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Impact of Intangible Capital on Firm Productivity and Wages: evidence from Uruguay 2013–2023

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Abstract

We analyze the impact of intangible capital on firm-level productivity in Uruguay over the period 2013–2023, replicating the empirical framework of Castillo and Crespi (2024) for Peru and adding some extensions. Using a panel of Uruguayan firms and multiple production function estimators (OLS, fixed effects, and control function methods of Olley-Pakes, Levinsohn-Petrin, and Ackerberg-Caves-Frazer), we find that intangible capital contributes positively and significantly to productivity. A one standard deviation increase in a firm's intangible intensity is associated with approximately a 3% higher total factor productivity, and our estimates suggest that the productivity premium of intangible assets is almost 1.3 times the marginal productivity of tangible investments. We also find that firms investing in intangibles pay moderately higher wages, but this wage premium does not fully offset the productivity gains from intangibles. In other words, a portion of the intangible-induced productivity improvement is retained as increased firm performance (profits or market share), consistent with imperfect spillovers and appropriability of returns. Some extensions of the analysis show that: (i) software-based intangibles yields especially high private returns, (ii) multi-product firms share a larger portion of gains with workers, and (iii) monopsony power in labor markets reduces wage pass-through of productivity premium. We discuss how these findings compare to evidence for Peru, highlighting that Uruguay's smaller, open economy context exhibits similar qualitative patterns—intangibles boost productivity and confer a capital productivity premium—though with some differences in magnitudes. The results underscore the policy importance of encouraging intangible investment and improving firms' capacity to absorb and utilize intangibles, especially given the currently low incidence of intangible investment in Uruguay.

JEL Codes: O30, O40, D24, J24, L60, L80

Keywords: Intangible capital, productivity, wages, Uruguay, firm-level data, econometric estimation

1 Introduction

Intangible capital—assets like research and development (R&D), software, data, workforce training, organizational know-how, and brand equity—has emerged as a key driver of firm productivity and economic growth in advanced economies and has increased over three times faster than tangible investment since 2008 (Corrado, Hulten, & Sichel, 2005, 2022; World Intellectual Property Organization, 2025). These knowledge-based assets enable firms to innovate, improve efficiency, and differentiate their products, often yielding returns that rival or exceed those of traditional physical capital (Corrado, Hulten, & Sichel, 2009). However, the role of intangible capital in developing or smaller economies is less understood. Uruguay provides a novel case study as a small open economy in Latin America with relatively high income levels but scarce empirical evidence on how intangibles relate to productivity. Existing literature on Latin America suggests that investments in innovation and knowledge can have sizable payoffs in some countries (Benavente, De Gregorio, & Núñez, 2005; Crespi & Zúñiga, 2012). Yet in such contexts intangible investments are not widespread, and their impacts may depend on sectoral and institutional factors (Crespi & Zúñiga, 2012; Hall & Lerner, 2010).

In Uruguay, the topic of intangibles and productivity has seen limited exploration to date. One notable study found that information and communication technology (ICT) investments significantly boosted productivity in Uruguayan service firms, but had weaker effects in manufacturing firms(Aboal & Tacsir, 2018). This sector-specific result hints that the contribution of intangibles may vary across the economy and underscores the need for a comprehensive analysis. Furthermore, most Uruguayan firms invest very little in intangible assets: our dataset shows that intangible capital comprises only about 3.1% of total capital stock for the average firm, and nearly 63% of firms report no intangible investment at all during 2013–2023. Even among firms that do invest in intangibles, the mean intangible intensity is about 11.7% of total capital, indicating that a small subset of firms undertakes the bulk of intangible investment. Such figures align with broader patterns in developing economies, where intangible investment is often a fraction of that in advanced countries (Haskel & Westlake, 2018). As shown in Figure 1 knowledge-intensive service industries like information services and finance exhibit the highest intangible intensities (10–20%), whereas many traditional manufacturing and utility sectors have negligible intangible capital.

The low prevalence but potentially high impact of intangibles in Uruguay presents a compelling case for study: if intangible capital can substantially raise productivity for the few firms that invest in it, expanding intangible investment more broadly could be a lever for improving aggregate productivity.

This paper contributes to the literature by analyzing firm-level data from Uruguay with an explicit focus on intangible capital and productivity, closely following the methodological approach of Castillo and Crespi (2024) for Peruvian firms. We estimate production functions augmented with an intangible capital variable, employing multiple estimators to address potential biases, and we examine the extent to which intangible-related productivity gains translate into higher wages for workers. The Uruguayan context offers an interesting comparison to larger economies: as a small open economy, Uruguay's firms operate under exposure to international competition and often specialize in natural-resource and service

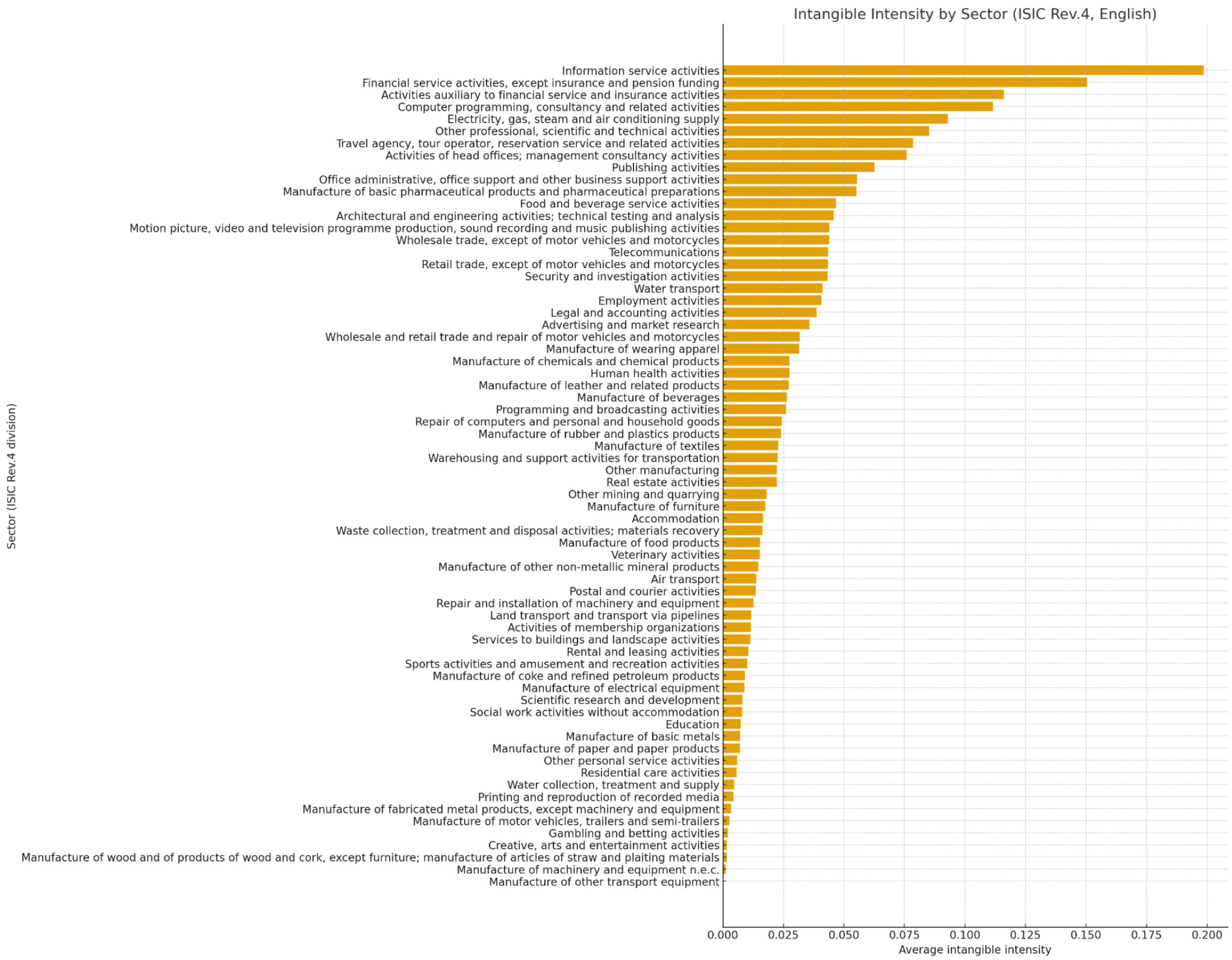

Figure 1: Intangible intensity by sector (intangibles as a share of total capital) (ISIC Rev.4, English).

sectors. The findings will shed light on whether intangibles provide a productivity edge in this setting and how their returns are distributed between firms and employees.

