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Diversity of Experience and Its Impact on Productivity in Creative Sectors

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Abstract

This study examines the relationship between workers' prior experience and labor productivity within Sweden's creative industries. The effectiveness of knowledge transfer relies on the cognitive differences among employees. Using longitudinal matched employer–employee data, I assess workplace skill portfolios based on (i) employees' previous occupations and (ii) the industries in which they have previously worked. The findings indicate that occupational experience diversity positively influences labor productivity, whereas industry experience diversity does not. Further distinguishing between related and unrelated experience, related occupational diversity enhances productivity, while unrelated occupational experience appears to negatively affect it. These results highlight the significance of the specific occupational skills that employees bring to new positions in driving labor productivity.

Keywords: Knowledge spillovers, Diversity, Skill relatedness, Labor mobility, Previous experience

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Introduction

Extensive research has highlighted the role of various forms of human capital in shaping firm performance [1, 2]. Yet, labor productivity is not only a function of individual skills but also depends on the coworkers with whom employees interact [3-6]. This raises the question of how the composition of skills within a workplace influences firm outcomes. This paper investigates how the diversity of skills derived from employees' prior experience affects labor productivity, focusing specifically on two dimensions: (i) previous occupations and (ii) prior industry experience. Building on Becker's [7] foundational work, scholars have long examined how occupation-specific and industry-specific human capital accumulated over a career impacts earnings and productivity [8-10]. As individuals transition across jobs, they carry knowledge from their prior roles into new positions [11]. Theoretically, workforce diversity can promote creativity and innovation, as novel combinations of differentiated skills generate new knowledge [12, 13]. However, excessive differences in skills may result in misunderstandings and conflicts, which can negatively affect performance.

For knowledge transfer and learning to occur, employees must share some degree of cognitive proximity [14]. Accordingly, I distinguish between related and unrelated forms of experience. Previous studies have assessed skill relatedness through education [15], prior industry experience [16], or occupational experience [17], all contributing to individual skill profiles. To my knowledge, only Östbring *et al.* [18] combined multiple measures, considering both education and prior industry experience. Yet, occupations are essential proxies for skills beyond formal education [19], as the specific work performed often holds more relevance than academic credentials [20]. This paper advances the literature by capturing workplace skill diversity through prior work experience, encompassing both occupational and industry-specific knowledge, which allows a deeper exploration of knowledge transfer, spillovers, and labor productivity mechanisms.

Creative industries are particularly suitable for this analysis. These knowledge-intensive sectors depend heavily on human creativity as a production input [20], host highly skilled individuals [21, 22], and feature autonomous, self-expressive work environments [20, 23]. Production in these industries is project-based and relies on short-term team interactions [24, 25], making employee interaction crucial for the productivity effects of skill diversity. Additionally, creative industries are widely recognized for their innovation potential, where the internal skill composition significantly drives innovative output [26, 27]. Focusing on a specific set of industries also mitigates sectoral heterogeneity concerns, which can otherwise obscure the relationship between diversity, relatedness, and firm performance [18]. Given their labor intensity, project orientation, and innovation potential, creative industries are an ideal context to study human capital diversity and labor productivity. Moreover, as key contributors to the knowledge economy, understanding productivity dynamics in these sectors has broader implications for regional and national economic development [20, 28].

To address these questions, I utilize longitudinal matched employer–employee data from 2007 to 2016, covering all firms and employees in Sweden's creative industries. Employees' prior five-year work histories are traced to construct skill diversity measures using a fractionalization index. Related and unrelated diversity are distinguished through Neffke and Henning's [29] labor flow-based relatedness index. Results indicate that occupational experience diversity positively affects labor productivity, while industry experience diversity does not. Unrelated occupational and industry experience negatively impacts productivity, whereas related occupational experience is positively associated with firm performance. When combining occupation and industry experience, their relatedness strongly correlates with productivity, emphasizing the importance of occupation-specific skills in driving labor productivity.

The structure of the paper is as follows. Section 2 reviews the theoretical background and literature on skills, knowledge spillovers, and firm growth. Section 3 outlines the data and variables, Section 4 presents the empirical results, Section 5 examines robustness, and Section 6 concludes.

Diversity, Relatedness, and Firm Performance

The literature on workforce diversity and firm performance is extensive. Some studies focus on team-level diversity through case studies [30] or analyze top management and founding team composition [31-33]. Others employ linked employer–employee datasets to study within-firm diversity [34-38]. Diversity can enhance performance by fostering new ideas and innovations [31, 39-41], and firms with heterogeneous knowledge bases tend to possess higher absorptive capacity, crucial for adopting and applying new knowledge [42].

However, some theoretical frameworks, such as Kremer's O-ring model, suggest that similar skills may be necessary for optimal productivity in certain tasks [43]. Employees may also prefer working with similar colleagues, and excessive diversity can lead to conflicts or reduced cooperation, negatively affecting outcomes [44-47].

Lazear [40] posits that for diversity to positively influence performance, workforce skills should be complementary yet relevant to one another and learnable at reasonable cost by other employees. Cognitive proximity or complementarity is essential for effective learning [14]. Too much similarity may cause lock-in, limiting firms' ability to adopt innovations, while excessive cognitive distance can hinder communication and knowledge sharing [48, 49]. Empirical findings suggest an inverted U-shaped relationship between cognitive distance and innovation, indicating that knowledge bases should be neither too similar nor too different.

To capture these dynamics, the concept of relatedness has been introduced, distinguishing between related and unrelated diversity [15, 17, 18, 50, 51], which allows a nuanced analysis of how workforce composition influences firm performance.

