Do agglomeration gains reach workers? Industrial clusters, digital transformation, and the decoupling of wealth and wages in Spanish provinces

Rudy Fernandez-Escobedo*

J.E. Cairnes School of Business and Economic, University of Galway, Galway, Ireland.

* Corresponding author: 49 Upper Newcastle, Galway, H91 YK8V;
rudy.fernandezescobedo@universityofgalway.ie
https://orcid.org/0000-0001-5121-1877

Abstract
Industrial agglomeration is widely credited with generating regional wealth, but whether those gains reach workers is a distinct and largely unanswered question. This paper examines the channels through which industrial clusters are associated with returns to labour across the 50 Spanish provinces (NUTS-3). Using a partial least squares structural equation model that links cluster presence, technology adoption, and regional competitiveness to earnings per worker, the analysis finds no direct channel connecting clusters to wages. Cluster presence is strongly associated with technology adoption, but neither clusters nor technology adoption show a positive direct association with earnings; competitiveness is by far the dominant correlate of labour returns. When indirect pathways are decomposed, the only route consistent with the data is sequential: clusters are associated with higher earnings exclusively where they foster technological upgrading that, in turn, strengthens regional competitive conditions. This chain accounts for approximately ninety per cent of the total indirect association between clustering and labour returns. Read against companion evidence on regional wealth creation, where cluster effects travel through multiple parallel channels, the findings reveal a decoupling between the geography of wealth and the geography of wages in agglomerated regions. The results imply that cluster and digitalization policies will not improve earnings unless they are embedded in broader competitiveness-building strategies. The paper contributes a mechanism-based, exploratory account of wage formation under agglomeration, and offers policy guidance on the sequencing of place-based interventions for regional development.

Keywords clusters; digitalization; competitiveness; wages; agglomeration; Spain; PLS-SEM

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1. Introduction

A long tradition in regional and urban economics holds that the spatial concentration of economic activity raises productivity and, through it, regional prosperity (Rosenthal and Strange 2004; Melo et al. 2009). A parallel and more policy-oriented literature has translated this insight into the language of industrial clusters, arguing that co-located, interconnected industries generate externalities that strengthen firm capabilities and territorial performance (Delgado et al. 2014; Ketels and Protsiv 2014). Both traditions, however, have concentrated overwhelmingly on aggregate outcomes and much less on a question that matters at least as much for regional welfare: whether the gains from agglomeration reach workers in the form of higher earnings.

The distinction is not semantic. Gross domestic product per capita and earnings per worker can, and often do, move apart, with countries as Ireland exemplifying this phenomenon at its best. Wealth created in agglomerated regions may accrue to capital, to land, or to a narrow segment of highly skilled labour, without translating into broad wage improvements (Groot et al. 2014). Recent European evidence sharpens the point: rising industrial market power shifts income from labour to profits, and the shift is stronger precisely in regions hosting superstar firms and specialized production networks (Capello et al. 2025a), while the regional presence of multinational enterprises widens between-firm wage dispersion (Duran and Siedschlag 2025). Indeed, the evidence on agglomeration wage premia is considerably more contested than the evidence on agglomeration productivity effects: sorting of skilled workers into dense areas explains a large share of observed urban wage differentials, and in some institutional contexts no cluster wage premium is detectable at all (De Blasio and Di Addario 2005; García-Suaza and Londoño 2025).

This question has acquired new urgency with digital transformation. Digital technologies were once expected to weaken the economic rationale of proximity; the accumulated evidence suggests instead that they complement it, with clusters acting as environments that lower the cost and risk of adopting information and communication technologies (ICT) and Industry 4.0 tools (Corradini et al. 2021; Grashof et al. 2021). Yet the relationship between technology adoption and wages is itself ambiguous. Skill-biased and routine-biased technological change can raise the earnings of some workers while displacing or devaluing others, so that the net effect of digitalization on average regional earnings is theoretically indeterminate (Acemoglu and Restrepo 2019). If clusters increasingly matter through digitalization, and digitalization has an uncertain relationship with wages, then the link between agglomeration and labour returns cannot be assumed but it must be traced.

This paper traces it, asking two research questions: RQ1 - Do industrial clusters exhibit a direct association with returns to labour at the regional level, or only an indirect one? And RQ2 - Through which mechanisms (technological upgrading, competitiveness, or their sequence) are agglomeration gains transmitted to worker earnings? To answer them, a conceptual model is built in which cluster presence, technology adoption, and regional competitiveness are linked to earnings per worker, and it is estimated with partial least squares structural equation modelling (PLS-SEM) on data for the 50 Spanish provinces (NUTS-3). The approach is explicitly exploratory and causal-predictive rather than confirmatory: the model structures observed spatial relationships and decomposes them into direct and indirect pathways, without claiming causal identification (Rigdon 2016; Shmueli et al. 2019; Hair et al. 2022).