The remainder of the paper is organized as follows. Section 2 reviews the literature on intangible capital and productivity. It begins with the conceptual underpinnings and global evidence (Section 2.1), and then turns to the specific findings for developing economies and Latin America (Section 2.2). Section 3 presents our methodology, describing the data and variables (Section 3.1) and the econometric models employed (Section 3.2). Section 4 reports the estimation results, including production function estimates for both value added and gross output (Sections 4.1 and 4.2), as well as wage pass-through and the calculation of the productivity premium of intangibles. Section 5 extends the analysis by distinguishing between software and other types of intangibles (Section 5.1), comparing multi-product and single-product firms (Section 5.2), and examining the role of labor market imperfections (Section 5.3). Section 6 discusses the main results in light of prior studies and the comparative evidence from Peru, highlighting mechanisms such as spillovers, appropriability, and market size. Finally, Section 7 concludes with implications for policy and avenues for future research, emphasizing the challenges of measurement and the importance of complementary factors for fostering productivity gains from intangibles.

2 Literature Review

2.1 Intangible Capital and Productivity: Concepts and Global Evidence

Intangible capital is broadly defined as non-physical assets that a firm accumulates to enhance its long-term value creation (Corrado et al., 2005). These include technological intangibles like software, databases, and patents; innovative and creative intangibles like R&D, design, and intellectual property; and economic competencies such as organizational structures, training, and brand equity (Corrado et al., 2005; OECD, 2013). Unlike tangible assets, intangibles are often scalable and non-rivalrous—once developed, an idea or software can be deployed across many units of production at near zero marginal (Haskel & Westlake, 2018). This scalability means intangibles can lead to increasing returns to scale and "superstar" productivity effects for firms that successfully leverage them (Brynjolfsson, Hitt, & Yang, 2002; Autor, Dorn, Katz, Patterson, & Van Reenen, 2020). At the same time, many intangibles are only partially excludable (knowledge can spill over or be imitated by others), which creates a wedge between private and social returns (Griliches, 1992; Jones & Williams, 1998). The theoretical literature (e.g., Romer (1990)) emphasizes that intangible knowledge assets drive endogenous growth, but also highlights market failures due to spillovers and the need for complementary investments (such as skilled labor and new organizational practices) to realize their full value (Aghion & Howitt, 1992).

Empirical studies in advanced economies overwhelmingly find that intangible capital has a significant positive effect on firm productivity. Production function estimates often show output elasticities with respect to intangible assets that are on par with or higher than those for tangible capital (Corrado et al., 2009; O'Mahony & Vecchi, 2009). For example, Corrado, Haskel, Jona-Lasinio, and Iommi (2013) and others document that software and other IT capital contribute strongly to productivity growth; Oliner, Sichel, and Stiroh (2008) report that intangible investment was a major driver of the post-1990s productivity surge in the US. In the UK, O'Mahony and Vecchi (2005) found the output contribution of ICT capital to exceed that of traditional capital. A broad consensus has emerged that in knowledge-driven economies, intangibles (from R&D to human capital and organizational know-how) account for an increasing share of productivity growth (Corrado et al., 2013; OECD, 2013).

Importantly, studies also find heterogeneity in the returns to intangibles. The benefits of IT and digital intangibles, for instance, are much larger in firms that simultaneously undertake complementary organizational changes (Brynjolfsson & Hitt, 2000; Bresnahan, Brynjolfsson, & Hitt, 2002; Crespi, Criscuolo, & Haskel, 2008). Firms that invest heavily in human capital and management improvements reap greater productivity gains from new technologies than those that do not, as shown by Bresnahan et al. (2002). This underscores that intangibles often work in tandem with other inputs. Additionally, because intangibles can diffuse, the full impact may extend beyond the investing firm. There is evidence of positive spillovers from R&D and technology adoption to other firms in the industry or region (Jaffe, Trajtenberg, & Henderson, 1993; Bloom, Schankerman, & Van Reenen, 2013). Nonetheless, the originating firm usually captures only part of the total gains (e.g., through temporary monopoly rents or lead-time advantages), with studies estimating that social returns to R&D are significantly higher than private returns (Hall, Mairesse, & Mohnen, 2010). This gap rationalizes policy interventions like R&D tax credits or subsidies to encourage more investment in intangibles than the market alone would provide.

2.2 Evidence from Developing Economies and Latin America

In developing economies, the adoption of intangible capital tends to lag behind that in advanced countries (OECD, 2013; World Bank, 2017). Firms in these contexts invest less in R&D, software, and training on average, due to factors such as financial constraints, skill shortages, and uncertainty about returns. However, emerging evidence suggests that when firms in developing countries do invest in intangibles, they can achieve substantial productivity improvements. Benavente et al. (2005) found positive returns to R&D in Chilean manufacturing comparable to those in developed economies. A multi-country study by Crespi and Zúñiga (2012) showed that in several Latin American countries (Argentina, Chile, and Uruguay), firms conducting R&D enjoyed significantly higher productivity—on the order of a 20–30% premium—compared to non-innovators. By contrast, in countries with weaker innovation systems (e.g., Colombia and Panama), the R&D effect was smaller or insignificant, underscoring the importance of complementary factors such as human capital and institutional quality for realizing the returns to innovation. Broadly, these studies confirm that intangibles can boost productivity in developing contexts, but the variability is greater and the outcomes less predictable than in advanced economies (Castillo & Crespi, 2024; Crespi, Garone, Maffioli, & Stein, 2020).

For Latin America, one of the first comprehensive analyses of intangible capital's impact is the recent work by Castillo and Crespi (2024) on Peruvian firms. They find that increasing a firm's intangible asset share by one standard deviation is associated with a 6.8–7.2% rise in total factor productivity (TFP). Moreover, their estimates suggest that intangible capital in Peru is up to twice as productive, in terms of output contribution per dollar, as conventional tangible capital. This "capital productivity premium" for intangibles implies high private returns for firms that invest in knowledge assets. They also examine how these productivity gains are split between firms and workers. While firms with greater intangible intensity do pay higher wages, the wage increases capture only about 88% of the productivity gains on average, leaving the remainder as additional profit or competitive advantage to the firm. This partial pass-through (or *partial appropriability*) is consistent with the presence of idea specificity—firm-specific intangible assets that competitors cannot easily replicate—and labor market frictions, which prevent workers from fully capturing the marginal product of their skills.

Other studies in the region point to nuanced effects of different types of intangibles. Aboal and Tacsir (2018) in Uruguay found that ICT capital investments led to productivity improvements in service sectors, where digital information flows are critical, but had limited measured impact in manufacturing sectors. This suggests that the effectiveness of intangible investments may depend on the technological intensity of the sector and the presence of complementary capabilities. In many traditional sectors, simply purchasing technology or software may not yield gains unless accompanied by organizational change or upskilling of workers (Brynjolfsson & Hitt, 2000). Likewise, investments in human capital (training, education) show high returns in some Latin American firm studies, but only a fraction of firms undertake formal training programs. The literature emphasizes that a small subset of "frontier" firms in these economies are pushing ahead with intangible accumulation and reaping large productivity benefits, while a long tail of firms remain far behind (Crespi, Fernández-Arias, & Stein, 2014). This bifurcation can lead to widening productivity dispersion: a phenomenon whereby intangibles contribute to a growing gap between leading firms and laggards when diffusion of knowledge is limited.

In summary, the literature indicates that intangible capital is a crucial but underutilized driver of productivity in developing economies. Uruguay exemplifies many of these patterns: a relatively low average investment in intangibles, but potentially high returns for those firms that do invest, conditioned by factors like sector, skills, and the broader innovation ecosystem. Our study builds on these insights by providing the first firm-level analysis (to our knowledge) that quantifies the productivity elasticity of intangible capital and its wage implications in Uruguay. By comparing results across estimation techniques and drawing parallels to the Peruvian case, we aim to deepen the understanding of how intangibles operate in a small open economy context and what that implies for policy.

3 Methodology

3.1 Data and Variables

The primary data source is the Economic Activities Annual Survey (Encuesta Anual de Actividad Económica EAAE) administered by Uruguay's statistical agency (INE). We also use information about sectoral output deflators from National Accounts compiled by the Central Bank of Uruguay and CPI from INE.

The EAAE aims to represent firms in manufacturing and services except the following sectors: agriculture, banking, construction, household work and extraterritorial organizations. Within each four-digit ISIC sector, the largest firms (in terms of employment or sales) are included in the sample (compulsory range), while a probabilistic sample is drawn from the remaining set of firms. The INE periodically revises sample coverage and includes new firms using an updated firm directory. The EAAE contains financial and operational information, including revenues, value added, labor (number of workers), investment and stock of fixed assets and a breakdown of intangible assets on the annual balance sheet.

We have data for the 2013-2023 period. After cleaning this data and removing outliers (we apply a consistent outlier detection rule to mitigate the influence of reporting errors or extreme values), the resulting unbalanced panel have 37,988 firm-year observations corresponding to 7,163 unique firms over the 11-year period. On average each firm is observed for 5.3 years, with 13% of companies being observed for only one year and 10% that are observed in all years.

All monetary values have been deflated to constant 2024 prices using appropriate price indices (sectoral deflators for output, value added, investment and assets and CPI for wages).

From this database, we obtain the following key variables needed for the estimation of the production function and wage equation. **Output** can be measured in two ways: (i) as *Gross Production Value* and (ii) as *Value Added*, which subtracts intermediate input costs from gross output. We perform analyses using both definitions. **Labor input** (L_{it}) is measured by the number of employees. **Capital** (K_{it}) is the total capital proxied by the net book value (at the beginning of the year) of tangible capital stock (property, plant, equipment) and intangible assets. We also use the value of **intermediate inputs** and **fixed capital investment**.