When assessing how skill diversity affects firm performance, much of the existing research has concentrated on educational background diversity, typically finding positive associations [34-36]. Boschma *et al.* [15] go further by analyzing the type of educational diversity within firms and report that firms with higher education-relatedness experience greater productivity growth. Similar patterns are observed by Östbring and Lindgren [51], with stronger effects in labor-intensive compared to capital-intensive sectors.

Nevertheless, using education as a proxy for workforce skills has been criticized, as educational quality varies across countries and even within regions of a single country [52, 53]. Moreover, a substantial portion of human capital is acquired through work experience, which formal education alone does not capture. Becker [7] distinguished between general human capital, which enhances productivity across jobs, and firm-specific human capital, which cannot be transferred across positions. Extending this perspective, researchers have highlighted that human capital can also be industry- or occupation-specific [54, 55]. As a result, when employees have highly heterogeneous skills, collaboration may not yield productivity gains due to insufficient mutual understanding, aligning with the cognitive proximity argument [14].

Another common approach to measuring human capital is through prior occupational experience [20, 56-58]. Occupations reflect practical skills that go beyond formal education [19, 59]. Although research on occupational diversity within firms remains limited, existing evidence suggests a positive influence on innovation [36, 38]. Östbring *et al.* [17] further show that the benefits of occupational diversity on productivity are primarily driven by relatedness, while unrelated occupations tend to have neutral or negative effects. In addition to education and occupation, industry experience constitutes an important component of human capital [55]. Östbring *et al.* [18] investigate the impact of industry experience relatedness on firm performance in knowledge-intensive business services, finding that both the variety of knowledge and prior industry experience positively influence outcomes, particularly in single-plant firms.

Overall, prior literature indicates that educational, occupational, and industry experience diversity can enhance firm performance, with related diversity showing stronger positive effects. Yet, some findings diverge: Timmermans and Boschma [16] report that unrelated diversity drives productivity growth for firms in Copenhagen, likely due to the predominance of service industries, which may benefit more from unrelated skill sets. Consequently, it remains unclear which type of diversity matters most in creative industries.

Moreover, most studies focus on the diversity of employees' current roles rather than their full occupational and industrial histories. Theoretically, workers' knowledge is shaped by prior experiences and tasks, which they carry into new positions [11]. While labor mobility has been extensively explored, there is limited understanding of the specific skills and knowledge employees bring into firms and how these affect performance [15, 16]. Skills may derive from prior occupations, previous industry experience, or a combination of both. Sullivan [10] emphasizes that human capital is simultaneously connected to both occupation and industry, and job polarization literature similarly conceptualizes a "job" as an occupation–industry interaction [60, 61]. Combining both dimensions is justified as industry factors can influence wages even when controlling for occupation.

Employee diversity in creative industries

The discussion above has not explicitly addressed creative industries, prompting questions about how skill diversity manifests in these sectors and what insights can be gained from studying them. Creative industries are particularly suitable for this investigation for several reasons.

First, workers in creative industries frequently collaborate in teams [24, 25, 62, 63]. The project-based nature of these industries requires employees to repeatedly form new teams, which can be challenging for smaller firms [64, 65]. Evidence suggests that creative industries benefit especially from teams with diverse skill sets [41, 66], making the broader literature on firm diversity and performance highly relevant. The higher likelihood of teamwork in these sectors also allows for clearer insights into how diversity affects knowledge spillovers and productivity.

Second, creative industries exhibit high labor mobility [20, 67]. Creative workers tend to be flexible in career choices, facilitated by transferable skills and education [20]. This aligns with the structure of these industries, which often comprise small firms with high turnover [68], increasing the probability that employees bring experience from other industries and occupations. Additionally, these sectors are labor-intensive and employ highly skilled individuals who generate new knowledge [22].

Third, occupational skills are particularly crucial in creative industries. By definition, these sectors rely on a high concentration of creative workers, and the "creative class" framework emphasizes occupations and daily tasks over industry affiliation [20]. The occupational composition across industries can be highly heterogeneous; for example, a high-tech firm may employ accountants, engineers, manufacturing staff, and service workers [69]. Barbour and Markusen [70] show that the occupational structures of California's high-tech industries differ from other regions in the US, suggesting that industry-specific skills may be less critical in creative sectors.

Data, Variables, and Method

To analyze how the relatedness of workers' prior skills influences labor productivity in creative industries, I utilize longitudinal matched employer–employee register data from Statistics Sweden, covering the years 2007–2016. Following previous research, plants with fewer than 10 employees are often excluded to ensure sufficient skill diversity [35, 36]. However, creative industries are predominantly composed of small firms, as illustrated in **Figure 1**. For clarity in the visualization, all plants with more than fifty employees are aggregated into the final category.

