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Intangible capital and agglomeration economies*

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Abstract

Intangible capital, an asset class central to the knowledge economy, has been shown to contribute substantially to productivity growth. However, the importance for agglomeration economies has received limited attention. We examine how the agglomeration effect varies with industries' intensity of intangible capital, combining international measures of industry-level intangible capital with rich Norwegian administrative employer–employee data. The analysis addresses methodological challenges related to endogenous intangible investment, unobserved worker characteristics, and correlation between worker moves and firm quality. We find that at mean intangible intensity, the elasticity of wages with respect to city size is 0.026, with each standard-deviation increase in intangible intensity raising the elasticity by 0.004. Dynamic wage returns to city-specific experience are also significantly higher in intangible-intensive industries. Employing the AKM framework and a complementary firm-based measure of local productivity, we show that our main results are robust to potential hierarchy effects arising from worker mobility. Moreover, we document that positive selection on unobserved ability into large cities is driven primarily by workers employed in intangible-intensive industries, irrespective of education level. We further document heterogeneity across intangible components, showing that agglomeration elasticities are strong for industries intensive in software and databases, and economic competencies. Taken together, these findings highlight the importance of intangible capital investments in shaping urban wage premia.

Keywords: Agglomeration economies, knowledge spillover, intangible capital, AKM-model, sorting, worker experience

JEL: J24, J31, J61, R12, R23

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1 Introduction

The productivity advantages of agglomeration are closely linked to the knowledge economy, a literature pioneered by Jacobs (1969). Much of the recent empirical literature in this tradition has focused primarily on workers and their skill composition as a source of agglomeration benefits. Less attention has been given to the production processes and capital inputs used by firms and industries.[1] This emphasis is consistent with findings such as Card et al. (2025), who show that while around half of the variation in city wages is explained by differences in worker characteristics, a substantial residual remains in the form of place effects. At the same time, a growing literature documents that intangible capital, encompassing assets such as R&D, software, organizational capital, and other non-physical investments, is highly complementary to the knowledge economy and a key driver of productivity growth in modern economies (Corrado et al., 2022; Roth, 2024).[2] Our contribution is to introduce intangible capital into the analysis of agglomeration economies. In doing so, we shed new light on the production-side foundations of urban spillovers and place effects.

The link between intangible capital and agglomeration economies has received limited attention. A natural starting point is the well-established role of intangibles for productivity growth. Brynjolfsson et al. (2021) argue that investment in intangible assets is critical for realizing the productivity gains from general-purpose technologies, as reflected in their "productivity J-curve". Similarly, Roth (2019) identifies three key barriers to productivity growth: low investment in ICT and complementary intangibles; widening investment gaps between frontier and laggard firms that constrain spillovers; and underinvestment in complementary intangible assets needed to fully exploit technologies such as artificial intelligence. Importantly, intangible-intensive industries rely on knowledge that is often tacit, difficult to codify, and embedded in human capital and organizational competence. These characteristics suggest a natural complementarity with dense urban environments, which facilitate face-to-face interactions, deep labor market pooling, and access to specialized inputs and infrastructure. These mechanisms align closely with the microfoundations of agglomeration economies reviewed by Duranton and Puga (2004), namely the 'Marshallian triad' of sharing, matching, and learning. Building on this insight, we empirically examine whether agglomeration economies are systematically stronger in industries that are intensive in intangible capital, both in terms of static urban wage premia and dynamic returns to city-industry-specific experience.

The key methodological challenge in the agglomeration literature concerns the sorting of workers and firms across locations. Following the influential work of Glaeser and Mare (2001), agglomeration effects are identified by tracking workers who move between cities, using information on job type, location, and experience (e.g., Baum-Snow and Pavan (2012), Carlsen et al. (2016), D'Costa and Overman (2014), De la Roca and Puga (2017), and Matano and Naticchioni (2016)). However, as shown by Card et al.

[1] There is, however, a prominent literature on the determinants of industry agglomeration and coagglomeration patterns; see, for example, Ellison and Glaeser (1997), Duranton and Overman (2005), and Ellison et al. (2010). For an overview of the links between agglomeration and innovation at the industry level, see Carlino and Kerr (2015); with Moretti (2021) providing complementary evidence for high-tech clusters.

[2] Recent research also points to dynamics in intangible capital investment and productivity growth, consistent with technology diffusion and catch-up (De Ridder, 2024; Goodridge & Haskel, 2023).

(2024, 2025), such designs may yield attenuated estimates of causal place effects when firm wage premia are correlated with the direction of worker moves. To address this concern, we employ the AKM two-way fixed effects model to study sorting behavior by both workers and firms. Applying the approach of Card et al. (2025), we assess the role of industry intangible capital intensity using average firm quality by region and industry as the outcome variable. We further show that our dynamic agglomeration results remain robust when firm-specific characteristics are absorbed by firm fixed effects. Another concern is that the intangible intensity of industries is unlikely to be exogenous. The decision to invest in intangible capital may reflect unobserved characteristics and productivity shocks. We mitigate this source of endogeneity by relying on industry-level measures of intangible capital intensity constructed from international data from countries outside of Norway.

Intangible capital assets are challenging to measure, as their value is typically not reflected in traditional balance sheets. We draw on international data from the EU-KLEMS & INTANProd database (Bontadini et al., 2023), which incorporates recent advances in the classification and valuation of intangible assets across industries.[3] The database offers broad industry coverage at a relatively disaggregated level, allowing for a detailed assessment of the role of intangible capital across industries. We define intangible capital intensity as the share of intangible assets in total assets, both in aggregate and decomposed into three core components: software and databases, innovative property (incl. R&D, new financial products, artistic originals, and design), and economic competencies (incl. organizational capital, employer-provided training, and brand). This enables us to move beyond the knowledge spillovers emphasized in the R&D literature (e.g. Jaffe et al. (1993); see Carlino and Kerr (2015) for a review). Instead, we examine a broader set of intangible assets that underpin modern production and may shape urban wage premia. We construct industry-level measures using data from seven advanced economies with institutional and economic characteristics comparable to Norway.

We use rich Norwegian administrative employer-employee data covering the period 2003-2019, complemented by workers' retrospective labor market histories from 1983 onward, and merge these data with industry-level measures of intangible capital intensity. Controlling for unobserved worker heterogeneity, we estimate the agglomeration effect dependent on the intangible capital intensity. At the mean level of intangible intensity, the elasticity of wages with respect to city size is 0.026, and each standard-deviation increase in intangible intensity raises the elasticity by 0.004. We further document that agglomeration elasticities increase with all intangible components. Across comparable shifts in intensity of one standard deviation, the contribution of innovative property, encompassing R&D, is half that of the other components. Extending the analysis to dynamic agglomeration effects, we show that returns to city-specific experience are significantly higher in intangible-intensive industries, a pattern that remains robust when firm fixed effects are introduced. We also examine selection mechanisms by comparing

[3] Corrado et al. (2022) offer an overview of the literature on the measurement and analysis of intangibles. The introduction of R&D as an additional production factor is old, but the capitalized value of R&D spending has never been shown to bridge much of the gap between accounts and market values. In contrast, the results concerning the broader concept of intangibles have proven more promising. Corrado et al. (2018) offer a key reference on measurement methodology and growth accounting related to intangible investment. They find that intangibles increase capital deepening and represent about 40% and 60% of capital in Europe and the US, respectively. The EU-KLEMS & INTANProd database builds on this framework and provides a more refined classification of intangible components.

distributions of worker fixed effects across locations. While prior work emphasizes positive selection of college-educated workers into large cities, we find that, once industry heterogeneity is allowed for, positive selection is driven primarily by workers employed in intangible-intensive industries, irrespective of education level. Finally, the results from the firm-based local productivity approach confirm that the agglomeration effect is affected by intangible capital intensity, accounting for the mobility-related biases.

This study relates to two strands of literature in particular. First, we contribute to the literature on agglomeration economies, and specifically to the debate over the extent to which industry and firm characteristics matter for spatial wage disparities. Recent overviews by Combes and Gobillon (2015) and Overman and Xu (2022) conclude that most observed wage differences across locations can be attributed to variation in individual characteristics and the spatial concentration of high-skilled workers. Similarly, Card et al. (2025), using a model with employer and employee fixed effects, find that differences in industry composition explain only a small fraction of average city wage premiums in the U.S. However, these findings may reflect limitations in how industry composition has been operationalized in prior work. Moreover, a growing literature emphasizes the importance of firm-level heterogeneity in shaping wage outcomes. For example, De Melo (2018) shows that worker-coworker sorting implies that firm fixed effects do not fully capture productivity differences, while Eeckhout et al. (2014) highlight skill complementarities in production that generate thick-tailed skill distributions in larger cities.[4]

Second, our study relates to the literature on regional development and intangible capital. Most work in this area relies on meso-level data at the regional or industry level and focuses on productivity growth or convergence, rather than on urban wage premia or agglomeration mechanisms. To our knowledge, only one study directly examines the relationship between agglomeration effects and intangible capital: Artis et al. (2012) incorporate variables such as knowledge, human capital, and entrepreneurial culture as proxies for intangible capital at the regional level and find that estimated agglomeration effects diminish once these factors are controlled for, suggesting a mediating role for intangibles.

Several other studies document positive effects of intangible capital on regional productivity and convergence. Melachroinos and Spence (2014) analyze the spatial effects of regional intangible measures on convergence within countries, while Peiro-Palomino (2016) extend the analysis to convergence across European regions. Gumbau-Albert (2024) focus on the relationship between intangible investment and productivity in Spanish regions. Across these studies, intangible capital emerges as an important determinant of regional economic performance.

