant correlations between the number of above-median *ASVAB* subtests and the industry sales dispersion. See Table A.8. In order to investigate potential non-linearities in the relation, I form four

versatility groups: (i) 0–2 above-median *ASVAB* subtest scores, (ii) 3–5 above-median scores, (iii) 6–8 above-median scores, and (iv) 9–10 above-median scores. Table A.9 displays the estimates. The relation between wages and the industry sales dispersion is more pronounced among all the versatility groups than that of the reference group with 0–2 above-median scores. However, the estimates do not suggest a linear relation, but reveal some concavity.

Appendix A.2. Evidence from Germany—Data and Auxiliary Results

In order to assess the impact of single industries on the paper’s main findings, I reestimate the third specification from Table 4, but exclude one of the fourteen industries in turn. Tables A.10 and A.11 present the sensitivity analysis. The interaction term between the versatility indicator variable and the industry value-added-per-worker dispersion is consistently estimated to be positive. All coefficient estimates are significant at least at the ten percent level.

Most notably, I estimate the relation between the versatility wage premium and the average establishment productivity within an industry to be positive and statistically significant in most specifications, once I do not control for the industry productivity dispersion across establishments. See Table A.12.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Versatility</i>	-1.785** (0.808)	-2.187** (1.019)	-1.902** (0.867)	-1.806** (0.729)	-1.365* (0.779)	-1.923*** (0.734)	-1.953** (0.960)	-1.773** (0.703)
<i>Versatility and sales dispersion interacted</i>	1.976** (0.803)	2.202** (0.991)	2.026** (0.912)	1.899*** (0.733)	1.429* (0.801)	2.058*** (0.749)	2.012** (0.944)	1.876*** (0.710)
<i>Education</i>								
No high school	-0.740 (1.445)	1.440 (1.929)	-4.706*** (1.741)	-0.608 (1.292)	-0.966 (1.281)	-0.526 (1.306)	1.270 (1.620)	-0.709 (1.270)
Some college	-0.274 (0.733)	-0.900 (0.989)	-0.591 (0.841)	-0.168 (0.667)	0.109 (0.687)	-0.250 (0.673)	-0.320 (0.819)	-0.110 (0.649)
College	0.359 (0.777)	0.357 (1.206)	-0.026 (0.839)	0.255 (0.705)	0.341 (0.748)	0.332 (0.724)	-0.187 (0.849)	0.292 (0.691)
Advanced	-0.092 (0.888)	0.301 (1.347)	0.228 (0.969)	0.079 (0.826)	0.809 (0.895)	-0.415 (0.857)	-0.855 (1.050)	0.149 (0.811)
<i>Education and sales dispersion interacted</i>								
No high school	0.294 (1.438)	-1.678 (1.902)	4.834*** (1.816)	0.396 (1.303)	0.763 (1.296)	0.269 (1.324)	-1.429 (1.621)	0.494 (1.281)
Some college	0.211 (0.738)	0.855 (0.965)	0.590 (0.887)	0.134 (0.675)	-0.154 (0.704)	0.213 (0.687)	0.277 (0.819)	0.078 (0.658)
College	-0.161 (0.759)	-0.134 (1.136)	0.232 (0.867)	-0.032 (0.694)	-0.123 (0.755)	-0.139 (0.721)	0.382 (0.826)	-0.070 (0.682)
Advanced	0.415 (0.883)	0.008 (1.279)	-0.017 (1.009)	0.236 (0.825)	-0.559 (0.922)	0.878 (0.871)	1.110 (1.026)	0.169 (0.812)
<i>Further controls</i>	x	x	x	x	x	x	x	x
<i>R-squared</i>	0.784	0.734	0.758	0.705	0.728	0.719	0.705	0.707
<i>Observations</i>	717	727	803	937	903	865	870	961

Table A.5: Ordinary least squares regressions of the logarithm of the hourly wage on the displayed variables and further controls as in the fourth specification of Table 3. Sample restricted to full-time employed white male workers aged 25–55 and born in the United States. Each specification excludes one of the eight industries: (1) mining, construction, and transportation, (2) manufacturing, (3) wholesale and retail trade, (4) information and communication, (5) finance, insurance, and real estate, (6) business services, (7) education, health, and social services, and (8) personal services. Standard errors in parentheses. Statistical significance at the 10, 5, and 1 percent level denoted by *, **, and ***, respectively. Author's calculations based on the 1979 *National Longitudinal Survey of Youth*. Sales dispersion statistics from Barth et al. (2014).