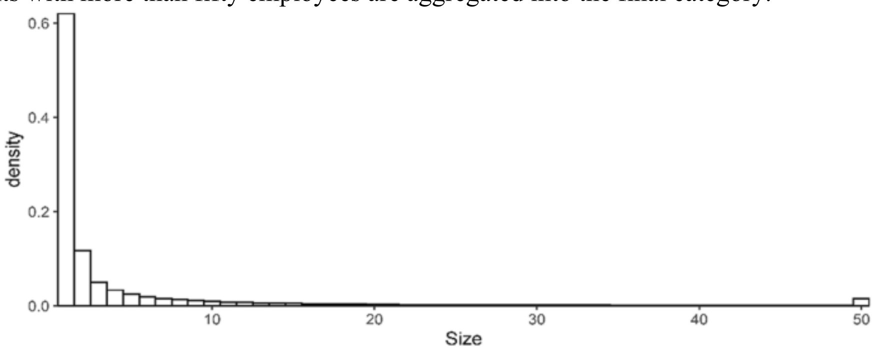

Figure 1. Distribution of Plant Size

The figure illustrates firm size distribution, revealing that around 62 percent of firms employ only one person, while an additional twelve percent have just two employees. To include a representative sample of creative industry firms without excluding too many, only firms with at least three employees are retained, ensuring a minimum level of skill diversity.
Employees' work histories are traced five years backward to capture the types of experience they bring. If an individual has changed occupations or industries multiple times, the most recent experience is used; if they have remained in the same role and industry, their current position is considered. Throughout the study period, workers in creative industries have experience spanning 113 occupations and roughly 700 industries. **Table 1** presents the ten most common occupations and industries among current employees in these sectors.

Table 1. The most frequent occupational backgrounds and prior industries among employees currently working in creative industries

Occupation	Industry
Specialists in computing and digital systems	Firms engaged in programming and software-development tasks
Assistants in applied sciences and technical engineering	Companies offering IT-oriented advisory and consultancy services
Professionals in architecture, engineering, and allied technical fields	Organizations active in construction, civil works, and technical project consulting
Individuals engaged in literary, artistic, or performing creative work	Agencies operating in advertising, promotion, and related creative communication
Associates in finance, commerce, and client-oriented services	Enterprises focused on industrial process planning and specialized technical consultancy
Supervisors or coordinators of small-scale business units	Consultancies providing managerial advice across business sectors
Retail-oriented staff such as shop or stall attendants and product demonstrators	Engineering firms working with environmental systems, energy solutions, plumbing, heating, and climate-control technologies
Professionals working in business administration and organizational affairs	Offices delivering architectural design and planning services
Technical assistants in computing and information systems	Companies involved in niche software publishing and digital product release
Associates in artistic expression, entertainment, and athletic activities	Laboratories and service providers conducting technical assessments, inspections, and analytical testing

Variables and Method

Dependent variable
The main performance indicator in this study is labor productivity, expressed as the log of value-added per worker. Earlier work in this field typically evaluates how the relatedness of employees' skills affects productivity growth by introducing time lags exceeding one year, acknowledging that knowledge spillovers often take time before materializing in measurable outcomes. Because many creative sectors operate through short-lived, project-driven activities, immediate spillover effects are also relevant; therefore, I apply a one-year lag. Consistent with Timmermans and Boschma [16], when a company operates multiple plants, the total value added is allocated across establishments according to their share of wage payments.
Although value added is frequently used to capture productivity, applying it to creative industries can be problematic [71]. Productivity, in broad terms, reflects a firm's capacity to convert inputs into outputs, yet service-oriented activities—common within creative sectors—do not resemble the input–output structures found in manufacturing, complicating measurement [72]. For this reason, in addition to the value-added specification, I also estimate models where **wages** serve as the dependent variable. Based on human capital theory, wages can be interpreted as a proxy for productivity [73, 74]. If knowledge circulates more effectively among employees, firms should exhibit greater productivity, which in turn is expected to be reflected in higher earnings.

Measuring diversity and relatedness of skills
The first step involves quantifying the variety of skills using a fractionalization index [75] following the approach of Parrotta *et al.* [36]. The measure is calculated for each plant as one minus the Herfindahl index:

$$Fract_{wt} = 1 - \sum_{S=1}^{S} P^{2}wst \tag{1}$$

Here, www denotes the plant, s refers to the category used to define diversity, and t identifies the year. The term p^2 is the squared proportion of workers in each category s. The index ranges from zero—where all workers belong to the same category—to its maximum when all categories are perfectly balanced. Diversity is computed for both occupational backgrounds and industry experience.

Beyond the level of diversity itself, the literature also highlights the importance of the degree of relatedness among the skill profiles present in a workplace. Entropy-based measures developed by Frenken *et al.* [50] have been widely applied to distinguish between related and unrelated variety [15, 17, 18, 51]. However, because such indices rely directly on occupational and industry classifications—systems that may not accurately reflect cognitive proximity due to their arbitrary boundaries [76]—they can fall short in capturing true relatedness.

To more reliably determine which industries or occupations are cognitively close or distant, I apply the skill-relatedness (SR) metric proposed by Neffke and Henning [29]. This measure rests on the idea that workers tend to move between industries where their accumulated skills remain useful. The procedure, based on Swedish labor flows, follows several steps. First, I construct a matrix of pairwise movements between all 5-digit industry codes for the years 2004–2007. As in Neffke and Henning [29], I exclude job changes involving individuals earning below the median wage of their industry and managers, since these groups are less likely to possess industry-specific competencies. The goal is to focus on transitions that genuinely represent similarity in required skills.

Next, a zero-inflated negative binomial model is estimated with the number of observed flows between each industry pair as the dependent variable. Explanatory variables include employment size, average wage levels, and wage growth in the origin and destination industries. From the resulting coefficients, predicted flow values are generated. The SR index is defined as:

$$SR_{ij} = \frac{F_{ij}^{obs}}{\widehat{F_{ij}}} \tag{2}$$

where F_{ij}^{obs} and $\widehat{F_{ij}}$ represent the observed and predicted job flows, respectively. When this ratio exceeds 1, transitions occur more frequently than expected, indicating skill similarity; values below 1 reveal weak or absent skill overlap. Finally, by assuming that the probability of an employee moving from industry i to industry j is

$$\hat{p}_{ij} = \frac{\widehat{F_{ij}}}{emp_i} \tag{3}$$

it becomes possible to statistically assess whether any observed flows are exceptionally high relative to expectations, thus identifying cases of genuine skill relatedness.