Spain is a suitable setting for the exercise. It combines pronounced territorial heterogeneity, long-standing cluster trajectories in traded industries, and markedly uneven digital adoption across its regions (Fernandez-Escobedo et al. 2024). Additionally, the NUTS-3 scale captures meaningful variation in industrial structure while remaining administratively relevant for policy.

Three results stand out. First, cluster presence shows no significant direct association with earnings per worker, nor with competitiveness; its only strong direct correlate is technology adoption. Second, technology adoption itself shows no positive direct association with earnings (the point estimate is, if anything, negative) while regional competitiveness is by far the dominant correlate of labour returns. Third, when the indirect pathways are decomposed, the single-mediator routes fail: neither technology alone nor competitiveness alone transmits cluster advantages to wages. What remains is one sequential chain: clusters to technology adoption to competitiveness to earnings, which concentrates roughly ninety per cent of the total indirect association between clustering and labour returns.

Taken together with the companion evidence on wealth creation, these results point to a decoupling: the channels through which agglomeration is associated with regional wealth are plural and partially direct (Fernandez-Escobedo 2024), whereas the channel through which it is associated with wages is single, sequential, and conditional. Clusters appear to raise earnings only where technological upgrading is converted into broad competitive conditions as innovation capacity, institutions, and infrastructure. Where that conversion fails, clustering and even digitalization coexist with stagnant labour returns.

The paper contributes to the regional science literature in three ways. It shifts the outcome of the cluster–digitalization debate from wealth creation to wage formation, a distributional dimension that existing mediation studies have not addressed. It provides a mechanism-based account, grounded in agglomeration micro-foundations, of why direct cluster and technology effects on wages should not be expected, and shows empirically that they do not appear. And it offers policy guidance on the sequencing of place-based interventions, suggesting that cluster and digitalization programmes must be coupled to competitiveness upgrading if wage improvement is the goal.

The remainder of the paper proceeds as follows. Section 2 develops the conceptual framework and research questions. Section 3 describes the data, the construction of the cluster indicator, and the PLS-SEM procedure. Section 4 reports the results. Section 5 discusses the findings against the literature and the companion wealth-creation evidence. Section 6 draws policy implications, and Section 7 concludes with limitations and avenues for future research.

2. Conceptual framework

2.1 Agglomeration and labour returns: what theory does and does not promise

The theoretical case for agglomeration effects on productivity rests on well-established micro-foundations: sharing of inputs and infrastructure, improved matching in labour markets, and learning through knowledge spillovers (Duranton and Puga 2004). Meta-analytical evidence confirms positive but heterogeneous productivity elasticities of density (de Groot et al. 2009; Melo et al. 2009; Groot et al. 2014). Crucially, however, these mechanisms operate on productivity, not directly on wages. Whether productivity gains show up in earnings depends on how they are distributed among capital, land, and labour and, within labour, across skill groups.

The empirical literature on urban and agglomeration wage premia reflects this gap. Dense areas pay higher nominal wages, but a substantial share of the differential is explained by the sorting of more productive workers into cities rather than by agglomeration itself (García-Suaza and Londoño 2025). At the level of industrial clusters, the evidence is more contested still: studies report wage premia in traded and high-technology clusters (Grashof and Fornahl 2021; Tavares et al. 2021), while others find no premium at all, notably De Blasio and Di Addario (2005) for Italian industrial districts. Theory, in short, licenses an expectation that agglomeration is associated with productivity; it does not license an expectation that agglomeration is directly associated with wages.

A note on terminology is warranted, since "cluster" and "agglomeration" are not interchangeable (Porter et al. 2007). Agglomeration economies in the broad sense encompass urbanization externalities (cities bundle production and consumption amenities well beyond the co-location of firms) (Caragliu et al. 2022). This paper works with the narrower construct of industrial clusters as geographic concentrations of traded, related industries (Delgado et al. 2016). The choice is deliberate: the mechanism under study is the conversion of localized industrial externalities into technological upgrading and competitiveness, for which traded-sector specialization, rather than raw urban density which confounds amenity effects, is the relevant measure.

2.2 Clusters and digital transformation: proximity as a complement, not a casualty

An early expectation held that digital technologies, by collapsing communication costs, would erode the value of proximity. The evidence points the other way. Face-to-face interaction and digital connectivity behave largely as complements: tacit knowledge exchange, trust formation, and collective experimentation lower the cost and perceived risk of adopting ICT and

Industry 4.0 technologies (Guo et al. 2020; Corradini et al. 2021; Grashof et al. 2021). Clusters frequently act as testbeds for emerging technologies, providing the institutional density within which adoption diffuses (Jasinska and Jasinski 2019; Temouri et al. 2021).

The relationship is not unconditional. Technological lock-in and path dependency can retard the uptake of disruptive technologies in mature clusters, particularly where dominant firms guard strategic information (Zhu and Pickles 2016; Elola et al. 2017). On balance, however, the accumulated evidence supports a positive association between cluster presence and regional technology adoption, and this is the first expected relationship in our model: provinces with stronger cluster structures should exhibit higher levels of digital and Industry 4.0 adoption.