Our variable of interest is **intangible capital intensity** (s_{it}^{IC}), defined as the share of intangible assets in the firm's total capital stock. This ratio captures the importance of intangibles in the firm's capital structure. We prefer this measure over the raw intangible stock for threee reasons: first, it normalizes for firm size, second, we avoid the loss of observations when taking the log of gross value (since many firms have zero intangible assets), and third, it aligns with the approach of Castillo and Crespi (2024) who focus on the share of intangibles as an explanatory variable. They show that a Cobb-Douglas production function, where the relevant measure of capital is the quality adjusted sum of tangible and intangible capital, can be formulated in terms of total capital (non-quality adjusted) and the ratio of intangible assets over total capital. In our data, s_{it}^{IC} is highly skewed: the majority of firm-year observations (63%) have $s^{IC} = 0$ (no recorded intangible assets), and among those with $s^{IC} > 0$, the distribution has a long upper tail (the 90th percentile of s^{IC} for investing firms is around 0.37, meaning some firms have nearly 40% of their capital in intangibles). Finally, for the wage analysis, we calculate the **average wage** at the firm (W_{it}) as total labor cost divided by number of employees. This is our measure of the average wage of each firm-year observation and is the dependent variable in our wage equation.

Table 1: Summary Statistics of Key Variables (2013–2023)

Variable	Mean	Std. Dev.	P10	P50	P90	Obs.
Employees (number)	52	210	11	20	79	37,988
Total Wages (annual, USD)	1,128,277	6,796,700	101,999	290,538	1,608,122	37,988
Wages per Employee (annual, USD)	17,527	14,608	7,005	13,733	31,617	37,988
Gross Output (annual, USD)	4,733,446	34,177,591	243,139	904,740	6,480,313	37,988
Value Added (annual, USD)	2,196,063	15,595,433	145,495	499,553	3,106,936	37,988
Labor Cost / Value Added	0.728	0.367	0.365	0.722	1.000	37,988
Intangible Assets / Total Capital (all firms)	0.031	0.121	0	0	0.049	37,988
Intangible Assets / Total Capital (if $IC > 0$)	0.117	0.212	0.001	0.023	0.373	14,191

Notes: Monetary values are in 2024 constant USD. P10, P50, P90 refer to the 10th, 50th (median), and 90th percentiles. Labor cost includes all salaries and benefits. Intangible intensity is the ratio of intangible capital to total capital; statistics for the subsample of firms with positive intangible investment are shown in the last row. Source: Authors' calculations based on EAAE firm survey data.

The summary statistics in Table 1 highlight the skewed nature of firm size and intangible investment. The median firm has 20 employees and no intangible assets, whereas the mean is driven up by a few very large firms (90th percentile employment is 79, and maximum in the thousands) and by firms with substantial intangible capital. The average share of intangibles across all firms is 3.1%, but conditional on having any intangibles it is 11.7%. These figures suggest that intangible capital in Uruguay is concentrated among a minority of relatively larger or more innovative firms. The average wage is USD 17,526, with a wide dispersion (standard deviation 14,608), indicating heterogeneity in workforce skill and/or labor productivity across firms.

3.2 Econometric Model

To estimate the productivity impact of intangible capital, we adopt a production function approach. We specify a Cobb-Douglas production function augmented with an intangible capital term. Following Castillo and Crespi (2024), if the relevant measure of capital is the quality adjusted sum of tangible and intangible, we can write the product or value added as a function of labor, total capital (non-quality adjusted) and the ratio of intangible assets over total capital. In value-added form, the model for firm i in year t can be written as:

$$y_{it} = \beta_L \, \ell_{it} + \beta_K \, k_{it} + \beta_I \, s_{it}^{IC} + \omega_{it} + \varepsilon_{it} \, , \tag{1}$$

where $y_{it} = \ln(Y_{it})$ is the log of output (value added), $\ell_{it} = \ln(L_{it})$ is the log of labor input, $k_{it} = \ln(K_{it})$ is the log of total capital, and s_{it}^{IC} is the intangible capital intensity defined above (the approximation $\ln(1 + s_{it}^{IC}) \approx s_{it}^{IC}$ is valid for small s_{it}^{IC}, which is the case here). The term ω_{it} represents unobserved firm-specific productivity shocks (or TFP, in logs) that are potentially known to the firm when making input decisions, and ε_{it} is an i.i.d. error term capturing unanticipated shocks. In a gross output production function, we include intermediate inputs (materials) as an additional regressor; we estimate such a model as a robustness check (results are presented in Section 4.2).

The coefficient β_I is of primary interest, as it measures the output elasticity with respect to intangibles— the percentage change in output in response to variations in the intangible intensity of total capital. Furthermore, under the conditions that allow this specification of the production function, the following relationship between β_K and β_I must be verified: $\beta_I = \beta_K \, \rho_I$ where ρ_I is the measure of the capital productivity premium of intangibles with respect to tangible capital. Therefore, this is other main parameter of interest that can be captured by estimating (1) ($\widehat{\rho}_I = \widehat{\beta}_I / \widehat{\beta}_K$)

Estimating (1) by ordinary least squares (OLS) could yield biased results because of two main issues: *endogeneity* of inputs and *unobserved heterogeneity*. High-productivity firms may systematically choose higher inputs (including intangibles), creating reverse causality, and there may be firm-specific characteristics (managerial ability, product quality, etc.) that affect productivity and correlate with intangible investment. To address these concerns, we employ multiple estimation strategies:

- **Pooled OLS:** As a baseline, we first estimate (1) by OLS, pooling all observations and including year fixed effects to control for macro shocks. This provides a benchmark but is likely biased because $\mathbb{E}[\ell_{it}\,\omega_{it}] \neq 0$, $\mathbb{E}[k_{it}\,\omega_{it}] \neq 0$, etc., if firms adjust inputs based on productivity.

- **Fixed Effects (FE):** We include firm fixed effects α_i in the production function ($y_{it} = \alpha_i + \beta_L \ell_{it} + \beta_K k_{it} + \beta_I s_{it}^{IC} + \varepsilon_{it}$) to control for time-invariant differences across firms (e.g., persistent managerial quality or technology level). The FE estimator uses within-firm variation over time to identify coefficients. While this controls for any constant unobserved heterogeneity, it does not fully solve endogeneity due to ω_{it} varying over time and influencing input choices. Moreover, if intangible intensity changes slowly or is measured with error, the within-firm estimates of β_I may be attenuated.

- **Olley-Pakes (OP) method:** The OP semi-parametric estimator (Olley & Pakes, 1996) addresses simultaneity by using investment as a proxy for the unobserved productivity shock ω_{it}. The idea is that firms respond to a positive productivity shock by increasing investment, so investment can reveal ω_{it}. OP involves a two-step procedure where one first estimates a non-parametric function of capital and investment to net out ω_{it}, and then uses the moment conditions of capital evolution and survival to identify the coefficients. OP can correct bias from endogeneity and also handle selection (the fact that low-productivity firms may exit).

- **Levinsohn-Petrin (LP) method:** The LP estimator (Levinsohn & Petrin, 2003) is similar to OP but uses intermediate inputs (e.g., materials) as the proxy for productivity shocks instead of investment. In our data, many firms report zero investment in some years (especially smaller firms), which can be problematic for OP's invertibility condition. LP's use of materials (which are almost always positive and variable) can provide a more robust proxy in such cases. The LP procedure, like OP, uses a two-stage estimation to recover $\beta_L, \beta_K, \beta_I$ while controlling for ω_{it}.

- **Ackerberg-Caves-Frazer (ACF) method:** Ackerberg, Caves, and Frazer (2015) refine the OP/LP approach by addressing an identification issue in the first stage (where labor appeared collinear with the proxy in OP/LP). The ACF estimator allows a more flexible timing assumption for labor and uses a generalized method of moments framework to obtain consistent estimates of all inputs' coefficients. We implement the ACF procedure as our most advanced estimator, which should mitigate both simultaneity and selection biases.

By applying all these methods, we can compare results to see how sensitive the estimated coefficients β_I and ρ_I are to different identification strategies. In general, we expect β_L (labor elasticity) from OLS to be upward-biased (because productive firms employ more labor) and β_K (capital elasticity) to potentially be biased as well; the control-function methods (OP/LP/ACF) typically yield lower labor coefficients and higher capital coefficients relative to OLS, as found in many studies. For β_I, if intangible investment is positively correlated with firm productivity (i.e., better firms invest more in intangibles), OLS might overestimate its effect, whereas FE might underestimate it if most variation is cross-sectional. The OP/LP/ACF estimates are expected to provide a more credible range for β_I by accounting for the endogeneity of s_{it}^{IC}.