SR exceeds the value of 1—and is statistically meaningful—for only about 4 percent of all possible industry pairs. A major complication in the construction of this measure arises from the substantial revision of the NACE classification system in 2007, which reorganized and redistributed industrial categories in ways that made it difficult to convert older codes into the updated structure. Because of this reclassification, the skill-relatedness index had to be recalculated for the revised codes using labor mobility data from 2010–2013.

Human capital, however, is shaped not only by the industry in which a worker is employed but also by the type of job performed. Previous research, such as the work by Gathmann and Schönberg [8], shows that individuals tend to change occupations in directions that allow them to build on their existing abilities. For this reason, a corresponding skill-relatedness matrix is produced for 3-digit occupational groups, using the same methodological logic applied to industries. The main procedural difference lies in the measurement frequency: occupation flows are recorded every second year rather than annually because full-population occupational information is gathered biennially. After a two-year window, roughly four-fifths of the population is covered, making occupation switches more reliable. Using this approach, approximately 13 percent of occupational combinations display statistically meaningful relatedness.

Once these relationships are identified, all industry and occupation pairs with meaningful skill connections are mapped. To translate this into plant-level measures, every possible combination of workers' industry and occupation backgrounds within a plant is enumerated. The portion of combinations that show significant relatedness—those with an SR greater than one—is divided by the total number of combinations to obtain the plant-level share of related skills. In a similar manner, the share of workers with identical industry experience is calculated. Whatever remains represents skill-unrelated combinations. Since these three components sum to one, the "similar skills" category is not included in the estimations.

Method

To explore how differences in skill relatedness correspond to variations in average labor productivity, the analysis relies on a fixed-effects linear regression model. The panel is unbalanced because firms may enter or exit over time. As is typical in studies focused on productivity outcomes, the starting point is a formulation inspired by the Cobb–Douglas production function, which expresses plant-level productivity for plant i at time t as a function of technology (A), capital inputs (K), and labor (L):

$$Y_{it} = AL_{it}^{\alpha} K_{it}^{\beta} \tag{4}$$

Since the focus of the analysis is on output per worker rather than total production, the standard Cobb–Douglas specification can be normalized by dividing by employment L. This yields a productivity expression of the form

$$\frac{Y_{it}}{L_{it}} = y_{it} = \frac{AL_{it}^{\alpha} K_{it}^{\beta}}{L_{it}} = AL_{it}^{\alpha-1} K_{it}^{\beta} \tag{5}$$

To make the model suitable for empirical estimation, the equation is then transformed into logarithms, treating the parameter A as the composite term that absorbs all control variables included earlier:

$$ln\, yit = \delta\, ln\, L_{it} + \beta\, ln\, K_{it} + \varphi_1 Div_{it-1} + \varphi_2\, ln\, \tau_{it} + \varphi_3\, ln\, Z_{rt} + \varphi_4 D_f + \varphi_5 D_t + u_{it} \quad (6)$$

where δ=α−1. Because α<1 by assumption, the elasticity of labor in this transformed equation is theoretically expected to be negative. The variables Divit−1 capture plant-level diversity and relatedness, lagged by one year to allow for spillovers in knowledge and skills to materialize. The vector τit contains plant-specific controls, while Zrt summarizes region-level characteristics; Df and Dt represent firm and time fixed effects.

A challenge widely discussed in the literature is that the disturbance term incorporates two components:

$$u_{it} = \omega_{it} + \eta_{it} \quad (7)$$

where ωit reflects productivity shocks known to firms but not to the econometrician, and ηit is observable to both. Conventional linear estimators tend to be biased in this context: labor coefficients are usually overstated, while those of capital become understated. To address this, the Olley and Pakes [77] (OP) framework is adopted. This semi-parametric methodology relies on identifying a proxy variable—typically investment—that responds systematically to firm-specific productivity shocks. In this setup, investment behavior serves as a control function that mitigates endogeneity in input choices. Consistent with Tao *et al.* [78], investment is proxied by changes in fixed assets. A similar multi-step identification strategy has been implemented in numerous productivity studies [35, 78, 79]

Control variables

In alignment with the Cobb–Douglas structure, labor and capital are core inputs included in all specifications. Additionally, the model accounts for the diversity of educational backgrounds, ensuring that the estimated effects of workplace diversity are not confounded by differences in training or schooling pathways. Prior research generally reports a positive association between educational heterogeneity and productivity [34-36]. Further controls include the proportion of highly educated employees, the establishment's age, and an indicator for multi-plant status [51, 80]. Because skills may also depend on experiences gained outside the local labor market, the share of employees with work histories in other regions is introduced to capture this dimension [15, 16]. The model also incorporates municipal population density to reflect potential agglomeration advantages influencing productivity and wages [80, 81]. **Table 2** summarizes all variables used in the empirical analysis.