2.3 Technology adoption and wages: an ambiguous link

If clusters foster digitalization, does digitalization raise earnings? Here the theoretical guidance is genuinely ambiguous, and the ambiguity is central to this paper. On one side, digital technologies improve productivity, information flows, and innovation speed (Usai et al. 2021; Stentoft et al. 2021), which should raise the ceiling for wages. On the other, the task-based literature on technological change shows that automation and digital tools can displace routine labour, compress the earnings of mid-skill workers, and shift income from labour to capital (Autor et al. 2003; Autor and Dorn 2013; Acemoglu and Restrepo 2019). Concerns about a digital productivity paradox (the adoption of technology without measurable performance gains) add a further layer of doubt (Ahmad and Schreyer 2016). Most directly relevant here, Capello, Lenzi, et al. (2025) show for European NUTS-2 manufacturing that automation reduces the labour share of income, and that this detrimental effect is amplified where production is highly specialized and geographically clustered: a territorial market power effect. In cluster environments, then, technology adoption may carry a specific downward pressure on labour returns that it does not carry elsewhere. The net association between regional technology adoption and average earnings per worker is therefore an empirical question, and there is no theoretical warrant to expect it to be positive in the aggregate.

2.4 Competitiveness as the conversion mechanism

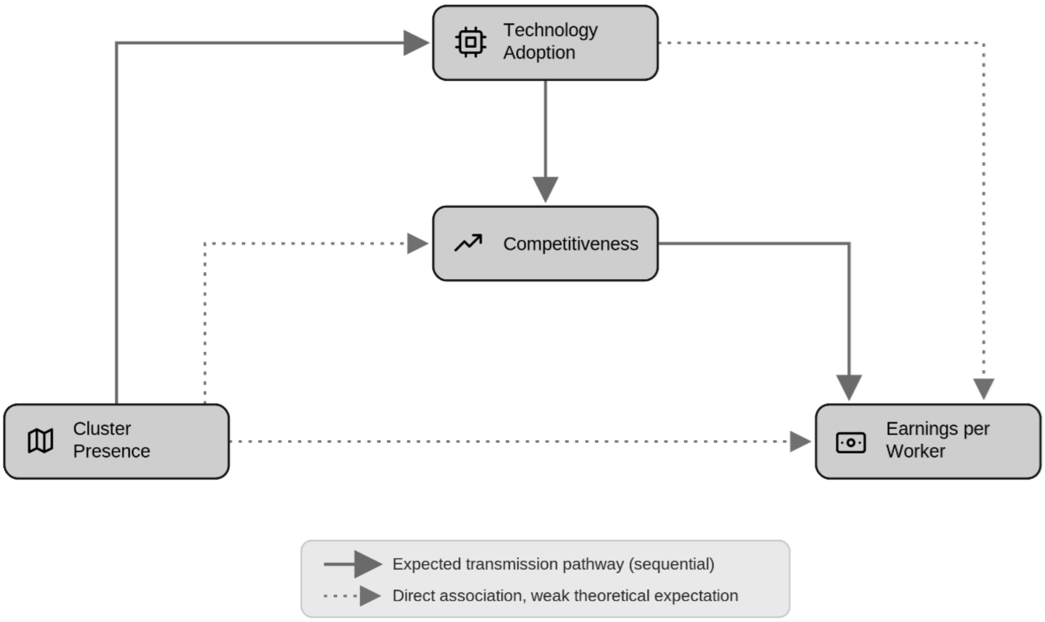
What determines whether technological upgrading translates into higher earnings? We argue that the answer lies in regional competitiveness, understood as a multidimensional construct spanning innovation capacity, productivity, human capital, institutional quality, and infrastructural foundations (D'Urso et al. 2022). Competitiveness captures precisely the complementary conditions under which technology becomes economically valuable: skilled labour able to work with new tools, institutions that support diffusion, innovation systems that recombine knowledge, and infrastructure that connects firms to markets (Awad and Albaity 2022; Calza et al. 2023). Regions endowed with these conditions can convert digital adoption into productivity that is broadly shared; regions without them may adopt technology and see the returns accrue narrowly or leak elsewhere.

Competitiveness is also the construct most plausibly linked to wage formation itself. Its constituent dimensions (productivity, human capital, institutional quality) are the canonical correlates of regional earnings levels (Buitrago et al. 2021). We therefore expect competitiveness to be the proximate correlate of returns to labour, standing between technological capabilities and earnings.

2.5 The conceptual model and research questions

The framework yields a sequential logic rather than a set of parallel direct effects. Clusters lower the cost of technology adoption (sharing and learning externalities); adoption strengthens the technological component of regional capabilities; competitiveness converts those capabilities into broadly distributed economic returns; and earnings per worker register the outcome. Direct short-cuts, like clusters to wages or technology to wages, are theoretically possible but not expected to be strong, for the reasons set out above: agglomeration mechanisms target productivity rather than wages, and technology has offsetting wage effects (**Figure 1**).