The remainder of the paper is organized as follows: section 2 describes our econometric strategy and data. Section 3 presents estimates of the static and dynamic agglomeration effects, allowing the elasticity to vary by the intangible intensity of industries. Section 4 examines heterogeneity across different components of intangible capital. Section 5 analyzes spatial sorting of unobserved worker abilities. Section 6 concludes and discusses directions for future research.

[4]A related strand of the literature focuses on human capital externalities as a source of regional productivity differences. Notable contributions include Moretti (2004), who examines the spillover effects of education on productivity, and Rosenthal and Strange (2008), who provide a broader overview of agglomeration mechanisms, including those linked to human capital.

2 Empirical strategy and data

The main methodological challenge of agglomeration studies is the geographic sorting of individual workers and firms. In addition, assessing the role of intangible capital for agglomeration effects requires mitigation of the potential endogeneity of intangible investment decisions. We address these concerns by combining rich Norwegian employer–employee panel data with advanced industry-level measures of intangible capital constructed from international sources. We start out with the identification of static agglomeration effects based on workers moving between cities, which allows us to attribute wage gains to agglomeration rather than individual characteristics. Next, we exploit the AKM-model to examine the possibility that firm wage premia can be correlated with direction of moves. The final extension estimates dynamic agglomeration effects dependent on intangibles taking into account the accumulation of experience, while again assessing the robustness of these results to firm-level heterogeneity.

2.1 Static agglomeration effects

We use administrative register data on hourly wages and worker characteristics during 2003–2019, with information on actual work experience dating back to 1983. The baseline estimation sample consists of full-time male workers aged 20-65 employed in the private sector, including 11,976,950 observations and 1,397,816 unique workers.[5]. Following Bhuller (2009), we divide Norway into 46 local labor markets. There are large differences in population size across these regions, with an average of about 100,000 inhabitants and a standard deviation of 200,000 (measured in 2003).[6] The capital, Oslo, is the most populous region, with about 1.3 million inhabitants (including nearby municipalities with commuters into Oslo). At the other end of the spectrum, about half of the regions have populations in the range 20,000 − 35,000.

We extend standard estimation of static agglomeration effects by allowing the agglomeration elasticity to vary with the intangible capital intensity of a worker's industry of employment. We run a hedonic regression of individual hourly wages for the period 2003-2019 on regional population size, controlling for observable worker characteristics and including worker and year fixed effects:

$$\begin{aligned} \ln w_{it} =& \alpha_1 \ln pop_{it} + \alpha_2 \ln pop_{it} \cdot intensity_{it} + \alpha_3 \ intensity_{it} + \alpha_4 \ Exp_{it} + \\ & \alpha_5 \ Exp_{it}^2 + \boldsymbol{X\alpha} + \gamma_t + \mu_i + \epsilon_{it} \end{aligned} \tag{1}$$

where w_{it} is hourly wage for worker i in year t, and pop_{it} is the population size (measured prior to estimation period, beginning-of-year 2003) of the individual's workplace location in year t. $intensity_{it}$ is the intangible intensity of the industry where the worker is employed in year t, and Exp_{it} represents years of work experience acquired by worker i up until year t. $\boldsymbol{X}$ is a vector of controls, including indicators for occupation groups based on task content (non-routine abstract, non-routine manual, and routine work).

[5]Further details on the dataset are given in Appendix A with descriptive statistics in Table A.1

[6]These geographic units are constructed using commuting flows between municipalities and are broadly consistent with NUTS-4 regions in the EU statistical classification.

Year and worker fixed effects are represented by γ_t and μ_i, respectively, and ϵ_{it} is an error term.[7] The static agglomeration elasticity is given by $\alpha_1 + \alpha_2 \cdot intensity_{it}$, and a statistically significant α_2 indicates that the agglomeration elasticity vary systematically with industry intangible intensity. The estimates control for sorting of workers based on both time-varying observable characteristics and unobservable characteristics (e.g. innate abilities). The identifying variation exploits within-worker changes associated with relocations across regions and industries. To correct for serial correlation, the standard errors are clustered at the individual level.

The regression is estimated both using the aggregate intangible intensity and separately for its three core components: software and databases, innovative property, and economic competencies. The log-log specification in Equation (1) implies that the agglomeration effect is constant in elasticities with respect to population size. As an alternative model specification, we introduce large city dummies and study the urban wage premium in Oslo and other large cities relative to small cities.

2.2 Intangible capital intensity

The intangible intensity of industries is unlikely to be exogenous. Firms invest in intangible capital, and the investment may reflect the productivity of the firm, leading to simultaneity between productivity and capital composition. To address this endogeneity, we rely on cross-industry variation in intangible intensity derived from international accounts of intangible capital, the EU-KLEMS & INTANProd database (Bontadini et al., 2023).[8] An important trait of these data, and why they may be suitable to mitigate reverse causation concerns, is that they originate from other countries and are thus not affected by investment decisions and productivity shocks of Norwegian firms. To further distance the information from the Norwegian setting, we also do robustness tests utilizing the same data from a pre-sample period.

The EU-KLEMS & INTANProd database is based on the conceptual framework developed by Corrado et al. (2005), and classifies intangible capital assets in three groups: 'Software and databases', 'Innovative property' (R&D, design, new financial products, and entertainment & artistic originals), and 'Economic competencies' (organizational capital, branding, and firm-specific training). Software and databases, R&D, and entertainment & artistic originals are measured by investment streams in national accounts. The more challenging measurement concerns intangible assets not covered by national accounts, notably design, new financial products, and economic competencies. They rely on data from supply-use tables (consistent with national accounts), as well as own-account components derived from survey data using a sum-of-costs approach.

We apply measures from seven advanced economies with the most complete data and with institutional and economic characteristics comparable to Norway: Austria, Denmark, Finland, Germany, Sweden, UK and the U.S. As discussed in the introduction, the use of international datasets can be argued on methodological grounds, to avoid endogenous intangible investment issues. Using cross-country measures

[7] In regressions without worker fixed effects, we control for workers' immigrant status and level of education.
[8] The EU-KLEMS & INTANProd database is available from the LUISS Lab of European Economics at LUISS University: https://euklems-intanprod-llee.luiss.it/.

of intangibles is not uncommon, e.g., the analysis of Demmou et al. (2019) apply U.S. data on intangible intensity by industry to study more than 30 countries. We extract data on total intangible assets ($Intang$) and total tangible assets ($Tang$) for relevant industries during our period of study, 2003–2019.[9] For each country i, industry j, and year t, we calculate an intangible asset intensity measure as follows:

$$intensity_{ijt} = \frac{Intang_{ijt}}{Intang_{ijt} + Tang_{ijt}} \tag{2}$$

The average intensity by industry (across countries and years) is presented in the first column of Table A.2 in Appendix A.[10] Intangible intensity for three core intangible components (software and databases, innovative property, and economic competencies) are calculated in the same way and shown in the next three columns. The final column illustrates how observations in our dataset are allocated across industries.

According to the aggregate measure, the most intangible-intensive industries are publishing, TV, and radio (80%), professional, scientific, and technical activities (75%), computer programming (75%), and financial and insurance activities (74%). At the other end of the scale, we find industries such as real estate activities (4%), water supply, sewage, and waste (17%), land transport (19%), and warehousing and support activities for transportation (20%).

Norwegian measurements of intangibles at the industry-level are less developed. Raknerud et al. (2020) examine how some intangible assets (such as R&D, ICT investments, and patents) are allocated across eleven main industries. They show that investment in intangible assets is highly concentrated, with four industries accounting for 82% of all R&D, 85% of patents and industrial design applications, and 75% of ICT software investments. This pattern is broadly consistent with the EU-KLEMS & INTANProd database, although the latter covers a wider range of industries at a more disaggregated level, thus providing a more detailed view of the relative importance of intangible capital across industries.

2.3 Firm heterogeneity

To address firm selection, we use the AKM model introduced by Abowd et al. (1999) and estimate individual-level wage equations with both worker and firm fixed effects:

$$\ln w_{it} = \mu_i + \delta_{f(i,t)} + \beta_1 \ Exp_{it} + \beta_2 \ Exp^2_{it} + \gamma_t + \epsilon_{it} \tag{3}$$

where $\delta_{f(i,t)}$ denotes firm fixed effects of all employees of firm f. All other variables are explained in relation to equation (1). As discussed by Kline (2025), causal interpretation of the firm wage effects relies on three assumptions based on the following empirical approximation: First, the wage component must not depend on past firm assignments. Second, understanding the AKM-model as a difference-in-difference specification, wages at origin and destination firm should follow a parallel trend. This is often called the

[9] Industries are defined based on the Standard Industrial Classification (SIC2007), either at the section level or the 2-digit division level.

[10] Although countries with a substantial degree of missing data over the study period are excluded, the seven countries in the sample still display some minor gaps. In these cases, the intangible capital intensity is determined by the information available for the other countries in the sample.

exogenous mobility assumption. Third, the wage effect of moving between a given pair of firms is not time-dependent.