Table 2. List of Variables and Descriptive Statistics

Variables	Description	Max	Min	Mean	SD
Outcome variables					
Avg_Prod (000)	Value added per employee	809,103.1	0.094	937.217	7396.918
Wages (00)	Average annual wage at the plant	25,718.73	3.667	3865.126	1366.513
Diversity and Relatedness Measures					
FRACT_occu	1 minus the Herfindahl index of occupational diversity	0.959	0	0.641	0.206
FRACT_ind	1 minus the Herfindahl index of industry diversity	0.976	0	0.568	0.245
Occ_R	Proportion of experience in related occupations	1	0	0.44	0.231
Occ_U	Proportion of experience in unrelated occupations	1	0	0.313	0.238
Ind_R	Proportion of experience in related industries	1	0	0.318	0.229
Ind_U	Proportion of experience in unrelated industries	1	0	0.337	0.255
Occ_Ind_R	Proportion of experience in related occupation-industry combinations	1	0	0.161	0.165
Occ_Ind_U	Proportion of experience in unrelated occupation-industry combinations	1	0	0.149	0.177
Control Variables					
K (000)	Capital	1.80E+08	0	29,533.66	1,137,329
L	Labor (plant size)	3,331	3	20.859	57.582
FRACT_Edu	1 minus the Herfindahl index of education diversity	0.91	0	0.578	0.215
Edu	Share of employees with at least a 3-year university degree	1	0	0.352	0.296
Change_LA	Share of employees with labor market experience elsewhere	1	0	0.221	0.221
Age	Years since the firm's establishment	30	1	12.577	8.17
Multiplant	Dummy variable = 1 if firm has multiple plants	1	0	0.297	0.457

Den	Population density (per km²)	5,496.4	0.2	1,575.774	1,943.169

All independent variables are measured at time t, except for the diversity and relatedness measures, which are recorded at t−1 to allow sufficient time for knowledge spillovers to occur. All monetary values are expressed in SEK.

The final columns of **Table 2** report descriptive statistics for the variables in their original, non-logged form. The fractionalization indices indicate that employees generally have diverse backgrounds, with occupational experience being more varied on average than industry experience. Approximately one-third of the workforce holds a higher education degree. The table also highlights that many workplaces are small, with an average size of 21 employees and a median of 9, which is typical in creative industries, as illustrated in Fig. 1. About 30% of the firms operate multiple plants.

Empirical Findings and Analysis

Table 3 displays the baseline estimation results. Columns 1(a)–(c) report linear regression results with average labor productivity as the dependent variable, while columns 2(a)–(c) present the Olley–Pakes estimates. Columns 3(a)–(c) show linear regression models using average wages as the dependent variable.

Table 3. Baseline results

	Value added – FE			**Value added – OP**			**Wages – FE**		
	1(a)	**1(b)**	**1(c)**	**2(a)**	**2(b)**	**2(c)**	**3(a)**	**3(b)**	**3(c)**
FRACT_occu	0.063***			0.038**			0.021***		
	(0.009)			(0.016)			(0.005)		
FRACT_ind	0.007			− 0.174***			− 0.025***		
	(0.008)			(0.016)			(0.004)		
Occ_R		0.026***			0.042***			0.024***	
		(0.008)			(0.014)			(0.004)	
Occ_U		− 0.010			− 0.184***			− 0.016***	
		(0.009)			(0.015)			(0.004)	
Ind_R		0.014*			− 0.010			− 0.003	
		(0.008)			(0.014)			(0.004)	
Ind_U		− 0.022***			− 0.235***			− 0.036***	
		(0.008)			(0.014)			(0.004)	
Occ_I			0.031***			0.126***			0.027***
			(0.009)			(0.018)			(0.005)
Occ_Ind_U			− 0.035***			− 0.296***			− 0.040***
			(0.009)			(0.016)			(0.005)
Capital	0.021***	0.021***	0.021***	0.020***	0.022***	0.021***	0.004***	0.004***	0.004***
	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.000)	(0.000)	(0.000)
Labor	− 0.077***	− 0.072***	− 0.072***	− 0.060***	− 0.073***	− 0.076***	− 0.022***	− 0.022***	− 0.022***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)
FRACT_Edu	0.079***	0.097***	0.097***	− 0.073***	− 0.021	− 0.057***	0.026***	0.032***	0.029***
	(0.011)	(0.011)	(0.011)	(0.018)	(0.017)	(0.017)	(0.006)	(0.005)	(0.005)
Edu	0.044***	0.050***	0.049***	0.191***	0.181***	0.188***	0.045***	0.047***	0.045***
	(0.011)	(0.011)	(0.011)	(0.014)	(0.013)	(0.014)	(0.006)	(0.006)	(0.006)
Age	0.002***	0.002***	0.002***	− 0.005	− 0.004	− 0.004	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.197)	(0.191)	(0.189)	(0.000)	(0.000)	(0.000)
Multiplant	0.036**	0.035**	0.035**	0.169***	0.146***	0.159***	0.005	0.005	0.005
	(0.015)	(0.015)	(0.015)	(0.009)	(0.009)	(0.009)	(0.004)	(0.004)	(0.004)
Change_LA	− 0.088***	− 0.083***	− 0.084***	− 0.036**	− 0.020	− 0.059***	− 0.050***	− 0.048***	− 0.051***
	(0.009)	(0.009)	(0.008)	(0.015)	(0.015)	(0.015)	(0.004)	(0.004)	(0.004)
Den	0.028***	0.027***	0.027***	0.051***	0.045***	0.047***	0.022***	0.022***	0.022***
	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)
Obs.	88,078	88,078	88,078	88,078	88,078	88,078	88,078	88,078	88,078

Plants	15,983	15,983	15,983	15,983	15,983	15,983	15,983	15,983	15,983
R-squared	0.785	0.785	0.785				0.894	0.894	0.894
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Robust standard errors are shown in parentheses for columns 1 and 3, while the OP estimations report bootstrapped standard errors based on 250 replications; significance levels are indicated as *** $p < 0.01$, ** $p < 0.05$, * < 0.1, and the constant term estimates are omitted.