Figure 1. Theoretical model of the cluster–earnings transmission mechanism.



Note: Solid arrows denote the hypothesized sequential transmission pathway (Cluster Presence → Technology Adoption → Competitiveness → Earnings per Worker); dotted arrows denote direct associations included in the estimated model but assigned weak theoretical expectation ex ante.

The model is estimated as a whole, and the two research questions stated in the introduction are answered by decomposing the estimated associations into direct and indirect components. RQ1 concerns the existence of direct cluster–earnings associations; RQ2 concerns the transmission mechanism. We deliberately do not formulate the expected relationships as formal hypotheses to be "confirmed": the design is cross-sectional and observational, and PLS-SEM is employed in its exploratory, causal-predictive capacity to assess whether the data are consistent with the proposed mediation structure and to evaluate the model's predictive relevance, not to test a structural theory in the confirmatory sense (Hair et al. 2014, 2022; Rigdon 2016; Shmueli et al. 2019).

3. Data and methods

3.1 Setting, sample, and period

The empirical analysis covers the 50 Spanish provinces (NUTS-3), combining official secondary data from the National Statistics Institute (INE), the Spanish Tax Office, Eurostat, and the Regional Competitiveness Index (RCI). The reference year is 2019, chosen on two grounds: it is the last complete year before the COVID-19 shock, whose sectoral and territorial asymmetries would contaminate any cross-sectional reading of structural relationships; and the design explores the structure of mechanisms rather than temporal dynamics, for which a stable pre-pandemic cross-section is appropriate. The NUTS-3 scale captures sufficient variation in industrial structure and socioeconomic conditions while corresponding to administratively meaningful units for policy.

3.2 Construction of the cluster indicator

The cluster presence indicator (C_Esh) is derived from a cluster mapping of the Spanish economy based on firm-level data covering 1,804,714 establishments classified under CNAE-2009, obtained from SABI database (Bureau van Dijk). The mapping follows the methodology established in Fernandez-Escobedo et al. (2024), which applied the traded-industries cluster definition framework of Delgado et al. (2016) to Spain at NUTS-2 level; here the procedure is extended and adapted to NUTS-3, accordingly to the finer territorial scale. The territorial presence of each cluster category is captured through top employment share: a dichotomous indicator (1–0) recording whether a given cluster category's employment share in a territory exceeds the threshold associated with meaningful specialization. The province-level C_Esh indicator used in this study is the count of cluster categories present by this criterion, so that higher values denote a broader concentration of traded, clustered activity in the province. The mapping itself is instrumental to this paper: it generates the agglomeration measure, but the methodological contribution belongs to the prior published work.

3.3 Constructs and indicators

Four constructs are modelled, each operationalized with formative indicators drawn from independent statistical sources:

- **Industrial clusters presence (Cl)**: C_Esh, the traded-cluster employment share described above.
- **Technology adoption (Tech Ad)**: ICT_Index, capturing basic digital infrastructure and readiness (broadband access, digital services usage); and IN4_Index, capturing adoption of Industry 4.0 technologies (automation, robotics, data-driven production). The two indicators distinguish general digitalization from higher-order technological upgrading, and were introduced at Fernandez-Escobedo et al. (2024).
- **Competitiveness (Comp)**: RCI_Basic, the "Basic" pillar of the RCI (institutions, macroeconomic stability, infrastructure, health, basic education); Prod_2019, labour productivity as gross value added per worker; and Innov_2019, provincial innovation activity. Together they span the institutional, efficiency, and innovation dimensions of the construct.
- **Earnings per worker (EpW)**: EpW_19, average earnings per worker in 2019 in euros per year, the outcome variable.

Because the indicators originate from independent sources and capture conceptually distinct manifestations of each construct, all constructs are specified as formative composites, consistent with current guidance for regional-level indices (Hair et al. 2022). Indicators enter in their original scales; PLS-SEM standardizes data internally during estimation.

3.4 Analytical strategy: exploratory PLS-SEM

The model is estimated with PLS-SEM in SmartPLS 4 (Ringle et al. 2022). PLS-SEM is preferred over covariance-based SEM for four reasons aligned with the design: it accommodates the small sample inherent to a 50-province population; it relies on bootstrapping rather than distributional assumptions; it handles formative composites natively; and it is the recommended variant for exploratory and predictive purposes (Dash and Paul 2021; Hair et al. 2022). Estimation uses bootstrapping with 5,000 subsamples; significance is assessed jointly through p-values and bias-corrected-and-accelerated confidence intervals (Aguirre-Urreta and Rönkkö 2018).