In addition to the production function, we estimate a **wage equation** to assess how intangibles affect worker outcomes. The wage equation is specified as:

$$w_{it} = \delta_I \, s_{it}^{IC} + \delta_\omega \, \widehat{\omega}_{it} + X_{it} \, \gamma + \mu_i + \nu_{it} \,, \tag{2}$$

where $w_{it} = \ln(W_{it})$ is the log of average wage in firm i, s_{it}^{IC} is intangible intensity, $\widehat{\omega}_{it}$ is the firm's estimated TFP (productivity term) from the production function and X_{it} capture additional control variables. We include firm fixed effects μ_i in some specifications, although our preferred approach follows Castillo and Crespi (2024) in using the two-step method: first estimate the production function to get $\widehat{\omega}_{it}$, then plug that into (2) and estimate by OLS. The coefficient δ_ω captures how much of productivity improvements are passed on to wages (we expect $\delta_\omega > 0$, as more productive firms tend to pay higher wages). The coefficient δ_I captures the direct wage premium associated with intangibles, holding productivity constant. Castillo and Crespi (2024) point out that if firms are price takers in the labor market and ideas embedded into intangibles are generic, the capital productivity premium of intangible assets should be equivalent to the average wage premium, i.e. $\delta_I = \rho_I$.

However, if δ_I is smaller than the productivity premium ρ_I, it implies only partial pass-through of intangible benefits to workers, with the remainder retained by firms. Therefore, we can interpret the ratio δ_I / ρ_I as the percentage of intangibles productivity premium that goes to workers' wages. We will compare the estimates of these coefficients to gauge this share, analogous to the analysis for Peru (where the wage capture of intangible returns was about 43%).

It is worth noting that the wage equation could also be augmented with worker characteristics (education levels, etc.) if available, but our firm-level data does not include a detailed workforce composition aside from average wage. We rely on firm fixed effects μ_i and the inclusion of $\widehat{\omega}_{it}$ to account for unobserved workforce quality to some extent and we also include the two additional controls regarding the firms' ownership (the share of foreign and public capital in the total capital). Year dummies are included in (2) to absorb macro-level wage trends (e.g., inflation, labor market conditions).

4 Results

4.1 Production Function Estimates: Value Added Model

Table 2 reports the estimated production function coefficients for value added output, along with the associated wage equation results, under each estimation method. The table is arranged in two panels: Panel A shows the output elasticities for labor, capital, and intangible intensity ($\beta_L, \beta_K, \beta_I$) from the value-added production function; Panel B shows the coefficients from the wage equations, specifically the effect of firm productivity (δ_ω) and the intangible wage premium (δ_I). Standard errors are in parentheses below each coefficient, and we indicate significance at the 10%, 5%, and 1% levels.

Table 2: Impact of Intangible Capital on Productivity and Wages (Value Added Model)

	OLS	FE	OP	LP	ACF
Production Function (Panel A)					
Labor (log L)	0.729***	0.601***	0.621***	0.518***	0.742***
	(0.005)	(0.008)	(0.007)	(0.007)	(0.000)
Capital (log K)	0.184***	0.056***	0.216***	0.197***	0.197***
	(0.002)	(0.003)	(0.000)[a]	(0.000)	(0.000)
Intangible Intensity (s^{IC})	0.247***	−0.012	0.291***	0.260***	0.260***
	(0.027)	(0.024)	(0.000)[a]	(0.000)	(0.000)
Wage Equation (Panel B)					
TFP (estimated ω)			0.151***	0.475***	0.384***
			(0.026)	(0.013)	(0.017)
Intangible Intensity (s^{IC})			0.357***	0.302***	0.306***
			(0.035)	(0.031)	(0.030)
Observations	35,407	35,407	28,664	35,363	35,363

Notes: Each column reports results for one estimator. The top panel shows production function coefficients (β_L, β_K, β_I). The bottom panel shows the corresponding wage equation coefficients (δ_ω, δ_I) estimated in the second stage using TFP from the production function. Robust standard errors in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Production function estimates (Panel A). Several important patterns emerge from Panel A. First, the OLS results (column 1) indicate large and significant coefficients on labor and capital, as well as a positive and significant coefficient on intangible intensity ($\beta_I = 0.25$, $p < 0.01$). According to the pooled OLS, one standard deviation increase in intangible assets intensity (0.12) is associated with about 3% higher value added on average. However, when we include firm fixed effects (column 2), the coefficient on intangible intensity becomes small and statistically insignificant (–0.012 and not different from zero). This stark difference between OLS and FE suggests that the positive OLS correlation between intangibles and output may be driven largely by time-invariant firm characteristics—i.e., firms that are consistently more productive also tend to have higher intangible shares. Once each firm is compared to itself over time, changes in intangible investment do not show an immediate impact on output in the FE model. It is worth noting that intangibles may exhibit persistence and measurement error that make the FE estimator less reliable (the within-firm variation is limited). In the FE results, the labor elasticity β_L is reduced (0.60) and capital elasticity β_K drops to 0.053, suggesting that firm fixed effects absorb much of the scale differences among firms.

The control function estimators (columns 3–5) provide our preferred estimates accounting for endogeneity of inputs. The Olley-Pakes (OP) method (column 3) yields $\beta_I = 0.29$ with a standard error effectively zero at three decimal places (significant at 1%). The Levinsohn-Petrin (LP) estimate (column 4) and the ACF estimate (column 5) show a value of $\beta_I = 0.26$, also highly significant. The fact that OP gives the highest β_I might indicate that intangible investment and firm exit are correlated (OP accounts for potential selection bias of exit; firms with low ω and high intangible might exit, so failing to account could bias down β_I—OP correcting that yields higher β_I). All three advanced estimators indicate a positive and statistically significant contribution of intangible capital to output, in the range of 0.26–0.29. These magnitudes are notably higher than those found in the FE model. The fixed effect model likely underestimates β_I due to attenuation from limited within-firm variation. Once we properly control for the simultaneity of input choices, intangibles emerge as a clearly important input in production.

Crucially, the intangible capital elasticity around 0.26 is economically meaningful. For perspective, at the sample mean intangible share (3%), a one standard deviation increase in s^{IC} (which is about 12 percentage points for the whole sample, or 21 points among investing firms) would increase output by roughly $0.26 \times 0.12 = 0.031$, i.e. 3.1% (using the ACF estimate). If we consider only firms that invest in intangibles, a one-sigma increase (0.21) would yield a 5.5% output gain under ACF estimates. These figures are somewhat lower than the 6.8–10.5% TFP increase per std. dev. reported for Peru, but they are also indicating a positive and non-trivial productivity effect of intangibles in Uruguay.

Looking at the other inputs: as expected, the labor coefficient drops when moving from OLS (0.73) to OP (0.62) and LP (0.52), consistent with OP/LP correcting an upward bias in OLS β_L. Interestingly, ACF yields a labor coefficient (0.74) slightly higher than OLS. This could be due to sampling or the fact that ACF uses a different moment condition; it may also reflect labor rigidity (if labor is decided before observing the productivity shock, ACF might treat it as predetermined, resulting in a higher estimate). Capital's coefficient rises slightly in control function estimates (0.20–0.22) compared to OLS (0.18), which is consistent with the idea that OLS underestimates capital's role due to endogeneity (productive firms with higher ω_{it} not fully captured invest more in capital). Overall, returns to scale (summing $\beta_L + \beta_K$) are around 0.84 in OP, 0.71 in LP and 0.94 in ACF. These sums suggest that under ACF, the average technology shows constant or slightly decreasing returns to scale.

Using the estimated results for capital elasticity together with the contribution of intangibles to total factor productivity we calculate that the productivity premium of intangibles on tangible capital (ρ_I) is 1.32 (based on the ACF results). In other words, the productivity of intangible assets is almost 30% higher than the marginal productivity of tangible investments.

From Panel A we conclude: *intangible capital significantly raises firm-level productivity in Uruguay.* The effect is robust across advanced estimation methods, though not detectable in a simple fixed-effects regression. One standard deviation increase in intangible assets intensity produces an increase of 3% in TFP. The productivity premium of intangible is almost 1.3 times the marginal productivity of tangible investments. This implies that intangible assets, while on average only a few percent of firms' capital stocks, punch above their weight in generating output. One interpretation is that those firms which do develop intangibles (software systems, new product designs, skills, etc.) realize efficiency or quality improvements that materially boost value added.

Wage equation and intangible wage premium (Panel B). Turning to Panel B of Table 2, we examine how much of the productivity benefit of intangibles is shared with workers in the form of higher wages. The OP/LP/ACF columns under the wage equation include two terms: the firm's TFP (estimated from the corresponding production function) and intangible intensity. Focusing on the ACF-based wage equation (column 5), we find a strongly significant coefficient on TFP, $\delta_\omega = 0.38$ (s.e. 0.017), indicating that a 1% increase in firm productivity is associated with about a 0.38% increase in average wages. In other words, more productive firms pay higher wages, which is intuitive and aligns with rent-sharing or efficiency wage theories. The coefficient on intangible intensity in the ACF wage equation is $\delta_I = 0.31$ (s.e. 0.03). This implies that even after controlling for the firm's productivity, a 10 percentage-point higher intangible share is associated with 3.1% higher wages. That suggests intangible assets may directly raise wages, perhaps because intangible investments often involve worker upskilling or creating more advanced job tasks that command a premium. Combining the estimate of coefficient δ_I with the productivity premium of intangibles (ρ_I), obtained from de estimation of the production function, suggest that almost only a fifth of the productivity premium goes to workers' wages ($\delta_I/\rho_I = 0.23$). This means about 23% of the output gain from intangibles is reflected in higher wages, while roughly 77% is not passed on to workers. Put differently, firms capture most, but not all, of the intangible-driven productivity gains.