	(1)	(2)	(3)	(4)	(5)
<i>Versatility</i>	-1.152** (0.499)	-1.154** (0.499)	-1.112* (0.597)	-1.707** (0.742)	-1.878** (0.848)
<i>Versatility and sales dispersion interacted</i>	1.161** (0.505)	1.159** (0.506)	1.180** (0.600)	1.811** (0.746)	1.968** (0.851)
<i>Education</i>					
Some college	0.053 (0.057)	-0.090 (0.447)	-0.025 (0.589)	-0.275 (0.683)	0.552 (0.773)
College	0.355*** (0.060)	0.158 (0.449)	0.330 (0.615)	0.297 (0.714)	0.489 (0.801)
Advanced	0.476*** (0.071)	-0.165 (0.485)	0.107 (0.724)	0.130 (0.829)	0.780 (0.925)
<i>Education and sales dispersion interacted</i>					
Some college	—	0.145 (0.459)	0.013 (0.598)	0.230 (0.692)	-0.634 (0.788)
College	—	0.207 (0.451)	-0.141 (0.608)	-0.088 (0.704)	-0.361 (0.797)
Advanced	—	0.679 (0.504)	0.186 (0.729)	0.161 (0.830)	-0.575 (0.927)
<i>Sales dispersion</i>	0.045 (0.263)	-0.127 (0.342)	—	—	—
<i>Attitudes and traits, and interactions with sales dispersion</i>	—	—	—	—	x
<i>Interacted ASVAB subtest scores, and interactions with sales dispersion</i>	—	—	—	x	x
<i>Industry, occupation, worker type, and region</i>	—	—	x	x	x
<i>ASVAB subtest scores, and interactions with sales dispersion</i>	x	x	x	x	x
<i>R-squared</i>	0.228	0.229	0.638	0.709	0.788
<i>Observations</i>	916	916	916	916	833

Table A.6: Ordinary least squares regressions of the logarithm of the hourly wage on the displayed variables for full-time employed white male workers aged 25–55 and born in the United States. Additionally, respondents without a high school diploma are excluded from the sample. Standard errors in parentheses. Statistical significance at the 10, 5, and 1 percent level denoted by *, **, and ***, respectively. Author's calculations based on the 1979 *National Longitudinal Survey of Youth*. Sales dispersion statistics from Barth et al. (2014).

	(1)	(2)	(3)	(4)	(5)
<i>Versatility</i>	-0.285 (0.396)	-0.229 (0.399)	-0.770* (0.465)	-1.276** (0.579)	-1.033 (0.652)
<i>Versatility and sales dispersion interacted</i>	0.310 (0.404)	0.254 (0.407)	0.860* (0.476)	1.402** (0.594)	1.165* (0.665)
<i>Education</i>					
No high school	-0.166* (0.092)	-0.807 (0.782)	-1.220 (1.117)	-0.861 (1.269)	-1.612 (1.419)
Some college	0.061 (0.057)	-0.114 (0.445)	-0.035 (0.575)	-0.301 (0.650)	0.381 (0.731)
College	0.382*** (0.060)	0.166 (0.443)	0.340 (0.597)	0.169 (0.687)	0.185 (0.767)
Advanced	0.501*** (0.071)	-0.136 (0.480)	0.228 (0.712)	0.061 (0.811)	0.470 (0.903)
<i>Education and sales dispersion interacted</i>					
No high school	—	0.658 (0.799)	0.977 (1.131)	0.656 (1.280)	1.675 (1.426)
Some college	—	0.178 (0.457)	0.038 (0.583)	0.301 (0.660)	-0.415 (0.745)
College	—	0.225 (0.445)	-0.130 (0.591)	0.051 (0.677)	-0.018 (0.763)
Advanced	—	0.674 (0.500)	0.069 (0.718)	0.251 (0.811)	-0.207 (0.905)
<i>Sales dispersion</i>	0.387* (0.219)	0.160 (0.315)	—	—	—
<i>Attitudes and traits, and interactions with sales dispersion</i>	—	—	—	—	x
<i>Interacted ASVAB subtest scores, and interactions with sales dispersion</i>	—	—	—	x	x
<i>Industry, occupation, worker type, and region</i>	—	—	x	x	x
<i>ASVAB subtest scores, and interactions with sales dispersion</i>	x	x	x	x	x
<i>R-squared</i>	0.252	0.254	0.645	0.710	0.780
<i>Observations</i>	969	969	969	969	881