Three clarifications delimit what the analysis can and cannot claim. First, the design is cross-sectional and observational: estimated paths are associations consistent with the proposed structure, not identified causal effects. Reverse causality (high-earning regions attracting technology investment) and omitted variables (notably the sorting of skilled workers) cannot be excluded, and no instrument credible at this scale is available. Second, in line with the modern methodological literature, PLS-SEM is used here as a composite-based, causal-predictive method: support for a pathway means that the data are consistent with it and that the model has out-of-sample predictive relevance, assessed through PLSpredict (Shmueli et al. 2016), not that the pathway is causally confirmed. The mediation decomposition follows Zhao et al. (2010) and Hair et al. (2022), with the variance-accounted-for (VAF) criterion applied only to complementary partial mediations. And third, because NUTS-3 provinces are geographically contiguous, spatial spillovers across provincial boundaries could be present in regional economic data. Unobserved spatial autocorrelation in key variables can violate the assumption of independent observations inherent in cross-sectional structural equation estimators. Although full spatial structural equation modelling is beyond the empirical scope of this paper, the current parameter estimates should be interpreted with this spatial spillovers dimension in mind.

4. Results

4.1 Measurement model

Descriptive statistics and correlations for all indicators are reported in **Table 1** and **Table 2**. Shapiro–Wilk (1965) tests indicate that most indicators deviate from normality, supporting the choice of a non-parametric estimation approach. Convergent validity of the formative constructs was assessed through redundancy analysis against reflective single-item measures of the same conceptual domain; path coefficients were 0.812 for Technology Adoption and 0.869 for Competitiveness, both above the 0.708 threshold (Hair et al. 2022). Variance inflation factors are all below the conservative 3.3 threshold (**Table 3**), indicating no problematic collinearity among formative indicators. Indicator weights and loadings (**Table 4**) are significant for all indicators except ICT_Index, whose weight is non-significant but whose loading exceeds 0.50; following standard guidance for formative measurement, the indicator is retained on grounds of absolute contribution (Cenfetelli and Bassellier 2009).

Table 1. Descriptive statistics of indicators (N=50).

	Mean	**Median**	**Std. Dev.**	**Min.**	**Max**
C_Esh	2.980	1.000	5.073	0.000	23.000
ICT_Index	0.550	0.588	0.149	0.245	0.829
IN4_Index	0.458	0.435	0.132	0.212	0.808
RCI_Basic	-0.084	-0.116	0.122	-0.213	0.302
Prod_2019	56861.339	55069.299	8698.692	41946.567	84400.958
Innov_2019	21.684	20.430	13.010	0.000	59.592
EpW_19	19518.308	19120.450	3554.472	14261.500	30146.685

Table 2. Correlations between indicators.

	C_Esh	**ICT_Index**	**IN4_Index**	**RCI_Basic**	**Prod_2019**	**Innov_2019**	**EpW_19**
C_Esh	1.000						
ICT_Index	.490**	1.000					
IN4_Index	.514**	.598**	1.000				
RCI_Basic	.447**	.304*	.718**	1.000			
Prod_2019	.335*	.407**	.610**	.452**	1.000		
Innov_2019	.451**	.289*	.350*	.196	.454**	1.000	
EpW_19	.484**	0.253	.573**	.501**	.803**	.503**	1.000

*Note: *Coefficients are significant at 5% level. **Coefficients are significant at 1% level.*

Table 3. Collinearity test to assess common method bias.

	Variance inflation factor (VIF) values
ICT_Index	1.558
IN4_Index	1.558
Inn_2019	1.260
RCI_Basic	1.256
Prod_2019	1.522

SOURCE: Author's calculations obtained with SmartPLS 4.

Table 4. Outer weights and loadings (bootstrapping, 5,000 subsamples).

	Outer weights	**Outer loadings**
ICT_Index → Tech Ad	0.042	0.625**
IN4_Index → Tech Ad	0.974**	0.999**
Inn_2019 → Comp	0.211**	0.570**
RCI_Basic → Comp	0.458**	0.767**
Prod_2019 → Comp	0.591**	0.894**

*Note: **The value shows statistical significance at 99% for both t-value and p-value.*

4.2 Structural model: direct associations

The model explains 27.2% of the variance in Technology Adoption, 59.6% in Competitiveness, and 67.5% in Earnings per Worker (**Table 5**). Direct path estimates are reported in **Table 6**.

Table 5. Explanatory power of the structural model (N = 50).

Endogenous variable	R^2	Explanatory capacity	f^2	Achieved Power
Tech Ad	0.272	Weak	0.374	0.988
Comp	0.596	Moderate	1.475	1.000
EpW	0.675	Substantial	2.077	1.000

Note: Reference for R^2 values (Ringle et al. 2022)*: >0.20 = weak; >0.33 = moderate; >0.67 = substantial. Reference for f^2 (total effect-size)* (Cohen 1988)*: >0.02 = small effect; >0.15 = medium effect; >0.35 = large effect.*

Table 6. Direct path assessment of the structural model.