Although the exact magnitudes differ, all three control-function based wage regressions confirm a positive and significant intangible wage premium and similar pass-through from productivity premium of intangibles to workers' wages. Workers in firms with higher intangible intensity earn more, even accounting for the firm's higher productivity. However, this premium is smaller than the productivity effect of intangibles, indicating partial pass-through. The finding is consistent with that of Castillo and Crespi (2024) for Peru, where about 43% of the intangible productivity benefit was reflected in wages. Our estimate for Uruguay is almost half of that value. This suggests that Uruguayan firms, like Peruvian ones, retain some of the gains from intangible capital. The reasons could include:

- *Imperfect competition or labor market frictions:* If the labor market is not perfectly competitive, firms with higher productivity might not fully bid up wages to match marginal productivity. We explore this question in the next section.
- *Specificity of intangible assets:* Intangibles such as proprietary software or patents might be firm-specific. Workers cannot take those assets with them, so even if those assets raise their productivity, their outside options (wages elsewhere) may not increase as much. This allows the firm to pay slightly less than the marginal product and still retain employees, capturing residual rents.
- *Skill supply constraints:* If intangible-intensive processes require specialized skills that are scarce, firms may pay wage premiums to attract talent, but once the key staff are in place, subsequent productivity gains go into firm profits until workers renegotiate or the market catches up.

In summary, the value-added model results indicate a clear positive impact of intangible capital on productivity and a partial transmission of that benefit to worker wages. Intangible-intensive firms enjoy a productivity edge and tend to share a majority—though not the entirety—of this advantage with their employees in the form of higher wages, leaving some portion as a return to intangible capital itself (which could manifest as higher profits or market share).

4.2 Production Function Estimates: Gross Output Model

We now consider an alternative specification where output is measured as gross production (total sales) rather than value added. In this model, intermediate inputs (materials) are an additional factor of production. We estimated a Cobb-Douglas gross output function with labor, capital, intangible intensity, and (for the appropriate estimators) materials as a proxy where required. Table 3 presents the results analogous to the previous table, with Panel A for the production function and Panel B for the wage equations.

The gross output results (Table 3, Panel A) show broadly similar qualitative patterns to the value-added case, but with some differences in magnitudes.

If we focus on the coefficients of intangible capital, the OLS intangible coefficient is 0.40 and highly significant, indicating a positive correlation of intangibles with gross output but higher in magnitude than in value added OLS (which was 0.25). The FE estimate is again near zero and insignificant, like value added FE. So even in gross output terms, within-firm changes in s^{IC} show no immediate effect on revenue controlling for firm fixed traits. The OP estimator yields a large $\beta_I = 0.47$ and highly significant for gross output. This suggests that once controlling for endogeneity, intangible capital has an even bigger impact on gross output. The LP and ACF estimates for β_I are both significant at 1% and similar to value-added estimates ($\beta_I = 0.28$).

Table 3: Impact of Intangible Capital on Productivity and Wages (Gross Output Model)

	OLS	FE	OP	LP	ACF
Production Function (Gross Output) (Panel A)					
Labor (log L)	0.787***	0.520***	0.572***	0.295***	0.380***
	(0.007)	(0.007)	(0.004)	(0.008)	(0.001)
Capital (log K)	0.1735***	0.0668***	0.236***	0.0854***	0.0855***
	(0.005)	(0.003)	(0.000)[a]	(0.000)	(0.003)
Intangible Intensity (s^{IC})	0.402***	−0.015	0.473***	0.136***	0.136***
	(0.050)	(0.021)	(0.000)[a]	(0.000)	(0.001)
Wage Equation (using TFP from Gross Output PF) (Panel B)					
TFP (estimated ω)			0.185***	0.029**	−0.018
			(0.024)	(0.014)	(0.011)
Intangible Intensity (s^{IC})			0.346***	0.285***	0.283***
			(0.035)	(0.031)	(0.031)
Observations (PF, firm-years)	35,407	35,407	28,664	35,363	35,363
Observations (Wage, firm-years)	37,889	37,889	28,650	35,336	35,336

Notes: Each column corresponds to an estimator. The upper block reports the coefficients of the production function (Gross Output). The lower block reports the coefficients of the wage equation using the TFP estimated from the corresponding production function. All equations include sector and year dummies, as well as the shares of foreign and public capital. The OP/LP/ACF methods use investment or materials as proxies for productivity in the simultaneity-control stage; those coefficients are not reported. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[a]Standard error rounds to 0.000 at three decimals.

The productivity premium of intangibles implicit in these estimates of the production function is much higher than for value added estimates. The parameter ρ_I under OP estimate is 2, and under LP and ACF is 1.6. So, this estimate of the productivity premium of intangibles, relative to tangible capital, doubles that estimated for value added case (60% vs 30% if we take de ACF estimate as a reference).

In Panel B, the wage equations using gross-output-based TFP show similar intangible coefficients (δ_I) as before (OP 0.35, LP 0.29, ACF 0.28), all significant. Taking together with the estimate of productivity premium of intangibles, these values mean that 18% of the output gain from intangibles is reflected in higher wages. This pass-through is slightly lower than in the value-added case.

Regarding the estimates of the TFP coefficient, the gross output results are less robust. OP and LP estimates are 0.19 and 0.03, respectively. A striking difference is the ACF wage equation yields a *negative* but non-significant TFP coefficient (−0.02). This is counterintuitive—one would expect more productive firms to pay higher wages, not lower. This likely indicates a problem with the ACF gross output TFP measure or multicollinearity between $\widehat{\omega}_{it}$ and s_{it}^{IC} in that regression. Perhaps the ACF proxy in gross output doesn't isolate productivity well, or intangibles correlate so strongly with the ACF productivity measure that including both flips the sign. We should also bear in mind that the ACF method normally fails identification when using gross output. In any case, it suggests that the ACF gross-output specification might be misspecified for the wage equation.

To summarize the gross output findings: Intangible capital still shows a positive impact on output under all advanced estimators. The conservative estimates (LP, ACF) suggest that increasing a firm's intangible asset share by one standard deviation is associated with a 1.6% rise in TFP (almost half of the value obtained in the added value case). Combined with the capital elasticity estimates, we can infer that the productivity premium of intangible assets is higher than the value-added case ($\rho_I = 1.6$ instead of 1.3). The wage premium results are qualitatively similar and the estimated pass-through of intangibles productivity to wage is slightly lower than in the value-added case. We take the value-added specification as our main result going forward, since value added is arguably a better measure for productivity analysis (it nets out intermediate inputs, isolating the efficiency gains).

5 Model Extensions

In this section, we explore three extensions of the analysis to examine heterogeneity in the results and the role of market structure. First, we distinguish between software and other types of intangible capital to see if their productivity contributions and appropriability differ. Second, we compare results for multi-product versus single-product firms to assess potential scope economies from intangibles. Third, we analyze the impact of imperfect competition in the labor market (monopsony power) on how intangible benefits are shared with workers.

5.1 Software vs. Other Intangible Assets

We decompose the intangible capital intensity into two components: s_{it}^{soft}, the share of software in total capital, and s_{it}^{othIC}, the share of all other intangible assets. Table 4 presents the production function and wage equation estimates when including these two variables instead of the aggregate s_{it}^{IC}. The results indicate that *software* has a substantially higher productivity elasticity than other intangibles. For example, in the ACF estimation, the coefficient on software intensity is around 0.41, more than double the coefficient on other intangible capital (approximately 0.19). This suggests that investments in digital information (software) are particularly potent in raising output. The implied productivity premium of software is nearly twice that of tangible assets.

In the wage equations, we also observe a larger coefficient for software-based intangible capital relative to other intangibles (e.g., 0.37 vs. 0.27 in the ACF specification, see Panel B of Table 4). However, because the productivity effect of software is so high, the *share* of its returns that is passed on to workers in wages is actually lower. Using the ACF estimates, we calculate that only about 18% of the productivity gain from software is reflected in higher wages, whereas for other intangibles roughly 59% of the productivity benefit is captured by workers. In other words, the returns to software investments exhibit a higher degree of appropriability by firms. This is consistent with the idea that software-based know-how is more firm-specific or excludable, while the benefits of other intangibles (such as general knowledge acquired by employees through training, experience or R&D) are more readily transmitted to workers or other firms.