When agglomeration effects are identified from workers' mobility across regions, hierarchy effects may arise (Card et al., 2025). In particular, changes in the productivity rank across firms may correlate with population size, generating a downward bias in the estimated effects. To address this concern, Card et al. (2025) propose measuring regional productivity as a weighted average of firm fixed effects from the AKM model and using this measure as a dependent variable in an aggregate agglomeration regression. Following their approach, we construct average firm fixed effects by local labor market and industry. Let δ_f denote the firm fixed effect for firm f. For each local labor market c and industry s, define the set of firms: $\mathcal{F}_{cs} = \{f \mid c(f) = c,\, s(f) = s\}$, where $c(f)$ maps firm f to its local labor market and $s(f)$ to its industry. The average firm effect in cell (c, s) is then given by:

$$\Psi_{cs} = \frac{\sum_{f\in\mathcal{F}_{cs}} N_f \delta_f}{\sum_{f\in\mathcal{F}_{cs}} N_f}, \tag{4}$$

where N_f denotes the number of person-year observations in our estimation sample for firm f. We then estimate specifications of the following form:

$$\Psi_{cs} = \gamma_1 \ln pop_c + \gamma_2 \ln pop_c \cdot intensity_s + \gamma_3\ intensity_s + \boldsymbol{X}_{cs}\boldsymbol{\gamma} + \epsilon_{cs}, \tag{5}$$

where $\ln pop_c$ is the logarithm of population size in labor market c, and $intensity_s$ is the intangible capital intensity of industry s. $\boldsymbol{X}$ is a vector of control variables that includes: (i) the weighted share of workers with high-school education and the weighted share with college education (primary education is the reference category), and (ii) the weighted shares of workers in occupations characterized by non-routine abstract skills and non-routine manual skills (routine-skill occupations are the reference category).

2.4 Dynamic agglomeration effects

The specification in equation (1) is extended to allow the return to experience to vary based on industry and region of accumulation. In this analysis, we use city dummies and separate between intangible-intensive industries and other industries by introducing a dummy variable ($intang_{it}$) that equals one if the intangible intensity exceeds a specified threshold:

$$\begin{aligned} \ln w_{it} =& \alpha_1\ city_{it} + \alpha_2\ city_{it} \cdot intang_{it} + \alpha_3\ intang_{it} + \alpha_4\ Exp_{it} + \alpha_5\ Exp_{it}^2 + \\ & \alpha_6\ Exp_{it}^{city} + \alpha_7\ (Exp_{it}^{city})^2 + \alpha_8\ Exp_{it}^{intang} + \alpha_9\ (Exp_{it}^{intang})^2 + \\ & \alpha_{10}\ Exp_{it}^{city,intang} + \alpha_{11}\ (Exp_{it}^{city,intang})^2 + \boldsymbol{X\alpha} + \gamma_t + \mu_i + \epsilon_{it} \end{aligned} \tag{6}$$

where $city_{it}$ is a dummy that equals one if the worker is employed in a large city in year t (separating between Oslo and other large cities), Exp_{it}^{city} and Exp_{it}^{intang} represent years of work experience acquired by worker i up until year t in large cities and in intangible-intensive industries, respectively, and $Exp_{it}^{city,intang}$

measures experience in intangibles acquired in large cities (separating between Oslo and other large cities). Work experience accumulated in large cities is more valuable than experience accumulated in small cities if $\alpha_6 + 2\alpha_7\tau > 0$, where τ represents years of experience. Work experience accumulated in intangible-intensive industries is more valuable than experience accumulated in other industries if $\alpha_8 + 2\alpha_9\tau > 0$, and if $\alpha_{10} + 2\alpha_{11}\tau > 0$, experience in intangibles is more valuable when accumulated in large cities compared to the rest of the country. The immediate static urban wage premium is given by the estimated coefficients on the large city dummy ($\alpha_1 + \alpha_2$ in intangible-intensive industries and $\alpha_1$in other industries), while the wage premium after τ years of experience is $\alpha_1 + \alpha_2 + (\alpha_6 + \alpha_{10})\tau + (\alpha_7 + \alpha_{11})\tau^2$ when the experience is accumulated in intangible-intensive industries and $\alpha_1 + \alpha_6\tau + \alpha_7\tau^2$ when the experience is accumulated in other industries. While we rely on movers between the three city region types to identify the static premium, the estimation of the dynamic experience effect is based on all workers (movers and stayers). In a robustness check, we analyze whether firm fixed effects affect the estimates of the dynamic agglomeration effects. In this case, the complete static effects are not identified.

3 Agglomeration effect and intangible intensity

We start by estimating the static agglomeration effect using individual panel data, as described by Equation (1) in Section 2. Using data on intangible capital assets, we examine whether the intangible intensity of a worker's industry of employment affects the agglomeration elasticity. As reported in column (1) of Table 1, the estimated population elasticity, controlling for worker fixed effects, experience, and occupational task content, is 0.026, implying that a doubling of the population size leads to 1.8 percent increase in hourly wages.[11] This estimate is nearly half the raw elasticity (reported in Table B.1 in the online appendix), suggesting substantial worker sorting. In column (2), we add industry fixed effects to the specification. The estimated agglomeration effect remains largely unchanged, consistent with prior evidence showing that controlling for industry fixed effects has limited influence on estimated returns to urban scale. However, this specification does not rule out heterogeneity in agglomeration elasticities across industries. To examine this possibility, column (3) introduces an interaction between city population size and industry-level intangible capital intensity. The result indicates a positive and statistically significant impact of intangible intensity on the agglomeration elasticity. This main finding is robust to an alternative measure of intangible intensity that uses pre-sample values, which helps address endogeneity concerns (see Table B.2 in the online appendix).

At the mean intangible intensity of 0.5, the predicted elasticity is 0.026. Each one-standard-deviation increase in intensity (approximately 0.165 units) raises the elasticity by 0.004, underscoring the importance of intangible capital in enhancing agglomeration benefits for workers. To illustrate the magnitude of these effects, we draw on the industry-specific intangible intensities reported in Table A.2. The least intangible-intensive industry, real estate activities, exhibits an agglomeration elasticity of 0.016, while the industry most reliant on intangible capital, publishing and broadcasting, has an elasticity of 0.033. Our

[11] A doubling of population size corresponds to a $(2^{\alpha} - 1) \cdot 100\%$ increase in hourly wages, where α is the estimated agglomeration elasticity.

Table 1: Static agglomeration effect and intangible intensity

	(1)	(2)	(3)	(4)	(5)
Log population	0.026***	0.028***	0.015***	0.012***	0.013***
	(0.0004)	(0.0004)	(0.0008)	(0.0009)	(0.0009)
Log population x Intangible intensity			0.022***	0.022***	0.018***
			(0.0014)	(0.0014)	(0.0014)
Intangible intensity			-0.175***	-0.173***	-0.140***
			(0.0182)	(0.0185)	(0.0185)
Experience	0.020***	0.019***	0.020***	0.020***	0.024***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$(\text{Experience})^2$	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Non-routine abstract	0.084***	0.078***	0.081***	0.026***	0.075***
	(0.0007)	(0.0007)	(0.0007)	(0.0061)	(0.0007)
Non-routine manual	-0.004***	-0.003***	-0.003***	-0.062***	-0.001*
	(0.0007)	(0.0007)	(0.0007)	(0.0060)	(0.0007)
Log pop x Non-routine abstract				0.004***	
				(0.0005)	
Log pop x Non-routine manual				0.005***	
				(0.0005)	
Log pop x High-school education					0.001*
					(0.0007)
Log pop x College education					0.008***
					(0.0009)
Industry fixed effects	No	Yes	No	No	No
Observations	11,976,950	11,976,950	11,976,950	11,976,950	11,976,950
Number of workers	1,397,816	1,397,816	1,397,816	1,397,816	1,397,816
R^2	0.20	0.20	0.20	0.20	0.20

The regressions are based on yearly data for full-time male workers in the private sector (excluding primary, oil and electricity industries) during 2003-2019. The dependent variable is the logarithm of hourly wages. Intangible intensity is a continuous variable between 0 and 1 measuring the aggregate intangible intensity of the worker's industry of employment (for 32 industries as described by Appendix Table A.2). The regional population level is measured in 2003. We separate between three occupation groups based on task content (non-routine abstract, non-routine manual, and routine) and three levels of education (primary, high school, and college). All regressions include year and worker fixed effects. The industry fixed effects in column (2) are at the 2-digit level and include 62 industries. The R-squared reported is within workers.

Robust standard errors (clustered by workers) are given in parenthesis. *, **, and *** indicate significance at the 10, 5 and 1 percent level, respectively.

estimates are well-aligned with existing agglomeration literature. For instance, a recent meta-analysis by Ahlfeldt and Pietrostefani (2019) reports a citation-weighted mean elasticity of wages with respect to population density of 0.04 and estimates roughly half that size when selection effects are taken into account. The wage effect of intangible intensity is positive and increases with the size of the local labor market. For the average worker employed in a city region of about 587,000 inhabitants, a one-standard-deviation increase in the intangible intensity is associated with wages that are 1.9 percent higher.[12]

In the final two columns of Table 1, we check the robustness of the finding that the static agglomeration elasticity increases with the intangible intensity of industries. First, we address the possibility that occupational differences across industries drive the estimated agglomeration effect. Based on individual-

[12]Based on the estimated coefficients in the third column of Table 1 and an average regional population size of 587,000 inhabitants, the wage effect of one-standard-deviation (0.165 units) increase in intangible intensity is calculated as $(0.022 \cdot \ln 587,000 - 0.175) \cdot 0.165 = 0.019$.

level data from the Netherlands, Koster and Ozgen (2021) show that the urban wage premium is higher for workers performing non-routine tasks, particularly analytical tasks. Our descriptive statistics (see Table A.1) reveal that intangible-intensive industries are overrepresented by workers in non-routine abstract occupations. By allowing the agglomeration effect to differ by task content (non-routine abstract, non-routine manual, and routine), we can assess whether our results are driven by a greater reliance on non-routine occupations in intangibles. Consistent with the literature, we find that the agglomeration elasticity is significantly higher for occupations emphasizing non-routine tasks. Importantly, the impact of intangible intensity on the agglomeration effect is still of the same magnitude and statistically significant. Second, considering the extensive literature showing that the college educated derive greater benefits from working in urban areas (Carlsen et al., 2016), column (5) investigates whether our results are driven by a higher concentration of college-educated workers in intangible-intensive industries. As expected, the agglomeration elasticity is significantly higher for college-educated workers compared to those with primary education, adding 0.008 to the elasticity. However, the intangible intensity of industries continues to matter for the agglomeration elasticity, with each standard-deviation increase in the intensity raising the elasticity by 0.003.