Path	β	*p-value*	f^2	95% Ci bias-corrected
Cl → Tech Ad	0.521	0.001	0.373	[0.208,0.724]
Cl → Comp	0.138	0.107	0.034	[-0.030,0.328]
Cl → EpW	0.138	0.067	0.041	[-0.007,0.294]
Tech Ad → Comp	0.691	0.000	0.859	[0.507,0.795]
Tech Ad → EpW	-0.164	0.086	0.032	[-0.368,0.019]
Comp → EpW	0.866	0.000	0.934	[0.650,1.028]

Note: The standardized path coefficient (β) is significant if both p-value is <0.05 and zero does not fall into the 95% Ci bias-corrected (Aguirre-Urreta and Rönkkö 2018; Hair et al. 2022)*. Reference for f^2 (effect-size)* (Cohen 1988)*: >0.02 = small effect; >0.15 = medium effect; >0.35 = large effect.*

Three patterns answer RQ1. First, cluster presence is strongly associated with technology adoption (β = 0.521, p = 0.001, f^2 = 0.373), a large effect, and the only strong direct correlate of clustering in the model. Second, cluster presence shows no significant direct association with competitiveness (β = 0.138, p = 0.107) nor with earnings per worker (β = 0.138, p = 0.067): the confidence intervals for both paths include zero. Third, and most strikingly, technology adoption shows no positive direct association with earnings; the point estimate is negative (β = −0.164, p = 0.086), with a confidence interval spanning zero [−0.368, 0.019]. By contrast, technology adoption is strongly associated with competitiveness (β = 0.691, p < 0.001, f^2 = 0.859), and competitiveness is by a wide margin the dominant correlate of earnings per worker (β = 0.866, p < 0.001, f^2 = 0.934).

The direct-effects picture is therefore unambiguous: there is no direct channel from clusters to wages, and none from technology to wages. Whatever connects agglomeration to labour returns must run through the chain of capabilities.

4.3 Mediation decomposition: the sequential pathway

Total effects establish that the constructs are connected in the aggregate: the total association of cluster presence with competitiveness (0.498, p = 0.001), of cluster presence with earnings (0.484, p < 0.001), and of technology adoption with earnings (0.435, p < 0.001) are all significant (**Table 7**). The question is through which routes these totals arise. Specific indirect effects are reported in **Table 8**.

Table 7. Total effects assessment of the structural model.

	Total effect	*p-value*	95% Ci bias-corrected
Cl → Comp	0.498	0.001	[0.177,0.697]
Cl → EpW	0.484	<0.001	[0.242,0.626]
Tech Ad → EpW	0.435	<0.001	[0.253,0.597]

Note: The total effect is significant if both p-value is <0.05 and zero does not fall into the 95% Ci bias-corrected (Aguirre-Urreta and Rönkkö 2018; Hair et al. 2022).

Table 8. Indirect effects assessment of the structural model.

	Indirect effect	*p-value*	95% Ci bias-corrected	Decision
Cl → Tech Ad -> Comp	0.360**	0.001	[0.157,0.546]	Supported
Cl → Tech Ad -> EpW	-0.085	0.094	[-0.219,-0.003]	Not supported
Cl → Comp -> EpW	0.120	0.113	[-0.026,0.299]	Not supported
Tech Ad → Comp → EpW	0.598**	<0.001	[0.384,0.776]	Supported

*Note: *Partial mediation; **Full mediation (accordint to Hair et al. (2022) and Zhao et al. (2010)). The indirect effect is significant if both p-value is <0.05 and zero does not fall into the 95% Ci bias-corrected* (Aguirre-Urreta and Rönkkö 2018; Hair et al. 2022).

The single-mediator routes largely fail. Technology adoption alone does not transmit cluster advantages to earnings (Cl → Tech Ad → EpW: −0.085, $p = 0.094$), and competitiveness alone does not either (Cl → Comp → EpW: 0.120, $p = 0.113$). Two mediations are supported, and both are full mediations: technology adoption fully mediates the association between clusters and competitiveness (Cl → Tech Ad → Comp: 0.360, $p = 0.001$), since no significant direct cluster–competitiveness path remains; and competitiveness fully mediates the association between technology adoption and earnings (Tech Ad → Comp → EpW: 0.598, $p < 0.001$), since the direct technology–earnings path is non-significant.

Chaining these two full mediations yields the paper's central result. The sequential pathway Cl → Tech Ad → Comp → EpW is significant and accounts for 90.2% of the total indirect association between cluster presence and earnings per worker (total indirect effect = 0.346) (**Table 9**). Answering RQ2: agglomeration gains reach workers through one route only, where clustering fosters technological upgrading, and that upgrading strengthens broad competitive conditions. No shortcut exists in the data.

Table 9. Specific indirect effects of the structural model.

	Indirect effect	*p-value*	95% Ci Bias Corrected
Cl → Tech Ad → Comp → EpW	0.312	0.004	[0.115,0.507]

Note: The specific indirect effect is significant if both p-value is <0.05 and zero does not fall into the 95% Ci bias-corrected (Aguirre-Urreta and Rönkkö 2018; Hair et al. 2022).