Table 4: Impact of Intangible Capital by Type (Software vs. Other) on Productivity and Wages

	OLS	OP	ACF
Production Function (Value Added) (Panel A)			
Labor (log L)	0.728***	0.619***	0.742***
	(0.005)	(0.003)	(0.000)
Capital (log K)	0.185***	0.221***	0.199***
	(0.002)	(0.000)	(0.000)
Software Intangible (s^{soft})	0.397***	0.494***	0.410***
	(0.046)	(0.000)	(0.000)
Other Intangible (s^{othIC})	0.174***	0.196***	0.188***
	(0.032)	(0.000)	(0.000)
Wage Equation (Value Added) (Panel B)			
TFP (estimated ω)		0.119***	0.374***
		(0.025)	(0.017)
Software Intangible (s^{soft})	0.500***	0.459***	0.372***
	(0.057)	(0.064)	(0.053)
Other Intangible (s^{othIC})	0.258***	0.313***	0.269***
	(0.038)	(0.041)	(0.036)
Observations (PF, firm-years)	35,407	28,664	35,363
Observations (Wage, firm-years)	37,889	28,650	35,336

Notes: Each column corresponds to an estimator. The upper block reports the coefficients of the production function (Gross Output). The lower block reports the coefficients of the wage equation using the TFP estimated from the corresponding production function. All equations include sector and year dummies, as well as the shares of foreign and public capital. The OP/LP/ACF methods use investment or materials as productivity proxies in the simultaneity-control stage; those coefficients are not reported. Robust standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]Standard error rounds to 0.000 at three decimals.

5.2 Multi-Product vs. Single-Product Firms

A potential advantage of intangible assets is their non-rival nature within the firm: the same knowledge or software can be applied across multiple product lines at low marginal cost. This suggests that multi-product firms might derive greater productivity gains from intangibles (scope economies) than single-product firms. To explore this, we split the sample into multi-product and single-product firms and re-estimate the models separately for each group, following a similar exercise by Castillo and Crespi (2024). The key coefficients are summarized in Table 5.

The results do not show a statistically significant difference in the *productivity* impact of intangibles between multi-product and single-product enterprises. In fact, the ACF estimate of β_I is slightly higher for single-product firms (around 0.24) than for multi-product firms (about 0.22), but this difference is within the margin of error. Accordingly, the inferred intangible capital productivity premium (relative to tangible capital) is only marginally greater in single-product firms (approximately 1.22) compared to multi-product firms (1.13).

Thus, we do not find evidence that intangibles are inherently more productive in firms with broader product scopes.

On the other hand, the distribution of intangible benefits between firms and workers does differ by firm type. The wage equation estimates indicate a larger intangible-related wage effect in multi-product companies. For instance, the ACF wage elasticity with respect to intangible intensity is about 0.39 for multi-product firms versus 0.27 for single-product firms. Based on these figures, roughly 34% of the intangible-induced productivity premium is passed on to workers in multi-product firms, compared to about 22% in single-product firms. In other words, multi-product firms appear to *appropriate less* of the returns from intangible capital—workers in those firms capture a greater share of the gains. These findings are in line with those reported for Peru by Castillo and Crespi (2024), who also found no higher productivity impact of intangibles in multiproduct firms but a lower appropriation by the firm (higher spillover to wages) in such companies. This pattern is consistent with the idea that intangible assets in multi-product firms may involve more general knowledge that is easier for others to learn or imitate, resulting in a larger leakage of benefits.

Table 5: Impact of Intangibles on Productivity and Wages: Multi-Product vs. Single-Product Firms

	Multi-Product Firms			Single-Product Firms		
Variable	OLS	OP	ACF	OLS	OP	ACF
Production Function (Value Added) (Panel A)						
Labor (log L)	0.792***	0.674***	0.805***	0.685***	0.597***	0.698***
	(0.007)	(0.020)	(0.000)	(0.007)	(0.007)	(0.000)
Capital (log K)	0.182***	0.212***	0.195***	0.181***	0.215***	0.194***
	(0.003)	(0.001)	(0.000)	(0.003)	(0.000)	(0.000)
Intangible Intensity (s^{IC})	0.207***	0.183***	0.221***	0.224***	0.292***	0.237***
	(0.041)	(0.000)	(0.000)	(0.036)	(0.000)	(0.000)
Observations	16,075	13,603	16,061	19,332	15,061	19,302
Wage Equation (Panel B)						
TFP (estimated ω)		0.284***	0.420***		0.093***	0.379***
		(0.054)	(0.026)		(0.028)	(0.021)
Intangible Intensity (s^{IC})	0.413***	0.443***	0.389***	0.302***	0.307***	0.267***
	(0.032)	(0.035)	(0.031)	(0.022)	(0.031)	(0.030)
Observations	16,075	13,603	16,061	19,332	15,061	19,302

Notes: Results from separate estimations for multi-product and single-product firms. Panel A shows production function coefficients (value added specification), Panel B shows wage equation coefficients. All equations include sector dummies, year dummies, share of foreign capital and share of public capital. All control function models correct for attrition of firms. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.3 Labor Market Imperfections

The final extension examines whether imperfect competition in the labor market affects the degree to which intangible-driven productivity gains are shared with workers. In the presence of monopsony power, firms face an upward-sloping labor supply curve, and wages may increase less than proportionally to productivity (i.e., a markdown on labor). Following the approach of Castillo and Crespi (2024), we test if the wage premium associated with intangible capital is lower in firms or sectors with more labor market power.

We utilize an external estimate of the average wage markdown (i.e. the ratio between the value of labor marginal revenue and the wage paid by de firm) by industry from Casacuberta and Gandelman (2024). They estimated industry-level (2-digit ISIC) markup and markdown measures inferred from estimates of output elasticities and factor shares in output, based on the approach of De Loecker and Warzynski (2012). The source of information for these estimates is the EAAE for the period 2007–2019. The markdown (denoted mkd) is the ratio of marginal productivity of labor to the wage in each 2-digit ISIC sector (averaged over 2007–2019), and serves as a proxy for the degree of monopsony power in that sector. We then interact this measure with our productivity (ω_{it}) and intangible intensity (s_{it}^{IC}) terms in the wage equation. The results are shown in Table 6. Consistent with expectations, we find that the coefficient on the interaction between TFP and the markdown is negative and significant in the ACF specification. In sectors with higher average markdown (greater labor market power), the pass-through of productivity into wages is smaller. The interaction between intangible intensity and the markdown is also negative (suggesting that intangibles translate less into wages when monopsony power is high), but this interaction term is not statistically significant. These patterns imply that monopsonistic labor markets can dampen wage growth stemming from productivity improvements, though the evidence for a direct interaction with intangibles is inconclusive.

Considering that the markdown variable does not show variability between firms in the same sector and does not present temporal variability, we use a more flexible approach to analyze the heterogeneous effects according to competition in the labor market. We divided the sample into three groups of industries: those with low, medium, and high average markdown (with cutoff values chosen at 1.10 and 1.13, based on the distribution of mkd). We then estimated the wage equation separately for each group. Table 7 summarizes the results. We find that both the pass-through of TFP to wages and the intangible-related wage premium are highest in low-markdown sectors and lowest in high-markdown sectors. For instance, in industries with low markdown (average $mkd \approx 1.08$), the intangible coefficient in the wage equation is about 0.376, whereas in high-markdown industries ($mkd \approx 1.23$) it is around 0.243. Likewise, the TFP coefficient drops from 0.452 in low-markdown sectors to 0.272 in high-markdown sectors. These differences imply that when labor markets are more competitive (low markdown), workers capture more of the gains from intangible-driven productivity improvements, whereas in more monopsonistic labor markets, firms retain a larger share of those gains.

In summary, these extension analyses reinforce the main message that intangible capital yields significant productivity benefits which are not fully passed on to workers, allowing firms to appropriate a portion of the returns. Moreover, the degree of appropriability varies by intangible type, firm scope, and labor market setting. Software investments seem to

Table 6: Impact of Intangibles on Wages: Interaction with Labor Market Imperfections (Log. of Average Markdown by Sector)

Variable	OLS	OP	ACF
TFP (δ_ω)		0.074	0.497***
		(0.054)	(0.026)
TFP × mkd		0.711*	−0.872***
		(0.372)	(0.128)
Intangible (δ_I)	0.274***	0.336***	0.333***
	(0.064)	(0.074)	(0.064)
Intangible × mkd	0.333	0.048	−0.306
	(0.506)	(0.533)	(0.505)
Observations	36,446	27,510	33,964

Notes: Estimated coefficients from wage equations augmented with interactions for labor market competition. *mkd* is the log of average wage markdown (monopsony measure) for the firm's sector (ISIC 2 digits) averaged over 2007–2019 estimated by Casacuberta and Gandelman (2024). δ_ω and δ_I denote the base wage elasticities with respect to TFP and intangible intensity, respectively. OP and ACF columns include the firm-level TFP term from the corresponding production function. All equations include sector dummies, year dummies, share of foreign capital and share of public capital. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Impact of Intangibles on Wages by Industry Markdown Group

	Low mkd	Medium mkd	High mkd
TFP (estimated ω)	0.452***	0.379***	0.272***
	(0.023)	(0.034)	(0.032)
Intangible Intensity (s^{IC})	0.376***	0.178***	0.243***
	(0.041)	(0.063)	(0.063)
Observations	15,434	11,675	6,855

Notes: Wage equation estimates for sub-samples of industries grouped by the average wage markdown *mkd* estimated by Casacuberta and Gandelman (2024) based on EAAE 2007-2019. Low markdown group includes industries with $mkd <$ 1.10; Medium for $1.10 \leq mkd < 1.13$; High for $mkd \geq 1.13$. TFP obtained from ACF production function. All equations include sector dummies, year dummies, share of foreign capital and share of public capital. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

offer higher private returns, multi-product firms face greater spillovers to employees, and competitive labor markets force firms to share more gains with workers. These insights highlight the nuanced ways in which firm characteristics and market conditions mediate the impacts of intangible capital.