Table 2: Agglomeration effect estimated with mean firm fixed effects by region and industry

	(1)	(2)	(3)	(4)
Log population	0.066***	0.063***	0.045***	0.043***
	(0.0031)	(0.0031)	(0.0079)	(0.0079)
Log population x Intangible intensity			0.043***	0.040***
			(0.0156)	(0.0155)
Intangible intensity			-0.430**	-0.454**
			(0.1793)	(0.1790)
Controls	No	Yes	No	Yes
Observations	2563	2560	2563	2560
R^2	0.11	0.14	0.11	0.14

The table presents robustness checks for the regressions in Table 1. Following Card et al. (2025), the dependent variable is the weighted mean of firm fixed effects by local labor market and industry. The fixed effects are derived from an AKM-regression on the logarithm of hourly wages. Controls consist of the weighted share of persons with high-school and college education (primary education as reference category) and weighted share with occupations categorized as demanding non-routine abstract skills and non-routine manual skills, respectively (routine skill occupations as reference category).
Robust standard errors are given in parenthesis. *, **, and *** indicate significance at the 10, 5 and 1 percent level, respectively.

As part of our robustness analysis, we also address the potential bias from hierarchy effects, whereby changes in firms' productivity ranks may correlate with city size (Card et al., 2025). To account for this, we follow the approach in equation (4) and use average firm fixed effects by region and industry as the dependent variable. Table 2 reports the results. Columns (1) and (2) show that a doubling of population size leads to an increase of about 6 percentage points in the average firm-specific wage premium. Columns (3) and (4) add the interaction with intangible intensity, revealing that the agglomeration effect is stronger in industries with higher intangible capital intensity. These findings reinforce our main result on the role of intangible capital in shaping agglomeration effects and further suggest that intangible-intensive firms located in sparsely populated areas are negatively selected.

Figure 1 plots the relationship between city size and productivity differentials between intangible-intensive and other industries using the dummy version of intangible intensity. The differentials are calculated using Equation (4), aggregated to the intangible/non-intangible industry level, and plotted against local labor market population. A clear positive relationship emerges: the estimated slope of 0.03 indicates that larger labor markets are associated with greater productivity advantages for intangible-intensive industries. Notably, the dispersion in productivity differentials is wider among smaller labor markets, suggesting greater heterogeneity in outcomes when scale is limited.

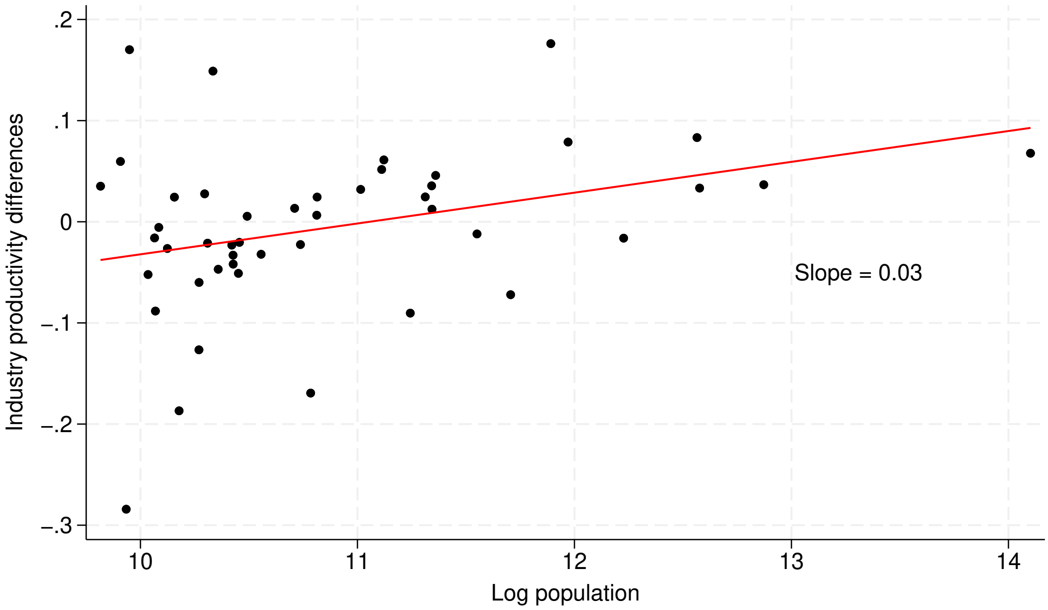

Figure 1: Differences in productivity between intangible and non-intangible industries by regional population size

Notes: The figure plots, for each local labor market, the productivity differential between intangible-intensive and non-intangible industries by population size. Intangible intensity is defined using a dummy variable with a threshold of 0.5. Productivity differentials are calculated after following the method of Card et al. (2025), as described in equation (4), and then aggregated to the intangible/non-intangible industry level.

To further enhance our understanding of the role of intangible-intensive industries for the agglomeration effect, we include the dynamics related to accumulation of experience. We estimate the urban wage premium in Oslo and other large cities relative to small cities, allowing the value of work experience to vary between industry and city region types, as specified in Equation (6) in Section 2. Intangible-intensive industries are defined as those exceeding the mean intensity value of 0.5. As seen from the first column of Table 3, the static Oslo wage premium is 3.6 percentage points higher in intangible-intensive industries compared to other industries, which amounts to a difference of about 60%. The dynamic component of the urban wage premium also varies by industry. In intangibles, experience accumulated outside large cities yields a 2% return in the first year, while experience in Oslo adds an additional 0.9 percentage

Table 3: Dynamic agglomeration effect and intangible intensity

	Baseline (Cutoff= 0.5) (1)	Young workers (2)	Excl. intensity [0.45, 0.55] (3)	Firm fixed effects (4)
Oslo	0.0709***	0.0746***	0.0601***	
	(0.0016)	(0.0018)	(0.0020)	
Other large cities	0.0402***	0.0420***	0.0303***	
	(0.0015)	(0.0016)	(0.0018)	
Oslo x Intangibles	0.0360***	0.0378***	0.0339***	
	(0.0016)	(0.0018)	(0.0021)	
Other large cities x Intangibles	0.0198***	0.0217***	0.0218***	
	(0.0015)	(0.0017)	(0.0021)	
Intangibles	0.0085***	0.0088***	0.0245***	
	(0.0013)	(0.0014)	(0.0018)	
Experience	0.0121***	0.0089***	0.0108***	0.0082***
	(0.0003)	(0.0004)	(0.0004)	(0.0003)
$(\text{Experience})^2$	-0.0006***	-0.0006***	-0.0005***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Experience in Oslo	0.0057***	0.0071***	0.0057***	0.0039***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
$(\text{Experience in Oslo})^2$	-0.0002***	-0.0003***	-0.0003***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Experience in other large cities	0.0019***	0.0022***	0.0023***	0.0010***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
$(\text{Experience in other large cities})^2$	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Experience in intangibles	0.0075***	0.0092***	0.0057***	0.0074***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
$(\text{Experience in intangibles})^2$	-0.0001***	-0.0002***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Experience in intangibles in Oslo	0.0033***	0.0039***	0.0054***	0.0050***
	(0.0003)	(0.0004)	(0.0004)	(0.0003)
$(\text{Experience in intangibles in Oslo})^2$	-0.0000**	-0.0001***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Experience in intangibles in other large cities	-0.0000	0.0001	0.0009**	0.0009***
	(0.0003)	(0.0004)	(0.0004)	(0.0003)
$(\text{Experience in intangibles in other large cities})^2$	0.0000**	0.0000	0.0000**	-0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Non-routine abstract	0.0810***	0.0831***	0.0758***	0.0779***
	(0.0007)	(0.0008)	(0.0009)	(0.0006)
Non-routine manual	-0.0047***	-0.0036***	0.0059***	-0.0024***
	(0.0007)	(0.0008)	(0.0009)	(0.0006)
Firm fixed effects	No	No	No	Yes
Observations	11,976,950	8,456,700	8,376,926	11,809,033
R^2	0.20	0.24	0.18	0.15

The dependent variable is the logarithm of hourly wages. Intangibles is a dummy variable equal to one if a worker's industry exhibits an intangible intensity above 0.5. Column (1) reports the baseline results, while columns (2) through (4) offer robustness checks. Column (2) re-estimates the regression for a sample of workers for whom we have a full history of experience (workers born after 1962). Column (3) excludes industries around the intensity cutoff value and compares workers in industries with intangible intensity above 0.55 to those in industries below 0.45. The last column includes firm fixed effects (in this scenario, static effects are not identified). All regressions include year and worker fixed effects.