Starting with the diversity measures, assessed using fractionalization indices (columns 1(a), 2(a), 3(a)), the findings indicate that variation in previous occupational experience among employees is positively associated with both labor productivity and wages in the following year. In contrast, the fractionalization of industry experience does not show a significant link to labor productivity, though it exhibits a negative and significant relationship in the OP estimation and for wages. These results suggest that bringing together employees from diverse occupational backgrounds benefits productivity, whereas assembling staff from a wide range of industries does not. The positive effects of occupational diversity align with findings from Parrotta *et al.* [36] and Söllner [38], though their research focused on innovation rather than productivity. Regarding industry experience, one potential explanation is the limited transferability of industry-specific human capital; communication and coordination challenges may arise from differences in routines and practices. Additionally, in creative industries, the focus is often on individual creativity linked more closely to occupational tasks than to industry-specific experience.

Examining the degree of diversity (columns 1(b), 2(b), 3(b)) provides further insights, as previous studies show inconsistent results due to different mechanisms underlying skill acquisition and types of knowledge. The results reveal that the relatedness of occupational experience is positively associated with productivity and wages, whereas relatedness of industry experience is generally not significant, except marginally in column 1(b) at a 10% level. The importance of related occupational experience is also supported by Östbring *et al.* [17]. However, the negative effect of industrial relatedness contrasts with the positive outcomes reported by Östbring *et al.* [18] for KIBS industries. Unrelatedness in both occupational and industrial experience is negatively associated with firm performance, implying that the positive effect observed for occupational diversity is primarily driven by related occupational experience rather than unrelated diversity. The negative relationship for unrelated experiences aligns with theories on cognitive proximity, where excessive differences in skills hinder knowledge spillovers [14].

In the final columns across the three specifications, the analysis considers the combined effect of relatedness and unrelatedness across both occupation and industry experience—a measure not commonly explored in firm relatedness literature, though labor economics emphasizes that skills derive from task engagement encompassing both dimensions. The results consistently show that related experience correlates positively with productivity and wages, while unrelated experience negatively affects firm performance. Notably, the coefficient magnitudes are higher than in columns 1(b), 2(b), and 3(b), highlighting the significance of combining occupational and industry skills for knowledge spillovers, which then translate into higher productivity or wages.

Overall, the findings suggest that occupational experience diversity enhances labor productivity, while industry experience diversity appears largely insignificant. When distinguishing between types of diversity, positive effects stem mainly from related occupational experience. These patterns generally align with the literature on knowledge flows and relatedness [15, 17, 18, 51]. Unrelated occupational and industrial experience exhibits either no effect or a negative impact on productivity and wages.

A question arises as to why firms might employ individuals with unrelated experience. One explanation is that firms may not fully control workforce composition [35], which is particularly relevant in Sweden, where firms often struggle to find ideal candidates—an issue more pronounced in knowledge-intensive sectors. Additionally, certain combinations of unrelated skills may still be complementary, potentially enhancing productivity and wages [6]. Limited information on optimal skill combinations may further explain such workforce composition, especially given that creative industries are predominantly small firms.

Endogeneity in hiring is another concern, as more productive firms may attract or select more productive workers, which could bias the regressions in **Table 3**. Instrumental variable approaches were attempted but proved weak and thus were excluded, as weak instruments can produce biased and uninformative results [82]. Nevertheless, economic theory and prior research suggest that the observed relationships between diversity and productivity likely hold in the expected direction, as diversity fosters idea generation, and the results on relatedness support existing studies.

Regarding controls, educational diversity is positively and significantly associated with productivity in linear models, consistent with previous research [34-36], though OP estimation shows a negative and significant effect, warranting cautious interpretation. Other control variables behave as anticipated: plant size exhibits a negative sign due to the labor-adjusted dependent variables; labor elasticity is high (~0.93), reflecting the labor-intensive nature of creative industries, while capital has a small but positive effect (~0.02). The proportion of highly educated employees and workplace age positively correlate with productivity and wages. Multi-plant and older firms show higher productivity, whereas hiring individuals with prior regional experience negatively affects productivity, potentially due to localized knowledge and differing routines or adjustment periods. Finally, workplaces in denser regions demonstrate higher productivity, as expected [80].

These findings have policy implications for workforce planning in creative industries. Instead of focusing solely on individual skills, firms should consider how new hires' skills complement the existing workforce. A higher degree of relatedness enhances labor productivity—whether measured through value added or wages—supporting firm growth. In contexts like Sweden, where knowledge-intensive firms face challenges in matching the right person to the right job, these results also suggest that plant location decisions should account for the local composition of labor market skills.

Robustness and stability

To further evaluate the consistency of the findings, three alternative model specifications are examined and discussed.

Experience diversity versus employee turnover

Creative industries are characterized by high labor mobility [20, 67], so it is crucial to determine whether the link between experience diversity and productivity reflects actual skill effects rather than the firm's hiring and departure patterns. To test this, two alternative approaches are employed. In the first, **Table 4** reports the results when controlling for both the proportion of newly hired employees and the proportion of employees who have exited the firm.