4.4 Predictive performance

The predictive relevance of the model was assessed using PLSpredict (Shmueli et al. 2016). All Q^2 values for the manifest variables were greater than zero, indicating that the model shows predictive relevance beyond explanatory adequacy (Hair et al. 2013).

Mean absolute error (MAE) values from PLSpredict were compared with those from linear regression benchmarks (LM). As shown in **Table 10**, four out of six indicators exhibited lower prediction errors under PLS compared with LM, suggesting medium predictive power (Shmueli et al. 2019). This highlights the model's ability to generate meaningful out-of-sample predictions for regional competitiveness and labor outcomes.

Table 10. Predictive relevance (Q^2) and predictive performance by the mean absolute errors (MAE).

	Q^2 predict	PLSpredict MAE	LM MAE
ICT_Index	0.194	0.110	0.106
IN4_Index	0.241	0.085	0.084
Inn_2019	0.161	9.138*	9.161
Prod_2019	0.070	6507.304*	6562.400
RCI_Basic	0.149	0.093*	0.094
EpW_19	0.168	2319.657*	2319.657

*Note: *The PLSpredict MAE value is lower than the LM MAE value* (Shmueli et al. 2019). *In some cases, the difference between values is not noticeable because is beyond the three decimal places.*

5. Discussion

5.1 The decoupling of wealth and wages

The results acquire their full meaning when read against the companion evidence on wealth creation. For GDP per capita, prior work found that cluster effects, while never direct, travel through multiple partially overlapping channels: technology adoption and competitiveness each independently transmit part of the association, alongside the sequential chain (Fernandez-Escobedo 2024; Fernandez-Escobedo et al. 2024). For earnings per worker, the present analysis shows a narrower architecture: the parallel channels collapse, and only the full sequence survives. Wealth, in other words, is associated with agglomeration through several doors; wages through one.

This asymmetry is what we term the decoupling of wealth and wages in agglomerated regions, and it is consistent with the theoretical expectations developed in Section 2. Agglomeration mechanisms target productivity, whose gains need not accrue to labour; technology adoption has offsetting effects on earnings, raising the returns to some tasks while displacing others. Only when technological upgrading is converted into broad competitive conditions (human capital, institutions, innovation capacity, infrastructure) does the region's wage level respond. Competitiveness, on this reading, is not merely another mediator: it is the gatekeeper of the distributional outcome. The distinction matters for how cluster performance is evaluated, since an assessment framed on aggregate output would register agglomeration gains that an assessment framed on labour returns would not.

5.2 The absent (and possibly negative) technology–wage link

The non-significant, negative point estimate for the direct technology–earnings path deserves attention rather than embarrassment. It aligns with the task-based literature on technological change: where adoption automates routine work without complementary upgrading of skills and institutions, average earnings need not rise and may face downward pressure (Autor et al. 2003; Acemoglu and Restrepo 2019). The interpretation is sharpened by the composition of the Technology Adoption construct itself. The indicator weights are strongly asymmetric: IN4_Index carries almost the entire weight of the construct, while the weight of ICT_Index is not significant. What the model captures under "technology adoption" is therefore predominantly Industry 4.0 adoption (automation, robotics, data-driven production) rather than general digital connectivity. The absent wage association is thus specifically an absent association between advanced automation and average earnings, which is precisely the relationship the task-displacement literature would lead one to expect.

This reading connects directly to the territorial market power evidence of Capello et al. (2025b), who find that the detrimental effect of automation on the labour share of income is strongest in highly specialized, geographically clustered European regions, the very environments the cluster construct captures here. Read jointly, their result and the present findings suggest that in cluster contexts automation redistributes value towards capital unless competitive conditions channel it back to labour; the profit-share evidence of Capello et al. (2025a) and the between-firm wage dispersion documented by Duran and Siedschlag (2025) point in the same direction. The finding also speaks to the digital productivity paradox debate (Ahmad and Schreyer 2016): adoption alone, unaccompanied by absorptive conditions, shows no wage dividend in these data.

5.3 Relation to the agglomeration wage literature

The absence of a direct cluster–wage association echoes De Blasio and Di Addario (2005) for Italian districts and the broader finding that observed urban wage premia owe much to sorting rather than to agglomeration per se (Groot et al. 2014; García-Suaza and Londoño 2025). Our contribution to this debate is mechanistic: rather than asking whether a premium exists, we trace the conditions under which one can arise. The answer, only through the technology-competitiveness sequence, reconciles the mixed premia evidence: clusters embedded in upgrading trajectories generate premia; clusters without them do not, regardless of density.