Table A.7: Ordinary least squares regressions of the logarithm of the hourly wage on the displayed variables for full-time employed white male workers aged 25–55 and born in the United States. All respondents with above-first-quartile scores in ten ASVAB subtests categorized as versatile. Standard errors in parentheses. Statistical significance at the 10, 5, and 1 percent level denoted by *, **, and ***, respectively. Author's calculations based on the 1979 *National Longitudinal Survey of Youth*. Sales dispersion statistics from Barth et al. (2014).

	(1)	(2)	(3)	(4)	(5)
<i>Above-median subtests</i>	−0.145 (0.131)	−0.131 (0.132)	−0.238 (0.166)	−0.272 (0.205)	−0.364 (0.242)
<i>Above-median subtests and sales dispersion interacted</i>	0.125 (0.132)	0.110 (0.133)	0.233 (0.165)	0.281 (0.205)	0.354 (0.241)
<i>Education</i>					
No high school	−0.154* (0.092)	−0.780 (0.781)	−1.245 (1.120)	−0.959 (1.275)	−2.011 (1.420)
Some college	0.057 (0.057)	−0.115 (0.445)	−0.025 (0.576)	−0.222 (0.655)	0.378 (0.734)
College	0.383*** (0.060)	0.159 (0.446)	0.379 (0.602)	0.211 (0.699)	0.178 (0.776)
Advanced	0.498*** (0.071)	−0.156 (0.481)	0.131 (0.714)	0.049 (0.817)	0.507 (0.908)
<i>Education and sales dispersion interacted</i>					
No high school	—	0.643 (0.798)	1.016 (1.134)	0.750 (1.287)	2.070 (1.429)
Some college	—	0.175 (0.457)	0.009 (0.584)	0.180 (0.664)	−0.451 (0.748)
College	—	0.234 (0.449)	−0.169 (0.597)	0.005 (0.691)	−0.022 (0.773)
Advanced	—	0.692 (0.501)	0.166 (0.720)	0.241 (0.817)	−0.266 (0.910)
<i>Sales dispersion</i>	−0.030 (0.531)	−0.216 (0.560)	—	—	—
<i>Attitudes and traits, and interactions with sales dispersion</i>	—	—	—	—	x
<i>Interacted ASVAB subtest scores, and interactions with sales dispersion</i>	—	—	—	x	x
<i>Industry, occupation, worker type, and region</i>	—	—	x	x	x
<i>ASVAB subtest scores, and interactions with sales dispersion</i>	x	x	x	x	x
<i>R-squared</i>	0.253	0.255	0.643	0.707	0.778
<i>Observations</i>	969	969	969	969	881

Table A.8: Ordinary least squares regressions of the logarithm of the hourly wage on the displayed variables for full-time employed white male workers aged 25–55 and born in the United States. Standard errors in parentheses. Statistical significance at the 10, 5, and 1 percent level denoted by *, **, and ***, respectively. Author’s calculations based on the *1979 National Longitudinal Survey of Youth*. Sales dispersion statistics from Barth et al. (2014).