6 Discussion of Key Results

Our findings for Uruguay share several qualitative features with those of Castillo and Crespi (2024) for Peru, but also exhibit some differences in magnitude. In both countries, intangible capital intensity significantly boosts firm productivity, and in both cases a smaller percentage of that gain is passed on to workers through higher wages, with a fraction retained by firms (indicating partial appropriability). However, the estimated "intangible capital productivity premium" in Uruguay appears somewhat lower. Castillo and Crespi (2024) reported intangibles being up to 2 times more productive than tangible assets in Peru, whereas in Uruguay our results suggest intangibles are roughly 1.3 times. One explanation could be differences in the composition of intangible investments. Peru's data may include a higher share of R&D or innovation-driven intangibles, which tend to have very high marginal returns, while Uruguay's intangible investments might skew towards other routine intangibles that, though beneficial, produce more modest productivity gains. Another factor is spillovers and market size. Uruguay's market is small, so a firm that develops a strong intangible asset (say a brand or a process) may face limited competition domestically and can appropriate much of the benefits, but also might have limited opportunities to scale up output. In Peru (a larger economy), successful innovators might scale more within the domestic market. That could potentially lead to a higher apparent productivity contribution of intangibles in a bigger market (more room to expand output using the same intangible asset). Another plausible explanation is a catching-up dynamic. For instance, Peru's firms may have been further from the global productivity frontier, leaving more "low-hanging fruit" opportunities for improvement through intangible investment, whereas Uruguay's firms — being closer to the frontier — have fewer such easy innovation gains available. Under this scenario, intangible capital can generate larger productivity boosts in Peru as part of a catch-up process, while in frontier-nearing Uruguay the gains from intangibles are more incremental. This catching-up hypothesis offers a reasonable contextual explanation for the difference in estimated intangible returns, but we note that it is not directly tested by our data.

Sectoral differences are likely important. Recall that intangible intensity in Uruguay is very uneven across sectors (Figure 1). Knowledge-intensive services (IT, finance) have high intangible shares and presumably saw strong productivity impacts from those assets. Traditional sectors (manufacturing, primary production) largely do not invest in intangibles, or if they do (perhaps adopting generic software or importing technology), they see limited gains unless they also reorganize. This mirrors the finding by Aboal and Tacsir (2018) where manufacturing firms in Uruguay did not experience measurable productivity improvement from ICT investments without complementary changes. Thus, one interpretation of our average results is that they are a mix of some firms with very high intangible returns and many firms with zero or negligible returns. The high OP intangible coefficient for gross output (0.468) might be capturing those high-return firms predominantly (since OP might overweight survivors that invest heavily in intangibles), whereas ACF and LP perhaps give more weight to the average effect including low-return cases. If so, the "true" underlying relationship might be nonlinear or heterogeneous: intangible capital can be extremely productive in the right conditions (e.g., a software company or a firm that uses a proprietary algorithm can scale output dramatically), but adding a little intangible capital in a traditional firm may do little. This heterogeneity is an important area for further research but beyond the scope of our aggregate analysis.

In comparison to Peru, Uruguay might also differ in the nature of spillovers. Peru's study concluded that appropriability channels were mainly idea specificity and labor market imperfections. Uruguay's economy is smaller and more concentrated. It is hard to generalize, but a plausible hypothesis is that Uruguay's intangible investments yield relatively higher private returns because there are fewer competitors (oligopolistic markets in some sectors), whereas Peru as a larger economy might have slightly more competitive pressure, albeit still with high appropriability. Our finding that intangible returns are not fully dissipated in wages is consistent with there being partial spillovers in Uruguay as well.

An important limitation of our analysis is that we cannot contrast the role of **human capital** in amplifying intangible returns. Our study not explicitly controlled for workforce educational levels in the production function (due to data limitations), yet we know from literature that skilled labor and intangibles are complementary (Bresnahan et al., 2002; Autor, Levy, & Murnane, 2003).

Finally, our results underscore the **measurement challenges**. We relied on balance-sheet intangible asset values, which likely underestimate true intangible investment (many firms may expense R&D or training, not recognizing it as an asset). In particular due to the fact that during this period Uruguay did not have tax credits for R&D. Moreover, different types of intangibles (software vs. patents vs. brand) might have different productivities. Policy-wise, even with these limitations, we found a positive effect, so the "true" effect could be larger if intangibles were fully captured. This aligns with arguments by Haskel and Westlake (2018) that conventional accounts undervalue intangibles, causing us to attribute some of their effect to TFP.

7 Conclusion

This paper provides evidence that intangible capital is an important driver of firm-level productivity in Uruguay, a small open economy where such evidence has been scarce. By applying rigorous production function estimation techniques to panel data on Uruguayan firms, we find that intangible assets (such as software, R&D, and organizational capital) have a positive and significant effect on output. The magnitude of the effect, while substantial, is slightly lower than analogous estimates for a larger middle-income economy (Peru). One standard deviation increase in intangible intensity is associated with roughly a 3% increase in productivity in Uruguay, compared to about 7% in Peru. Furthermore, intangible capital in Uruguay appears to be about 30% productive as tangible capital, while in Peru it is approximately double, suggesting that Uruguayan firms may not yet be fully exploiting the high-return potential of knowledge-based assets.

We also examined how the benefits of intangible investment are distributed. The analysis of wage equations indicates that workers do share in the gains from intangibles—firms with higher intangible intensity tend to pay higher average wages, even after accounting for their higher productivity. However, the pass-through is incomplete: we estimate that one fifth of the productivity gains from intangibles are reflected in higher wages, with the rest accruing to firms as a return on capital. This partial appropriability is consistent with the idea that intangible assets often create firm-specific advantages (e.g., proprietary knowledge or efficiency gains that are not entirely competed away or bargained away). For policymakers, this has a double-edged implication: On one hand, firms have an incentive to invest in intangibles because they can retain some rents; on the other hand, because some benefits do leak to workers and possibly to other firms via spillovers, there remains a rationale for supporting intangible investments through public policy (to encourage firms to invest at socially optimal levels).

Some extensions of the analysis show that: (i) software yields especially high private returns, (ii) multi-product firms share a larger portion of gains with workers, and (iii) monopsony power in labor markets reduces wage pass-through.

Our findings carry several policy-relevant insights for Uruguay. First, the low prevalence of intangible investment—about 60% of firms report none—highlights a significant untapped source of productivity growth. Policies that reduce barriers to investing in intangibles (such as improving access to finance for innovation, providing tax incentives for R&D and training, or supporting digital adoption in small firms) could raise the intangible investment rate. International experience suggests that when more firms engage in innovation and capability-building, overall productivity gains can be substantial (Griffith, Redding, & Van Reenen, 2004; Hall & Rosenberg, 2010).

Second, while our estimates do not allow us to directly test the role of complementary factors such as skilled labor or managerial practices, the heterogeneity we observe across types of intangibles and firm contexts is consistent with the view that such complementarities are crucial. Prior literature suggests that policies need to be holistic; simply subsidizing software purchases, for instance, may not yield results unless accompanied by managerial training or the hiring of skilled IT staff. Building human capital through education and vocational training remains essential for companies to have the absorbtive capacity to take advantage of new technologies (Cohen & Levinthal, 1990; Nelson & Phelps, 1966). The continuous upgrade of the skills of the workforce in STEM and digital literacy will further support the intangible economy.

Third, the partial but significant pass-through of intangible returns to wages is encouraging from an inclusion perspective—intangible-led growth can benefit workers via higher pay. However, it also suggests that if only a few firms invest in intangibles, only a segment of the workforce (those employed by those firms) will see these gains, potentially widening wage disparities between leading and lagging firms. This points to a need for diffusion policies: helping spread best practices and technologies from the frontier firms to the wider economy. Mechanisms might include industry extension services, innovation hubs or clusters where firms can learn from each other, and support for mobility of skilled labor (which can carry knowledge across firms). Care must be taken though, as too much spillover without reward can deter the original investors—hence, a balance via intellectual property rights and incentives is needed to maintain innovation incentives while promoting knowledge diffusion.

In conclusion, our replication of the Castillo and Crespi (2024) framework in the Uruguayan context provides evidence that even in a smaller economy, intangible capital matters for productivity. The results support the view that policies to stimulate intangible investment—ranging from innovation grants and training programs to strengthening intellectual property frameworks—could be pivotal for Uruguay's productivity growth. However, those policies should go hand in hand with efforts to build complementary assets (skills, organizational capabilities) and to broaden the base of firms engaging in innovation. As advanced economies have shown, an "intangible-rich" economy tends to be more dynamic and competitive; Uruguay's challenge and opportunity will be to cultivate its own intangible assets and ensure that the benefits of those investments are widely shared, thereby boosting productivity growth.