The links between clusters, digitalization, and competitiveness are not themselves new territory. Borodina and Nataliia Trushkina (2021) examine the digitalization of cluster-based governance within regional strategy, Salimova et al. (2020) address cluster and competitiveness dynamics under digital transformation, and Safarov et al. (2022) discuss the interplay between clustering, digital adoption, and regional competitive positioning. The present study differs from that literature in three respects. First, the outcome: prior work centres on competitiveness or governance capacity as the endpoint, whereas competitiveness is treated here as an intermediate mechanism, with the analysis asking whether the resulting gains reach labour, a distributional question those studies do not pose. Second, the analytical strategy: rather than a conceptual treatment of the cluster–digitalization–competitiveness relationship, the paper formally decomposes direct and indirect associations, identifying which specific pathways the data support and which they do not. Third, the comparative frame: read against companion evidence on wealth creation, the results isolate a wealth–wages divergence that single-outcome designs cannot reveal. The contribution is therefore not the discovery of a cluster–digitalization–competitiveness link, but a mechanism-based account of where that link does, and does not, reach workers.

5.4. Policy implications

The findings carry a sequencing message for place-based economic policy. Cluster initiatives, taken alone, should not be expected to raise wages: their reliable correlate in these data is technological adoption, not earnings. Digitalization programmes, taken alone, should not be expected to raise wages either: absent competitive complements, the technology–earnings association is null or negative. What the evidence supports is integration; coupling cluster and digital-adoption instruments, such as digital innovation hubs, adoption incentives, and collaborative research and development schemes, with sustained investment in the regional competitiveness base: human capital, innovation capacity, institutional quality, and foundational infrastructure.

Two qualifications should frame what follows. The estimates are cross-sectional associations rather than identified causal effects, and the sample of fifty provinces does not permit the subgroup or interaction analysis that would be required to test whether transmission differs across regional types. The territorial reading offered below therefore extends the estimated mechanism as a policy conjecture consistent with the results, not as a tested finding.

So framed, the sequential structure implies that uniform instruments will produce uneven wage outcomes across asymmetric territories. Where institutional quality, human capital, and innovation capacity are already strong, the conversion mechanism is in place, and agglomeration and technological upgrading would be expected to register in both aggregate output and labour returns. Where those foundations are weak, the same instruments would be expected to stall at the first link of the chain: adoption occurs, but the competitive conditions that pass value to labour are absent. Under such conditions, and consistent with the territorial market power mechanism identified by Capello et al. (2025b), productivity gains may accrue disproportionately to capital or to non-local firm owners while local earnings remain flat.

For Spain specifically, the pronounced provincial heterogeneity in cluster presence and digital adoption makes provinces with established cluster structures but weak competitive foundations the critical policy cases: they possess the first link of the structural chain while lacking the conversion mechanism. The implication is a shift in emphasis from adoption incentives towards the absorptive capacity that makes adoption pay for workers: workforce upskilling, institutional and administrative quality, and innovation capacity in the terms captured by the Basic pillar of the RCI.

The governance architecture complicates this sequencing in a way worth stating plainly. In Spain, competitiveness-building instruments, such as vocational training systems, regional innovation and smart specialisation strategies, are largely designed and delivered at the autonomous community level, while cluster and digitalization programmes frequently originate in nationally designed, nationally disbursed schemes (except for *sui generis* regions as the Baque Country, which explain partially its success in this matters). Where the two are not coordinated, instruments may arrive in a territory without the complements this analysis identifies as necessary. EU Cohesion Policy funding and its associated technical assistance offer one route to aligning them, but the alignment is an institutional task rather than a funding one, and it is a plausible reason why the coupling the results call for is not already the norm.

6. Conclusions

This paper asked whether agglomeration gains reach workers, and through which mechanisms. Across the 50 Spanish provinces, the answer is conditional and sequential: industrial clusters show no direct association with earnings per worker; their gains reach wages only where clustering fosters technological upgrading that strengthens regional competitiveness. That single pathway concentrates roughly ninety per cent of the indirect association between clustering and labour returns. Set against companion evidence that wealth creation responds to agglomeration through multiple channels, the results reveal a decoupling between the geography of wealth and the geography of wages; a distinction with direct consequences for how cluster and digitalization policies should be designed and evaluated.

Several limitations bound the claims. The design is cross-sectional, for a single pre-pandemic year, and the estimates are associations rather than identified causal effects; reverse causality and skill sorting remain live alternative explanations. The sample is the population of 50 provinces, which limits statistical power and precludes subgroup analysis. The NUTS-3 units, while policy-relevant, are administrative boundaries subject to the modifiable areal unit problem (Openshaw and Taylor 1979). Finally, PLS-SEM structures and predicts relationships among composites; it does not substitute for causal identification. Future research should extend the framework longitudinally to exploit within-province variation, complement the composite approach with spatial econometric methods to assess spillovers across provincial boundaries, and take the analysis to the microdata level, where the sorting and task-composition mechanisms suggested here can be tested directly. Comparative extensions to other European countries at NUTS-3 would establish whether the wealth–wages decoupling is a Spanish particularity or a general feature of agglomerated economies.

Data availability *The author confirms that the data supporting the findings of this study are available within the article. These data were derived from public sources: INE (www.ine.es), OEPM (www.oepm.es), and the European Commission Regional Competitiveness Index (https://ec.europa.eu/regional_policy/en/information/maps/regional_competitiveness/).*

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