Table 4. Productivity estimations when controlling for new hires and those who have left the firm

	Value added – FE			**Value added – OP**			**Wages – FE**		
	1(a)	**1(b)**	**1(c)**	**2(a)**	**2(b)**	**2(c)**	**3(a)**	**3(b)**	**3(c)**
FRACT_occu	0.031***			0.024			0.004		
	(0.009)			(0.016)			(0.004)		
FRACT_ind	−0.028***			−0.121***			−0.044***		
	(0.008)			(0.015)			(0.004)		
Occ_R		0.021***			0.050***			0.022***	
		(0.008)			(0.014)			(0.004)	
Occ_U		− 0.016*			−0.166***			−0.019***	
		(0.009)			(0.015)			(0.004)	
Ind_R		− 0.004			0.028**			−0.013***	
		(0.008)			(0.014)			(0.004)	
Ind_U		−0.044***			−0.182***			−0.047***	
		(0.007)			(0.014)			(0.004)	
Occ_Ind_R			0.019**			0.151***			0.021***
			(0.009)			(0.017)			(0.005)
Occ_Ind_U			−0.053***			−0.246***			−0.049***
			(0.009)			(0.015)			(0.004)
Share hires	−0.356***	−0.359***	−0.357***	−0.576***	−0.544***	−0.572***	−0.192***	−0.189***	−0.187***
	(0.009)	(0.009)	(0.009)	(0.015)	(0.015)	(0.015)	(0.004)	(0.004)	(0.004)
Share left	0.017*	0.018*	0.017*	0.066***	0.054***	0.056***	0.013***	0.013***	0.012***
	(0.010)	(0.010)	(0.010)	(0.016)	(0.016)	(0.016)	(0.004)	(0.004)	(0.004)
Observations	88,078	88,078	88,078	88,078	88,078	88,078	88,078	88,078	88,078
Plants	15,983	15,983	15,983	15,983	15,983	15,983	15,983	15,983	15,983
R-squared	0.791	0.791	0.791				0.898	0.898	0.898

Robust standard errors are reported in parentheses for columns 1 and 3, while the OP estimations use bootstrapped standard errors with 250 replications. Significance levels are indicated as ***$p < 0.01$, **$p < 0.05$, and * < 0.1. The constant term is not reported, and all specifications include control variables and year fixed effects.

When accounting for employee turnover, the diversity and relatedness measures generally show similar patterns to the baseline results. Occupational diversity is significant only in the first specification (column 1(a)), with occupational relatedness positively affecting productivity and occupational unrelatedness having a negative effect. Industry relatedness is positively associated with value added in the OP estimation but negatively related to wages, while unrelated industry experience consistently reduces productivity. The last columns across the three specifications (1(c), 2(c), 3(c)) confirm these relationships. Notably, the share of newly hired employees has a negative impact on both productivity and wages, suggesting that the benefits from employee turnover may take time to materialize, as teams tend to become more effective with prolonged collaboration.

Further robustness checks were conducted on a subset of plants with no workforce changes during the sample period. Although this limits the sample, it helps clarify the mechanisms underlying labor productivity. The results, shown in the appendix, reveal that diversity measures now exhibit a negative relationship with productivity, while relatedness measures for occupation and industry are mostly insignificant, and unrelated experience remains negatively associated with productivity. However, a higher proportion of related occupational and industry experience continues to positively affect productivity, while unrelated experience maintains its negative effect. This indicates that part of the positive impact of related experience may be driven by workforce churn, where new related knowledge contributes to productivity gains, but even in stable workforces, related experience remains beneficial.

Plant size

To examine potential differences between smaller and larger workplaces, the sample is divided into firms with at least 10 employees and those with fewer than 10 employees. It is worth noting that prior studies often exclude firms with fewer than 5 employees [18] or 10 employees [35, 36]. The findings are summarized.

They largely align with previous findings for larger firms. The key difference is that smaller plants do not appear to benefit from occupational or industry relatedness individually, but do gain from combined industry–occupation relatedness. Nonetheless, unrelatedness remains negatively associated with productivity. There are two possible reasons why occupational relatedness does not show significant effects: smaller firms may not reach the same levels of relatedness as larger firms, resulting in too little variation for statistical significance, and the limited workforce might require employees to perform multiple tasks collectively rather than in specialized teams. It is also possible that a certain firm size is necessary to capitalize on relatedness. Still, the combined relatedness of industry and occupation is significant for both small and large plants.

Plant age

Following Timmermans and Boschma [16], **Table 6** reports results for plants at least five years old, since younger firms face the liability of newness [83]. In this sample, roughly 26% of plants are excluded.

Table 6. Regression results when only firms that are at least 5 years old are included

	Value added – FE			Value added – OP			Wages – FE		
	1(a)	1(b)	1(c)	2(a)	2(b)	2(c)	3(a)	3(b)	3(c)
FRACT_occu	0.069***			0.051**			0.026***		
	(0.010)			(0.020)			(0.005)		
FRACT_ind	0.010			− 0.107***			− 0.022***		
	(0.009)			(0.017)			(0.004)		
Occ_R		0.041***			0.081***			0.031***	
		(0.009)			(0.018)			(0.005)	
Occ_U		− 0.001			− 0.174***			− 0.010*	
		(0.011)			(0.019)			(0.005)	
Ind_R		0.025***			0.041**			0.002	
		(0.009)			(0.018)			(0.004)	
Ind_U		− 0.014			− 0.178***			− 0.031***	
		(0.009)			(0.016)			(0.004)	
Occ_Ind_R			0.042***			0.191***			0.031***
			(0.011)			(0.021)			(0.005)
Occ_Ind_U			− 0.040***			− 0.267***			− 0.039***
			(0.012)			(0.019)			(0.005)
Observations	65,424	65,424	65,424	65,424	65,424	65,424	65,424	65,424	65,424
Plants	12,020	12,020	12,020	12,020	12,020	12,020	12,020	12,020	12,020
R-squared	0.780	0.780	0.780				0.899	0.899	0.899

Standard errors are reported in parentheses for columns 1 and 3, and the OP estimates use bootstrapped standard errors based on 250 replications. Significance is denoted as *** $p < 0.01$, ** $p < 0.05$, * < 0.1, with the constant term omitted, and all regressions control for covariates and year fixed effects.