	(1)	(2)	(3)	(4)	(5)
<i>Above-median subtests</i>					
3–5 subtests	–0.551 (0.589)	–0.598 (0.596)	–1.112 (0.738)	–0.922 (0.907)	–0.899 (1.033)
6–8 subtests	–1.734** (0.770)	–1.744** (0.773)	–2.191** (0.920)	–2.730** (1.145)	–3.091** (1.338)
9–10 subtests	–1.469 (0.988)	–1.370 (0.991)	–2.120* (1.198)	–2.888* (1.476)	–3.457** (1.732)
<i>Above-median subtests and sales dispersion interacted</i>					
3–5 subtests	0.547 (0.595)	0.600 (0.602)	1.163 (0.735)	0.982 (0.904)	1.052 (1.028)
6–8 subtests	1.736** (0.778)	1.748** (0.782)	2.288** (0.920)	2.902** (1.153)	3.316** (1.347)
9–10 subtests	1.422 (0.995)	1.321 (1.000)	2.188* (1.193)	3.131** (1.486)	3.650** (1.737)
<i>Education</i>					
No high school	–0.157* (0.093)	–0.915 (0.793)	–1.445 (1.135)	–0.857 (1.282)	–2.109 (1.445)
Some college	0.052 (0.057)	–0.068 (0.446)	0.116 (0.578)	–0.040 (0.660)	0.568 (0.735)
College	0.370*** (0.060)	0.189 (0.446)	0.451 (0.603)	0.420 (0.698)	0.345 (0.777)
Advanced	0.493*** (0.071)	–0.190 (0.482)	0.155 (0.717)	0.324 (0.823)	0.823 (0.915)
<i>Education and sales dispersion interacted</i>					
No high school	–	0.779 (0.810)	1.223 (1.150)	0.654 (1.294)	2.173 (1.456)
Some college	–	0.122 (0.458)	–0.134 (0.587)	0.004 (0.670)	–0.645 (0.749)
College	–	0.191 (0.449)	–0.252 (0.598)	–0.214 (0.691)	–0.216 (0.775)
Advanced	–	0.725 (0.502)	0.153 (0.724)	–0.018 (0.824)	–0.579 (0.918)
<i>Sales dispersion</i>	–0.266 (0.464)	–0.523 (0.507)	–	–	–
<i>Attitudes and traits, and interactions with sales dispersion</i>	–	–	–	–	x
<i>Interacted ASVAB subtest scores, and interactions with sales dispersion</i>	–	–	–	x	x
<i>Industry, occupation, worker type, and region</i>	–	–	x	x	x
<i>ASVAB subtest scores, and interactions with sales dispersion</i>	x	x	x	x	x
<i>R-squared</i>	0.258	0.260	0.647	0.712	0.784
<i>Observations</i>	969	969	969	969	881

Table A.9: Ordinary least squares regressions of the logarithm of the hourly wage on the displayed variables for full-time employed white male workers aged 25–55 and born in the United States. Standard errors in parentheses. Statistical significance at the 10, 5, and 1 percent level denoted by *, **, and ***, respectively. Author’s calculations based on the 1979 National Longitudinal Survey of Youth. Sales dispersion statistics from Barth et al. (2014).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Versatility</i>	-1.118*** (0.400)	-1.105*** (0.407)	-1.167*** (0.407)	-0.932** (0.423)	-1.255*** (0.448)	-1.144*** (0.411)	-1.127*** (0.414)
<i>Versatility and sales dispersion interacted</i>	1.391*** (0.479)	1.371*** (0.489)	1.448*** (0.491)	1.167*** (0.505)	1.562*** (0.529)	1.397*** (0.499)	1.400*** (0.500)
<i>Industry, occupation, worker type, and region</i>	x	x	x	x	x	x	x
<i>Education interacted with productivity dispersion</i>	x	x	x	x	x	x	x
<i>PIAAC basic skills scores, and interactions with productivity dispersion</i>	x	x	x	x	x	x	x
<i>Education, and a third- order polynomial in age</i>	x	x	x	x	x	x	x
<i>R-squared</i>	0.725	0.738	0.747	0.771	0.749	0.757	0.740
<i>Observations</i>	761	762	739	500	709	697	717

Table A.10: Ordinary least squares regressions of the logarithm of the hourly wage on the displayed variables for full-time employed male workers aged 25–55 and born in Germany. Each specification excludes one of the fourteen industries: (1) agriculture, forestry, and fishing, (2) mining and quarrying, (3) energy and water supply, waste management, and remediation activities, (4) manufacturing, and construction, (6) trade, and (7) transportation and storage. Standard errors in parentheses. Statistical significance at the 10, 5, and 1 percent level denoted by *, **, and ***, respectively. Author's calculations based on the *Programme for the International Assessment of Adult Competencies* and the *Linked Employer–Employee Data from the Institute for Employment Research*.