Robust standard errors (clustered by workers) are given in parenthesis. ***, ** and * indicate significance at the 1, 5 and 10 percent level, respectively.

points to this return. In other industries, the first-year return to experience accumulated outside large cities is 1.2%, with experience in Oslo contributing an additional 0.6 percentage points. The economic significance of having urban experience, particularly in intangible-intensive industries, is substantial. Given the average work experience of 14.3 years for all workers across all regions, the dynamic effect significantly enhances the Oslo wage premium.[13] The total Oslo effect in intangibles is 18.2%, consisting of a static effect of 10.7% and an experience effect of 7.5% over the average years of work experience. In other industries, the combined static and dynamic agglomeration effect amounts to 10.2%.[14] The Oslo-gap between intangible-intensive industries and other industries consequently is 8 percentage points. Intangible-intensive industries exhibit a dynamic agglomeration effect that is 4.3 percentage points higher than that of other industries. The dynamic effect accounts for about a third of the total Oslo wage premium in both industry types, broadly consistent with De la Roca and Puga (2017), where about half the total effect is accounted for by the dynamic element.

A consequence of these findings is that the urban wage premium trajectories depend on the industry composition of cities. The calculated wage gaps are based on 14.3 years of experience, while Figure 2 shows the trajectories of the Oslo wage premium for workers in intangibles and other industries. The static

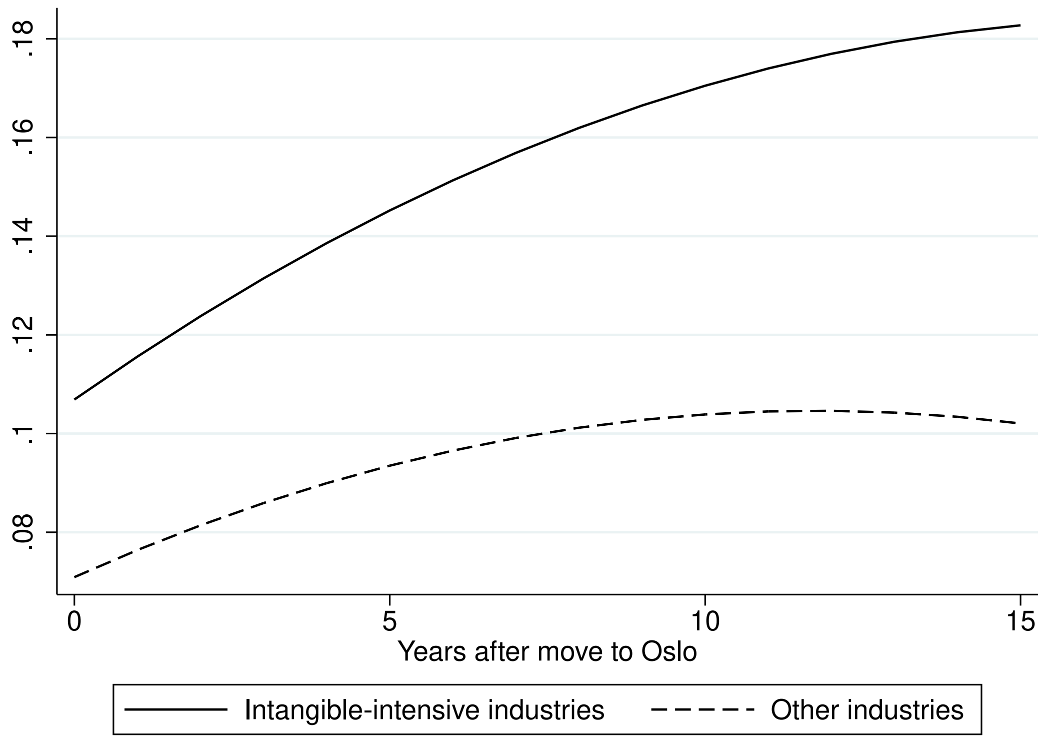

Figure 2: Urban wage premium trajectories for workers in intangibles and other industries, years after move to Oslo

[13]In large cities outside Oslo, intangible-intensive industries exhibit a static premium that is 2 percentage points higher than that observed in other industries. Regarding the dynamic effects, although the return to experience is higher than in small cities, there is no statistically significant difference in the return to experience in large cities between intangible-intensive and other industries.

[14]The calculation of the dynamic part of the urban wage premium follows from the estimated coefficients on Oslo experience in Table 3 and equals $0.009\tau - 0.00026\tau^2$ and $0.0057\tau - 0.00024\tau^2$ for Oslo experience accumulated in intangibles and in other industries, respectively, where τ represents years of experience.

urban wage premium is higher in intangible-intensive industries and the difference between intangibles and other industries increases over time. The return to experience is higher in Oslo, and in particular when the experience is accumulated in intangible-intensive industries.

A limitation of our analysis is that worker experience data is only available from 1983 onward, which means we lack the complete experience history for many workers in the sample. To address this, we repeat the analysis for a subsample of younger workers born after 1962 (accounting for 72% of workers in the baseline sample). The main finding, that returns to experience are higher in cities, particularly when accumulated in intangible-intensive industries, persists and is slightly stronger in this subsample (see column (2) of Table 3). When all workers are included, the effect of experience may be underestimated due to measurement error. Alternatively, the differences could reflect stronger returns early in a worker's career, or in newer times.

In the baseline regression, the threshold for intangible-intensive industries is set at the mean intensity of 0.5. To assess the sensitivity of our results to this cutoff and address that industries close to the cutoff may be observationally similar, we exclude workers near the cutoff and compare workers in industries with intangible intensity above 0.55 to those below 0.45. Observations with intangible intensity between 0.45 and 0.55 are excluded, also in the calculation of overall experience and experience by region and industry type. As seen from column (3), the main findings remain robust under this specification.

In the last column of Table 3, we examine the robustness of the dynamic part of the urban wage premium with the inclusion of firm fixed effects (in this case, the full static effects are not identified and therefore not reported). This specification allows us to assess whether returns to experience are influenced by firm-specific characteristics. The dynamic urban wage premium is significantly higher in intangible-intensive industries compared to other industries, and the additional dynamic benefit received in intangibles is even higher when firm fixed effects are included. The dynamic part of the Oslo wage premium is now 5.5 percentage points higher in intangibles compared to other industries.

Following the approach described in De la Roca and Puga (2017), we assess the robustness of our findings using a two-step estimation procedure, with results reported in Table B.3 in the online appendix. The conclusions are qualitatively similar. The interaction coefficient between intangible intensity and population size matches the baseline estimate: each standard-deviation increase in the intensity raises the short-term elasticity by 0.004. For the medium-term elasticity, evaluated at the mean years of experience, the predictions range from 0.046 in the least intangible-intensive industry to 0.073 in the most intangible-intensive industry. The impact of one standard-deviation increase in the intensity is stronger for the medium-term elasticity, amounting to 0.006. This pattern is consistent with the dynamic agglomeration effect becoming more pronounced as intangible intensity increases.

4 Heterogeneity by intangible components

The availability of detailed data on intangible capital components allows us to further characterize the production-side foundations of agglomeration economies. To this end, we distinguish between three core intangible components, as detailed in section 2: software and databases, innovative property, and economic competencies. The distribution of industries varies substantially across the three components. Software and databases are particularly important in information and communication, as well as financial and insurance activities. Innovative property is concentrated in selected manufacturing industries, while economic competencies are especially relevant in wholesale and retail trade.

As shown in column (1) of Table 4, the agglomeration elasticity increases with the intensity of each component. Due to differing standard deviations across components, direct comparison of coefficient estimates is challenging. A more meaningful comparison is obtained by evaluating the impact of a one-standard-deviation increase in each component. Under this standardization, economic competencies and software and databases exhibit roughly twice the effect on agglomeration elasticity compared to innovative property. This pattern is confirmed by robustness checks in columns (2) and (3), which allow the agglomeration effect to vary by occupational task content and education level, respectively.

We further investigate heterogeneity by distinguishing between intangible capital components measured within national accounts and those derived from other sources. According to Corrado et al. (2021), assets such as software and databases are calculated from national accounts, while economic competencies are measured outside the national accounting framework. As reported in Table 3, both the national account based component software and databases and the non-national account based component economic competences exhibit strong positive interactions with population scale, with standardized effects of similar magnitude.

A more nuanced picture emerges when we decompose the innovative property component, which combines both national accounts and non-national account elements. While most sub-components contribute positively to agglomeration economies, the national-account-based measure of R&D intensity stands out as an exception, displaying a statistically significant negative interaction effect of 0.055. The negative agglomeration effect of R&D-intensity is surprising given the broad understanding that knowledge spillovers are important for R&D. This may be explained by the dominance of manufacturing firms with high R&D intensity in a modern resource-oriented economy where production primarily takes place outside of large cities. These findings underline the importance of using broad measures of intangible capital and accounting for heterogeneity across intangible components.