The findings largely mirror the baseline results: occupational experience diversity is positively linked to labor productivity, while industry experience diversity does not show a notable effect. When considering relatedness, both occupational and industry relatedness, as well as their combination, are positively associated with productivity, though industry relatedness alone is not significant in wage models. In contrast, unrelatedness in either domain is negatively correlated with firm performance, emphasizing the value of cognitive closeness among employees for knowledge sharing and productivity benefits. To examine the factors contributing to success in new ventures within creative industries, **Table 7** reports the results for start-ups instead of mature firms.

Table 7. Labor productivity in startups

	Value added – FE			Value added – OP			Wages – FE		
	1(a)	**1(b)**	**1(c)**	**2(a)**	**2(b)**	**2(c)**	**3(a)**	**3(b)**	**3(c)**
FRACT_occu	0.092***			0.066**			0.025***		
	(0.016)			(0.028)			(0.008)		
FRACT_ind	0.032**			– 0.239***			– 0.024***		
	(0.015)			(0.027)			(0.007)		
Occ_R		0.017			0.034			0.012*	
		(0.014)			(0.024)			(0.007)	
Occ_U		– 0.003			– 0.170***			− 0.009	
		(0.015)			(0.025)			(0.008)	
Ind_R		0.017			− 0.059**			− 0.015**	
		(0.015)			(0.025)			(0.007)	
Ind_U		– 0.020			– 0.294***			– 0.035***	
		(0.014)			(0.024)			(0.007)	
Occ_Ind_R			0.032**			0.117***			0.013*
			(0.016)			(0.029)			(0.008)
Occ_Ind_U			– 0.031**			– 0.294***			– 0.027***
			(0.015)			(0.025)			(0.007)
Observations	32,259	32,259	32,259	32,259	32,259	32,259	32,259	32,259	32,259
R-squared	0.770	0.770	0.770				0.903	0.903	0.903

Robust standard errors are reported in parentheses for columns 1 and 3, while the OP estimations present bootstrapped standard errors based on 250 replications. Significance levels are indicated as *** $p < 0.01$, ** $p < 0.05$, * < 0.1, and the constant term is not shown. All models include control variables.

The results are less straightforward but resemble those observed for smaller plants in **Table 6**. Occupational diversity continues to exhibit a positive relationship with productivity, whereas the results for industry diversity are inconsistent: fixed-effect estimates for value added are positive, but other models (columns 2(a) and 3(a)) show a negative association. Additionally, most relatedness measures are either statistically insignificant or inconsistent when considered separately. However, the combined relatedness of industry and occupation aligns with previous findings: related experience boosts productivity, while unrelated experience hinders it. These patterns suggest that for start-ups, employee experience should be diverse but not excessively so. Smaller teams increase the likelihood of close collaboration, so related diversity in both industry and occupation is particularly beneficial during the early stages. These results support Koster and Andersson [84], who highlight the importance of occupational skills in addition to industry skills for start-up survival, implying that focusing on only one dimension of prior experience is insufficient to enhance productivity.

Conclusions

This study investigates how employee work experience diversity influences labor productivity in Sweden's creative industries, based on the idea that workers bring their expertise and knowledge when they change jobs. While labor mobility is widely recognized for its positive effects, the specific types of knowledge and skills transferred to firms have received less attention. Some studies suggest that firm performance depends on the type of knowledge acquired and its alignment with the existing knowledge base [15, 16, 18], while others emphasize the role of knowledge diversity in promoting innovation or productivity growth [35, 36]. Yet, no prior research has explicitly examined how the diversity of employees' past experience, across occupations and industries, relates to labor productivity.

The findings indicate that occupational experience diversity positively affects productivity, whereas industrial experience diversity is either insignificant or negatively associated. When distinguishing between related and unrelated experience, the positive effects are primarily driven by relatedness, consistent with previous studies on relatedness and firm performance [18, 19, 85]. This effect is stronger when relatedness is measured as a combination of industry and occupational experience rather than separately, suggesting that individual human capital is connected to both dimensions.

Beyond contributing to the literature on knowledge spillovers and productivity mechanisms stemming from prior experience, these findings have policy relevance. Given the role of creative industries in regional development, understanding the drivers of labor productivity benefits the broader economy. The results also underline the importance of matching the right employee to the right position, particularly in knowledge-intensive firms in Sweden, which often struggle to recruit suitable talent. Considering employees' experience composition—hiring individuals with related occupational or combined industry–occupation experience—can enhance productivity, reflected in both value added and wages. Since most firms recruit locally, these findings also suggest that creative, knowledge-intensive firms may benefit from locating in regions with a high concentration of workers with related skills.

The study opens several avenues for further research. Given the demonstrated importance of occupation-specific skills, it would be valuable to examine which occupational combinations most enhance productivity. While prior research emphasizes that non-overlapping skills foster new knowledge creation [86], the literature on occupational combinations remains limited. Additionally, exploring these dynamics from an innovation perspective would be insightful. Furthermore, extending the analysis to consider skill complementarity, which is not captured by the diversity or relatedness measures, could provide a deeper understanding of the links between workforce composition and productivity. Finally, as the study lacks suitable instruments or exogenous shocks to establish causality, future work could aim to investigate causal relationships in this context.

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