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
<i>Versatility</i>	-1.101*** (0.398)	-1.172*** (0.401)	-1.108*** (0.397)	-1.280*** (0.408)	-1.133*** (0.395)	-1.078* (0.622)	-1.117*** (0.399)
<i>Versatility and sales dispersion interacted</i>	1.372*** (0.479)	1.449*** (0.480)	1.359*** (0.476)	1.574*** (0.488)	1.409*** (0.473)	1.347* (0.732)	1.383*** (0.479)
<i>Industry, occupation, worker type, and region</i>	x	x	x	x	x	x	x
<i>Education interacted with productivity dispersion</i>	x	x	x	x	x	x	x
<i>PIAAC basic skills scores, and interactions with productivity dispersion</i>	x	x	x	x	x	x	x
<i>Education, and a third- order polynomial in age</i>	x	x	x	x	x	x	x
<i>R-squared</i>	0.742	0.736	0.737	0.738	0.735	0.742	0.736
<i>Observations</i>	723	763	735	691	739	726	761

Table A.11: Ordinary least squares regressions of the logarithm of the hourly wage on the displayed variables for full-time employed male workers aged 25–55 and born in Germany. Each specification excludes one of the fourteen industries: (8) information and communication, (9) accommodation and food service activities, (10) financial and insurance activities, (11) professional, scientific, and commercial services, (12) education services, (13) human health and social work activities, and (14) other services. Standard errors in parentheses. Statistical significance at the 10, 5, and 1 percent level denoted by *, **, and ***, respectively. Author's calculations based on the *Programme for the International Assessment of Adult Competencies* and the *Linked Employer–Employee Data from the Institute for Employment Research*.

	(1)	(2)	(3)	(4)	(5)
<i>Versatility</i>	-4.434* (2.272)	-3.220 (2.333)	-5.670** (2.435)	-6.084** (2.652)	-5.798** (2.718)
<i>Versatility and industry characteristics interacted</i>					
Productivity	0.428** (0.217)	0.312 (0.223)	0.545** (0.232)	0.622** (0.255)	0.584** (0.261)
Investment activity	—	—	—	-0.764 (0.804)	-0.629 (0.818)
Innovation activity	—	—	—	0.432 (0.749)	0.424 (0.796)
R&D activity	—	—	—	-1.432 (1.413)	-1.041 (1.472)
R&D employment share	—	—	—	3.799 (8.752)	2.891 (9.203)
<i>Education interacted with all industry characteristics</i>	—	—	—	—	x
<i>PIAAC basic skills scores interacted with all industry characteristics</i>	—	—	—	x	x
<i>Industry, occupation, worker type, and region</i>	—	—	x	x	x
<i>Education interacted with productivity</i>	—	x	x	x	x
<i>PIAAC basic skills scores, and interactions with productivity</i>	x	x	x	x	x
<i>Education, and a third-order polynomial in age</i>	x	x	x	x	x
<i>R-squared</i>	0.381	0.387	0.740	0.756	0.765
<i>Observations</i>	771	771	771	771	771

Table A.12: Ordinary least squares regressions of the logarithm of the hourly wage on the displayed variables for full-time employed male workers aged 25–55 and born in Germany. The industry standard deviation of log-value-added-per-worker is excluded from the controls. Standard errors in parentheses. Statistical significance at the 10, 5, and 1 percent level denoted by *, **, and ***, respectively. Author’s calculations based on the *Programme for the International Assessment of Adult Competencies* and the *Linked Employer–Employee Data from the Institute for Employment Research*.