Having established substantial heterogeneity in static agglomeration effects across intangible components, we now turn to the dynamic dimension. As shown in Table 3, the estimated return to experience is significantly higher in large cities, particularly when experience is accumulated in industries with high intangible intensity. To examine whether the dynamic element of the agglomeration effect varies across different types of intangible assets, we classify industries as intangible-intensive for each core intangible component.[15] We then estimate the urban wage premium while allowing the return to experience to differ between industries that are intensive in a specific intangible component and other industries. In these component-specific regressions, we exclude industries where the aggregate intangible intensity exceeds 0.5 but the specific component intensity falls below the specified cutoff. This restriction prevents comparing industries that excel in different intangible dimensions, ensuring a more precise evaluation of

Table 4: Static agglomeration effect: Heterogeneity by intangible components

	(1)	(2)	(3)
Log population	0.016***	0.012***	0.013***
	(0.0008)	(0.0009)	(0.0010)
Log pop x Software and databases	0.045***	0.040***	0.038***
	(0.0048)	(0.0049)	(0.0049)
Log pop x Innovative property	0.011***	0.010***	0.007***
	(0.0019)	(0.0019)	(0.0019)
Log pop x Economic competencies	0.022***	0.025***	0.020***
	(0.0027)	(0.0027)	(0.0027)
Software and databases	-0.208***	-0.148**	-0.157**
	(0.0636)	(0.0644)	(0.0643)
Innovative property	0.061**	0.068***	0.096***
	(0.0247)	(0.0247)	(0.0247)
Economic competences	-0.406***	-0.448***	-0.390***
	(0.0342)	(0.0344)	(0.0340)
Experience	0.020***	0.020***	0.024***
	(0.0003)	(0.0003)	(0.0003)
(Experience)^2	-0.001***	-0.001***	-0.001***
	(0.0000)	(0.0000)	(0.0000)
Non-routine abstract	0.079***	0.026***	0.073***
	(0.0007)	(0.0062)	(0.0007)
Non-routine manual	-0.007***	-0.071***	-0.006***
	(0.0007)	(0.0059)	(0.0007)
Log pop x Non-routine abstract		0.004***	
		(0.0005)	
Log pop x Non-routine manual		0.005***	
		(0.0005)	
Log pop x High-school education			0.002**
			(0.0007)
Log pop x College education			0.008***
			(0.0010)
Observations	11,976,950	11,976,950	11,976,950
Number of workers	1,397,816	1,397,816	1,397,816
R^2	0.20	0.20	0.21

The table presents baseline results for components of intangible capital in column (1) and robustness checks in the next two columns. Column (2) allows the agglomeration effect to vary by occupation groups according to task content (non-routine abstract, non-routine manual, and routine), and column (3) allows the agglomeration effect to vary by level of education. The regional population level is measured in 2003. The regressions include worker and year fixed effects. The R-squared reported is within workers.

Robust standard errors (clustered by workers) are given in parenthesis. *, **, and *** indicate significance at the 10, 5 and 1 percent level, respectively.

[15] Using the component-specific intensities reported in Table A.2, we define high intensity as the mean plus one standard deviation for each component. This gives cutoff values of 0.116 for software and databases, 0.279 for innovative property, and 0.367 for economic competencies.

each component's distinct effect on the urban wage premium.

The results, reported in Table B.4 in the online appendix, indicate that the dynamic element of the agglomeration effect also varies by intangible asset type. In industries with strong reliance on software and databases or innovative property, the return to Oslo-based experience is significantly higher than in industries with low intangible intensity, with similar magnitudes across these two components. For workers in industries dependent on economic competencies, the dynamic agglomeration effect is not significantly different from that observed in low-intensity industries.[16] Consistent with Table 4, the additional static urban wage premium in intangible-intensive industries, relative to other industries, is more than twice as large in industries reliant on software and databases or economic competencies compared to those focused on innovative property. By combining static and dynamic agglomeration effects, we find that, relative to other industries, the additional benefit from working in intangible-intensive industries in large cities is 9.2 percentage points for software and databases, 7.9 percentage points for economic competencies, and 3.6 percentage points for innovative property.

5 Worker sorting

The existing literature finds positive selection of high-ability workers into large cities primarily among the college-educated, a pattern summarized in the concept of 'smart cities'. Key references include Glaeser and Saiz (2004), Shapiro (2006), Combes et al. (2008), and Winters (2011). Using Norwegian register data, Carlsen et al. (2016) have reached the same conclusion. A natural extension of this literature is to ask whether selection operates not only through worker skills, but also through industry composition, raising the question of whether some industries are "smarter" in cities than others.

As a preliminary analysis of worker sorting, we compare agglomeration elasticities estimated with and without worker fixed effects across the full range of intangible intensity (see the last two columns of Table B.1 in the online appendix). The results indicate that sorting of high-ability workers into large cities becomes more pronounced as industry intangible intensity rises. For most levels of intangible capital intensity, introducing worker fixed effects lowers the elasticity, consistent with positive selection of higher-ability workers into urban labor markets. In contrast, industries with low intangible intensity (below 0.27) display negative selection, implying that lower-ability workers are more likely to be employed in these industries in large cities.

To formally test for selection, we compare worker ability distributions in Oslo and small cities, excluding workers in the intermediate-sized.[17] Each worker's fixed effect is linked to the region and industry (intangible-intensive vs. other industries) in which the worker was employed in 2019, or in their last observed year in the data. Intangible-intensive industries are defined as those with intangible intensity

[16] Professional, scientific and technical activities are excluded because of high dependency on both innovative property and economic competencies, making it impossible to isolate the effect of a single component. When this industry is included, we observe an additional dynamic agglomeration effect for industries reliant on economic competencies. However, we cannot determine which component drives this effect.

[17] As a proxy for unobserved ability, we use worker fixed effects estimated from the wage regression in column (1) of Table 3, which captures the dynamic benefits of larger cities and allows for heterogeneous effects across industry types.

exceeding 0.5. Following the methodology of Combes et al. (2012), we approximate the distribution of worker fixed effects in Oslo by shifting, dilating and truncating the corresponding distribution observed in small cities. Table 5 reports the estimated shift parameters by worker group, defined jointly by education level and industry of employment.

Across all workers, the fixed-effects distribution in Oslo is shifted 0.025 units to the right compared to that in small cities, suggesting a higher average ability level among workers in Oslo. This aggregate pattern, however, conceals substantial heterogeneity across industries. When separating by industry of employment, we observe strong positive selection into Oslo among workers in intangible-intensive industries: their ability distribution is 0.057 units to the right of the corresponding distribution in small cities. In contrast, for workers in industries with low intangible intensity, the Oslo distribution is 0.025 units to the left of the small-city distribution, indicating negative selection.

Table 5: Comparison of worker fixed effects distributions: Oslo vs. small cities

	Shift ($\hat{A}$)	*Pseudo* R^2	Observations
Panel A: All workers			
All	0.025***	0.80	807,226
	(0.0035)		
Workers in intangible-intensive industries	0.057***	0.85	431,892
	(0.0043)		
Workers in other industries	-0.025***	0.89	375,334
	(0.0052)		
Panel B: Primary-educated workers			
All	0.009	0.43	174,261
	(0.0060)		
Workers in intangible-intensive industries	0.034***	0.72	70,057
	(0.0079)		
Workers in other industries	-0.009	0.53	104,204
	(0.0076)		
Panel C: High school-educated workers			
All	-0.001	0.90	393,429
	(0.0036)		
Workers in intangible-intensive industries	0.024***	0.85	203,410
	(0.0044)		
Workers in other industries	-0.033***	0.94	190,019
	(0.0057)		
Panel D: College-educated workers			
All	0.040***	0.77	239,458
	(0.0066)		
Workers in intangible-intensive industries	0.038***	0.78	158,388
	(0.0068)		
Workers in other industries	0.018	0.68	81,070
	(0.0118)		

Worker fixed effects are estimated by the regression in column (1) of Table 3. The distribution of worker fixed effects in Oslo is approximated by shifting, dilating and truncating the distribution of worker fixed effects in small cities. We estimate shift, dilation and truncation parameters aggregate and for each education group, and within groups, also separately for workers in intangible-intensive industries (intensity of at least 0.5) and other industries. The table reports the estimated shift parameters, while the estimated dilation and truncation parameters are available upon request.

Bootstrapped standard errors are given in parenthesis (re-estimating worker fixed effects in 100 bootstrapped iterations based on 10% random samples with replacement).*, **, and *** indicate significance at the 10, 5 and 1 percent level, respectively.

To examine whether college-educated workers drive the results for intangible-intensive industries, we compare ability distributions between Oslo and small cities across different education levels, as reported in panels B-D of Table 5. Consistent with the existing literature, we find that positive sorting on worker ability into large cities only applies to those with a college degree. However, allowing for heterogeneity by industry of employment reveals a different pattern: within intangible-intensive industries, workers across all education groups exhibit positive selection into Oslo of similar magnitude. In contrast, in other industries, workers without college degree display negative selection into large cities, while positive selection among the college educated is roughly half the magnitude compared to those in intangible-intensive industries and not statistically significant. These findings highlight the importance of industry affiliation, rather than education alone, for spatial sorting on unobserved abilities.

6 Concluding remarks

Agglomeration economies are closely intertwined with the knowledge economy, yet their production-side foundations remain poorly understood. In particular, while intangible capital has emerged as a central driver of modern productivity growth, its role in shaping agglomeration effects have received limited attention. Combining advanced measures of intangible capital with rich register data, and using frontier empirical methods, this paper shows that intangible capital intensity is a key dimension along which agglomeration benefits vary.

Controlling for unobserved worker ability, we estimate a static agglomeration elasticity of 0.026 at the mean level of intangible intensity, with each one-standard-deviation increase in intensity raising the elasticity by 0.004. Industries with intangible intensity exceeding 0.5 exhibit agglomeration effects that are 60% greater than those below this threshold. We further show that dynamic returns to experience in cities are substantially higher in intangible-intensive industries. While all core components of intangible capital contribute positively, economic competencies and software and databases exhibit twice the effect on agglomeration elasticity compared to innovative property.

Importantly, we also document that worker sorting patterns vary systematically by industry: positive selection into cities characterize workers in intangible-intensive industries regardless of education, whereas in less intangible-intensive industries positive selection is confined to the highly educated. Together, these findings challenge the view that production-side factors are unimportant for regional wage differentials and underscore the relevance of intangible capital in shaping agglomeration economies.

Our analysis opens up several promising avenues for future research. Because intangible capital intensity is measured at the industry level, we are unable to examine within-industry variation, specifically related to its distribution across geographic space. A natural extension would be to investigate whether firms in urban areas invest differently in intangible assets compared to their rural counterparts, provided that credible strategies are available to address the endogeneity of intangible investment decisions. Moreover, recent evidence relates intangibles to slowdowns in labor productivity growth (e.g., De Ridder (2024) and Goodridge and Haskel (2023)). This raises the question of whether the interaction between intangible capital and agglomeration economies varies over periods of technological diffusion and catch-up. Future research could also explore how these relationships differ across institutional contexts, particularly in developing economies where labor market dynamics, firm organization, and the accumulation of technology and intangible capital may alter the mechanisms through which agglomeration economies operate.

Our findings have implications for urban and regional policy. If intangible-intensive industries derive greater benefits from agglomeration, then investments in digital infrastructure, innovation capacity, and workforce training in urban areas may yield amplified productivity gains. However, such targeted interventions may also contribute to widening regional disparities, especially if it dampens sorting behavior. Policymakers may thus face a trade-off between reinforcing urban productivity and mitigating spatial inequality, underscoring the importance of monitoring and gaining new knowledge on how capital investments shape regional economic trajectories.

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Appendices

A Data

The individual-level dataset is derived from three administrative registers: employment, tax, and education. The employment register links workers to firms and provides detailed data on work contracts, including contract type, duration, and weekly hours worked. From this, we calculate annual hours worked and combine these with annual wage income from the tax register to compute hourly wages for all employees. Information about work contracts dating back to 1983 allows us to measure actual full-time experience for each worker. We separate between overall experience, experience by industry type (intangible-intensive industries vs. other industries), and experience by region (Oslo, other large cities, and small cities). The experience variables, measured in years, are calculated based on the number of days worked. For the 1983-1994 period, where detailed data are unavailable, full-time contracts within a year are counted as one full year of experience. Additional individual characteristics include age, gender, immigrant status, occupation group, industry affiliation, firm affiliation, and home region. By linking occupational data to O*NET characteristics, we classify workers into three groups according to the task content of occupations: non-routine abstract, non-routine manual, and routine, as further described by Leknes et al. (2022). For firms, we identify the region where the largest share of employees resides, which serve as a proxy for workplace location. The wage measure includes payroll taxes, which vary by region. Between 2003 and 2006, payroll tax zones correspond to employees' home region, while from 2007 onward, they are based on workplace location.

The employment register separates between three contract types: full-time contracts with at least 30 hours of work per week, part-time contracts with 20–29 hours of work per week, and part-time contracts with fewer than 20 hours of work per week. Our analysis concentrates on full-time male workers aged 20-65 employed in the private sector. We exclude industries that are predominantly public sector or resource-based, where wages do not reliably reflect labor productivity: Public administration and defense (industry code O), Education (code P), Health and social work activities (code Q), Agriculture, forestry and fishing (code A), Mining and oil/gas extraction (code B), and Electricity supply (code D). Workers in industry codes T and U (Activities of household as employers; Activities of extraterritorial organizations) are excluded due to missing data on intangible intensity. The tax register provides annual earnings for each work contract. For workers holding two or three full-time contracts in a year, we retain only the main contract, defined as the one with the most days worked or, if equal, the highest wage. Contracts with identical duration and wage are excluded (a negligible number of cases). Workers with more than three full-time contracts in a year are removed, as are all part-time contracts. Additional exclusions apply to workers with contract length of one month or less, as well as workers with missing data on hours worked, annual earnings, education level, occupation group, or industry affiliation. To mitigate outliers, we drop the top and bottom 1% of the wage distribution. The resulting dataset comprises 11,976,950 observations and 1,397,816 unique workers.

Descriptive statistics are reported in Table A.1, both in aggregate and separately for intangible-intensive industries and other industries, using 50% cutoff for intangible intensity. The average worker in the dataset is 41 years old, has 14 years of work experience, is employed in a region with approximately 584,000 inhabitants, and works in an industry with an intangible intensity of 49%. Regarding education, 25% of the sample has college education, 54% have completed high school, and 20% have only primary education. Geographically, 35% of individuals work in the Oslo region, 43% in other large cities, and 22% in small cities. Immigrants constitute 12% of the sample. Intangible-intensive industries account for 56% of all observations, with their prevalence increasing with city size (60% in Oslo compared to 50% in small cities). Relative to workers in other industries, those in intangible-intensive industries earn higher average wages, are more likely to have a college education, and are more often employed in (and have prior work experience from) the Oslo region. When categorizing workers by the task content of their occupations, workers in intangible-intensive industries are overrepresented in occupations with non-routine abstract tasks.

Table A.1: Descriptive statistics (mean values across workers): Aggregate and by industry of employment

	All	Intangible-intensive industries	Other industries
Log hourly wage (in 2010 NOK)	5.63	5.70	5.54
Industry intangible intensity	0.50	0.60	0.36
Regional population size	587,057	617,221	548,695
Oslo	0.36	0.38	0.33
Other large cities	0.43	0.43	0.43
Small cities	0.22	0.19	0.24
Age	41.38	41.48	41.25
Immigrant	0.12	0.10	0.15
Primary	0.20	0.16	0.26
High-school	0.54	0.53	0.56
College	0.26	0.32	0.18
Non-routine abstract	0.41	0.50	0.28
Non-routine manual	0.32	0.31	0.33
Routine	0.27	0.18	0.38
Experience	14.29	14.61	13.87
Experience in Oslo	4.97	5.44	4.38
Experience in other large cities	6.05	6.17	5.91
Observations	11,976,950	6,704,914	5,272,036
Share of observations	1	0.56	0.44

The dataset covers full-time male workers aged 20–65 employed in the private sector (excluding primary, oil and electricity industries) over the period 2003-2019. Intangible-intensive industries are defined as those with an aggregate intangible capital intensity exceeding the mean of 50%. The geographic dimension distinguishes between the region of Oslo, other large cities with at least 84,000 inhabitants in 2003 (11 regions), and small cities (the remaining 34 regions). The average regional population size is measured for the average worker, rather than across 46 regions. Work experience covers full-time experience from 1983 onward, calculated in days and expressed in years.

Table A.2: Industries by intangible intensity: Aggregate and intangible components

Industry code	Industry	Intangible intensity: Aggregate	Software and databases	Innovative property	Econ. comp.	Obs.
C10-C12	Food products, beverages, tobacco	0.458	0.033	0.092	0.333	434,826
C13-C15	Textiles, wearing apparel, leather	0.571	0.044	0.164	0.363	29,337
C16-C18	Wood, paper, printing, reproduction	0.389	0.040	0.116	0.232	299,931
C19	Coke and refined petroleum products	0.219	0.002	0.090	0.126	12,348
C20	Chemicals and chemical products	0.459	0.028	0.238	0.193	120,416
C21	Pharmaceutical	0.716	0.035	0.443	0.237	21,002
C22-C23	Rubber, plastic, non-metallic mineral products	0.432	0.038	0.166	0.228	191,671
C24-C25	Basic and fabricated metals	0.438	0.044	0.151	0.244	441,344
C26-C27	Computer, electronic and optical products, electrical equipment	0.656	0.067	0.386	0.204	192,409
C28	Machinery and equipment n.e.c.	0.590	0.056	0.293	0.241	262,984
C29-C30	Motor vehicles and transport equipment	0.556	0.041	0.328	0.187	383,102
C31-C33	Furniture; other; repair and installation	0.602	0.056	0.222	0.324	256,109
E	Water supply; sewerage; waste	0.172	0.020	0.065	0.087	143,602
F	Construction	0.501	0.022	0.278	0.201	2,286,036
G45	Wholesale/retail trade and repair of motor vehicles and motorcycles	0.429	0.045	0.033	0.386	541,827
G46	Wholesale trade, other	0.569	0.095	0.072	0.402	1,089,195
G47	Retail trade, other	0.497	0.067	0.033	0.396	580,835
H49	Land transport and pipelines	0.185	0.022	0.034	0.130	600,994
H50	Water transport	0.285	0.031	0.038	0.216	121,041
H51	Air transport	0.312	0.039	0.034	0.239	57,181
H52	Warehousing and support activities for transportation	0.203	0.035	0.031	0.137	257,948
H53	Postal and courier activities	0.576	0.144	0.100	0.332	49,013
I	Accommodation and food services	0.335	0.027	0.015	0.293	283,552
J58-J60	Publishing; TV, radio etc.	0.802	0.104	0.386	0.312	268,584
J61	Telecommunications	0.421	0.183	0.063	0.175	137,695
J62-J63	Computer programming, consultancy, information services	0.751	0.265	0.147	0.339	448,532
K	Financial and insurance activities	0.739	0.178	0.231	0.330	348,377
L	Real estate activities	0.035	0.004	0.008	0.024	152,961
M	Professional, scientific and technical activities	0.753	0.083	0.297	0.373	892,323
N	Administrative and support service activities	0.351	0.045	0.039	0.267	748,398
R	Arts, entertainment and recreation	0.379	0.035	0.134	0.210	145,466
S	Other service activities	0.530	0.065	0.064	0.401	177,911
Mean		0.496	0.062	0.162	0.274	
Std. dev.		0.164	0.054	0.117	0.093	

Intangible capital intensity is derived from the EU-KLEMS & INTANProd database using data for seven Western economies (Austria, Denmark, Finland, Germany, Sweden, United Kingdom, and the USA) during 2003-2019. Industries are defined based on the Standard Industrial Classification (SIC2007), either at the section level or the 2-digit division level. The intensity is measured as intangible assets as share of total assets and is calculated aggregate and for three core components of intangible capital: software and databases, innovative property, and economic competencies.The final column illustrates how observations in our dataset are allocated across industries, while the bottom two rows report the mean and standard deviation of intangible intensities across workers.

Online Appendix

Online Supplementary Material for "Intangible capital and agglomeration economies."

B Additional results

Table B.1: Static agglomeration effect and intangible intensity

	(1)	(2)	(3)	(4)
Log population	0.050***	0.008***	0.010***	0.015***
	(0.0002)	(0.0007)	(0.0006)	(0.0008)
Log pop x Intangible intensity		0.073***	0.041***	0.022***
		(0.0014)	(0.0011)	(0.0014)
Intangible intensity		-0.388***	-0.359***	-0.175***
		(0.0177)	(0.0141)	(0.0182)
Experience			0.037***	0.020***
			(0.0001)	(0.0003)
(Experience)^2			-0.001***	-0.001***
			(0.0000)	(0.0000)
Non-routine abstract			0.213***	0.081***
			(0.0007)	(0.0007)
Non-routine manual			0.032***	-0.003***
			(0.0006)	(0.0007)
High-school education			0.100***	
			(0.0006)	
College education			0.245***	
			(0.0009)	
Immigrant			-0.015***	
			(0.0008)	
Worker fixed effect	No	No	No	Yes
Observations	11,976,950	11,976,950	11,976,950	11,976,950
Number of workers	1,397,816	1,397,816	1,397,816	1,397,816
R^2	0.06	0.10	0.32	0.20

The regressions are based on yearly data for full-time male workers in the private sector (excluding primary, oil and electricity industries) during 2003-2019. The dependent variable is the logarithm of hourly wages. Intangible intensity is a continuous variable between 0 and 1 measuring the aggregate intangible intensity of the worker's industry of employment. The regional population level is measured in 2003. All regressions include year fixed effects. In column (4), the R-squared reported is within workers.

Robust standard errors (clustered by workers) are given in parenthesis. *, **, and *** indicate significance at the 10, 5 and 1 percent level, respectively.

Table B.2: Robustness analyses: Pre-sample intangible capital intensity

	(1)	(2)	(3)
Log population	0.020***	0.016***	0.017***
	(0.0008)	(0.0008)	(0.0009)
Log population x Pre-sample intangible intensity	0.015***	0.015***	0.011***
	(0.0016)	(0.0016)	(0.0016)
Pre-sample intangible intensity	-0.086***	-0.078***	-0.043**
	(0.0204)	(0.0206)	(0.0207)
Experience	0.020***	0.020***	0.024***
	(0.0003)	(0.0003)	(0.0003)
$(\text{Experience})^2$	-0.001***	-0.001***	-0.001***
	(0.0000)	(0.0000)	(0.0000)
Non-routine abstract	0.082***	0.019***	0.076***
	(0.0007)	(0.0061)	(0.0007)
Non-routine manual	-0.003***	-0.058***	-0.001**
	(0.0007)	(0.0060)	(0.0007)
Log pop x Non-routine abstract		0.005***	
		(0.0005)	
Log pop x Non-routine manual		0.004***	
		(0.0005)	
Log pop x High-school education			0.002**
			(0.0007)
Log pop x College education			0.009***
			(0.0009)
Observations	11,976,950	11,976,950	11,976,950
Number of workers	1,397,816	1,397,816	1,397,816
R^2	0.20	0.20	0.20

The regressions are based on yearly data for full-time male workers in the private sector (excluding primary, oil and electricity industries) during 2003-2019. The dependent variable is the logarithm of hourly wages. The pre-sample intangible intensity is a continuous variable between 0 and 1 measuring the aggregate intangible intensity of the worker's industry of employment, but measured in the pre-sample period 1995-2002. The regional population level is measured in 2003. We separate between three occupation groups based on task content (non-routine abstract, non-routine manual, and routine) and three levels of education (primary, high school, and college). All regressions include year and worker fixed effects. The R-squared reported is within workers.

Robust standard errors (clustered by workers) are given in parenthesis. *, **, and *** indicate significance at the 10, 5 and 1 percent level, respectively.

Table B.3: Robustness analyses: Two-step procedure for exploring static and dynamic agglomeration effects, specific to industry type

	Initial premium		Medium-term premium	
	(1)	(2)	(3)	(4)
Log population	0.056***	0.045***	0.062***	0.046***
	(0.0024)	(0.0063)	(0.0026)	(0.0064)
Log pop x Intangible intensity		0.022*		0.034***
		(0.0123)		(0.0124)
Intangible intensity		-0.244*		-0.183
		(0.1416)		(0.1424)
Observations	2574	2574	2574	2574
R^2	0.13	0.13	0.15	0.20

The table reports robustness checks for the results presented in Tables 1 and 3. Following the two-step procedure described in De la Roca and Puga (2017), the dependent variables in columns (1) and (2) are labor market-by-industry fixed effects. In columns (3) and (4), the dependent variables are the same labor market-by-industry fixed effects, augmented to also capture dynamic effects arising from experience accumulated across industries and labor markets. The experience component is evaluated at the mean years of experience, 14.3 years.

Robust standard errors are given in parenthesis. *, **, and *** indicate significance at the 10, 5 and 1 percent level, respectively.

Table B.4: Dynamic agglomeration effect: Heterogeneity by intangible components

	Software and databases (1)	Innovative property (2)	Economic competencies (3)
Oslo	0.0579***	0.0575***	0.0441***
	(0.00219)	(0.00209)	(0.00215)
Other large cities	0.0336***	0.0348***	0.0294***
	(0.00196)	(0.00185)	(0.00195)
Oslo x Intangibles	0.0781***	0.0179***	0.0782***
	(0.00447)	(0.00367)	(0.00273)
Other large cities x Intangibles	0.0387***	0.0085***	0.0441***
	(0.00445)	(0.00312)	(0.00271)
Intangibles	0.0391***	0.0648***	-0.0593***
	(0.00421)	(0.00257)	(0.00234)
Experience	0.0115***	0.0119***	0.0125***
	(0.00046)	(0.00044)	(0.00044)
$(\text{Experience})^2$	-0.0006***	-0.0005***	-0.0005***
	(0.00001)	(0.00001)	(0.00001)
Experience in Oslo	0.0065***	0.0064***	0.0064***
	(0.00031)	(0.00030)	(0.00032)
$(\text{Experience in Oslo})^2$	-0.0003***	-0.0002***	-0.0002***
	(0.00001)	(0.00001)	(0.00001)
Experience in other large cities	0.0021***	0.0025***	0.0024***
	(0.00029)	(0.00028)	(0.00031)
$(\text{Experience in other large cities})^2$	-0.0001***	-0.0001***	-0.0001***
	(0.00001)	(0.00001)	(0.00001)
Experience in intangibles	0.0148***	0.0050***	0.0049***
	(0.00063)	(0.00047)	(0.00038)
$(\text{Experience in intangibles})^2$	-0.0003***	-0.0001***	-0.0001***
	(0.00001)	(0.00001)	(0.00001)
Experience in intangibles in Oslo	0.0017**	0.0017**	-0.0002
	(0.00070)	(0.00065)	(0.00047)
$(\text{Experience in intangibles in Oslo})^2$	-0.0000***	-0.0000	0.0000
	(0.00002)	(0.00002)	(0.00001)
Experience in intangibles in other large cities	-0.0026***	0.0008	-0.0003
	(0.00072)	(0.00058)	(0.00047)
$(\text{Experience in intangibles in other large cities})^2$	0.0001***	-0.0000**	0.0000**
	(0.00002)	(0.00002)	(0.00001)
Non-routine abstract	0.0760***	0.0740***	0.0714***
	(0.00110)	(0.00103)	(0.00096)
Non-routine manual	0.0035***	0.0028***	0.0101***
	(0.00109)	(0.00099)	(0.00097)
Observations	6,117,958	6,400,117	6,539,142
R^2	0.16	0.15	0.15

The dependent variable is the logarithm of hourly wages. Intangibles is a dummy variable equal to one if a worker's industry exhibits a component-specific intangible intensity above a specific threshold. We define high intensity as the mean plus one standard deviation for each intangible component: Software and databases (threshold = 0.116), Innovative property (threshold = 0.279), and Economic competencies (threshold = 0.367). In each component-specific regression, industries are excluded if their aggregate intangible intensity exceeds 0.5 while the specific component intensity falls below the cutoff. Industry code M (professional, scientific and technical activities) is excluded because it is highly dependent on both innovative property and economic competencies, making it impossible to isolate the effect of a single component. All regressions include year and worker fixed effects.

Robust standard errors (clustered by workers) are given in parenthesis. ***, ** and * indicate significance at the 1, 5 and 10 percent level, respectively.