References

Aboal, D. & Tacsir, E. (2018). Innovation and productivity in services and manufacturing: the role of ICT. *Industrial and Corporate Change*, *27*(2), 221–252. doi:10.1093/icc/dtx040

Ackerberg, D. A., Caves, K., & Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, *83*(6), 2411–2451. doi:10.3982/ECTA13408

Aghion, P. & Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, *60*(2), 323–351. doi:10.2307/2951599

Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *Quarterly Journal of Economics*, *135*(2), 645–709. doi:10.1093/qje/qjaa004

Autor, D., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: an empirical exploration. *Quarterly Journal of Economics*, *118*(4), 1279–1333. doi:10.1162/003355303322552801

Benavente, J. M., De Gregorio, J., & Núñez, M. (2005). Rates of return for industrial R&D in chile. *Central Bank of Chile Working Papers*, (317). Retrieved from https://si2.bcentral.cl/public/pdf/documentos-trabajo/pdf/dtbc317.pdf

Bloom, N., Schankerman, M., & Van Reenen, J. (2013). Identifying technology spillovers and product market rivalry. *Econometrica*, *81*(4), 1347–1393. doi:10.3982/ECTA9466

Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: firm-level evidence. *Quarterly Journal of Economics*, *117*(1), 339–376. doi:10.1162/003355302753399526

Brynjolfsson, E. & Hitt, L. M. (2000). Beyond computation: information technology, organizational transformation and business performance. *Journal of Economic Perspectives*, *14*(4), 23–48. doi:10.1257/jep.14.4.23

Brynjolfsson, E., Hitt, L. M., & Yang, S. (2002). Intangible assets: computers and organizational capital. *Brookings Papers on Economic Activity*, *2002*(1), 137–198. doi:10.1353/eca.2002.0003

Casacuberta, C. & Gandelman, N. (2024). *Market power pass-through to prices and wages: evidence from uruguay.* Universidad ORT, Uruguay. Retrieved from https://www.bcu.gub.uy/Estadisticas-e-Indicadores/estudios/Documents/casacuberta_gandelman.pdf

Castillo, R. & Crespi, G. (2024). The impact of intangible capital on productivity and wages: firm-level evidence from peru. *Estudios de Economía*, *51*(1), 45–84. Retrieved from https://www.econstor.eu/bitstream/10419/312790/1/1898495440.pdf

Cohen, W. M. & Levinthal, D. A. (1990). Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly*, *35*(1), 128–152. doi:10.2307/2393553

Corrado, C., Haskel, J., Jona-Lasinio, C., & Iommi, M. (2013). Innovation and intangible investment in europe, japan, and the united states. *Oxford Review of Economic Policy*, *29*(2), 261–286. doi:10.1093/oxrep/grt017

Corrado, C., Haskel, J., Jona-Lasinio, C., & Iommi, M. (2022). Intangible capital and modern economies. *Journal of Economic Perspectives*, *36*(3), 3–28. doi:10.1257/jep.36.3.3

Corrado, C., Hulten, C. R., & Sichel, D. E. (2009, September). Intangible capital and u.s. economic growth. *Review of Income and Wealth*, *55*(3), 661–685. doi:10.1111/j.1475-4991.2009.00343.x

Corrado, C., Hulten, C., & Sichel, D. (2005). Measuring capital and technology: an expanded framework. In C. Corrado, J. Haltiwanger, & D. Sichel (Eds.), *Measuring capital in the new economy* (pp. 11–46). NBER chapter. University of Chicago Press. Retrieved from https://www.nber.org/system/files/chapters/c0202/c0202.pdf

Crespi, G., Criscuolo, C., & Haskel, J. E. (2008). Productivity, exporting and the learning-by-exporting hypothesis: direct evidence from uk firms. *Canadian Journal of Economics*, *41*(2), 619–638. doi:10.1111/j.1540-5982.2008.00479.x

Crespi, G., Fernández-Arias, E., & Stein, E. (Eds.). (2014). *Rethinking productive development: sound policies and institutions for economic transformation*. New York: Palgrave Macmillan and Inter-American Development Bank. doi:10.1057/9781137397632

Crespi, G., Garone, L. F., Maffioli, A., & Stein, E. (2020). Public support to r&d, productivity, and spillover effects: firm-level evidence from chile. *World Development*, *130*, 104948. doi:10.1016/j.worlddev.2020.104948

Crespi, G. & Zúñiga, P. (2012). Innovation and productivity: evidence from six latin american countries. *World Development*, *40*(2), 273–290. doi:10.1016/j.worlddev.2011.07.010

De Loecker, J. & Warzynski, F. (2012). Markups and firm-level export status. *American Economic Review*, *102*(6), 2437–2471. doi:10.1257/aer.102.6.2437

Griffith, R., Redding, S., & Van Reenen, J. (2004). Mapping the two faces of R&D: productivity growth in a panel of oecd industries. *Review of Economics and Statistics*, *86*(4), 883–895. doi:10.1162/0034653043125194

Griliches, Z. (1992). The search for R&D spillovers. *Scandinavian Journal of Economics*, *94*, 29–47. doi:10.2307/3440244

Hall, B. H. & Lerner, J. (2010). The financing of R&D and innovation. In B. H. Hall & N. Rosenberg (Eds.), *Handbook of the economics of innovation* (Vol. 1, pp. 609–639). Amsterdam: Elsevier. doi:10.1016/S0169-7218(10)01014-2

Hall, B. H., Mairesse, J., & Mohnen, P. (2010). Measuring the returns to R&D. In B. H. Hall & N. Rosenberg (Eds.), *Handbook of the economics of innovation* (Vol. 2, pp. 1033–1082). Elsevier. doi:10.1016/S0169-7218(10)02008-3

Hall, B. H. & Rosenberg, N. (Eds.). (2010). *Handbook of the economics of innovation*. Amsterdam: Elsevier.

Haskel, J. & Westlake, S. (2018). *Capitalism without capital: the rise of the intangible economy*. Princeton, NJ: Princeton University Press. doi:10.1515/9780691183299

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, *108*(3), 577–598. doi:10.2307/2118401

Jones, C. I. & Williams, J. C. (1998). Measuring the social return to R&D. *Quarterly Journal of Economics*, *113*(4), 1119–1135. doi:10.1162/003355398555856

Levinsohn, J. & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *Review of Economic Studies*, *70*(2), 317–341. doi:10.1111/1467-937X.00246

Nelson, R. R. & Phelps, E. S. (1966). Investment in humans, technological diffusion, and economic growth. *American Economic Review*, *56*(1/2), 69–75.

OECD. (2013). *Supporting investment in knowledge capital, growth and innovation*. Paris: OECD Publishing. doi:10.1787/9789264193307-en

Oliner, S. D., Sichel, D. E., & Stiroh, K. J. (2008). Explaining a productive decade. *Brookings Papers on Economic Activity*, *2007*(1), 81–152. doi:10.1353/eca.2008.0004

Olley, G. S. & Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, *64*(6), 1263–1297. doi:10.2307/2171831

O'Mahony, M. & Vecchi, M. (2005). Quantifying the impact of ICT capital on output growth: a heterogeneous dynamic panel approach. *Economica*, *72*(288), 615–633. doi:10.1111/j.1468-0335.2005.00435.x

O'Mahony, M. & Vecchi, M. (2009). R&D, knowledge spillovers and company productivity performance. *Research Policy*, *38*(1), 35–44. doi:10.1016/j.respol.2008.09.003

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, *98*(5), S71–S102. doi:10.1086/261725

World Bank. (2017). *Trouble in the making? the future of manufacturing-led development*. Washington, DC: World Bank. doi:10.1596/978-1-4648-1174-6

World Intellectual Property Organization. (2025). World intangible investment highlights 2025: better data for better policy. Retrieved from https://www.wipo.int/edocs/pubdocs/en/wipo_pub_2000_2025.pdf

A Annex: Definition and Descriptive Statistics of Intangible Capital in the EAAE

A.1 Definition of intangible capital in the EAAE

In the Economic Activities Annual Survey (EAAE), **intangible assets** include the value of computer programs and other items such as trademarks, patents, royalties and goodwill, as long as they form part of the firm's fixed assets. The survey classifies intangible assets into the following categories:

1. **Software**.
2. **R&D**: Research and Development.
3. **Mining exploration and evaluation**.
4. **Entertainment, literary and artistic originals**.
5. **Other**).

A.2 Descriptive statistics: Intangible investment by type

Table 8 reports the share of investment in each type of intangible asset over total investment (intangible investment plus physical capital investment). We report this share for (i) the full set of firms and (ii) the subsample of firms that invest in intangible assets.

Table 8: Investment in each intangible type over total investment (intangibles + physical capital), %

	Total firms	Only firms investing in intangibles
Intangible assets (total)	3.1	11.7
1 – Software	1.3	4.8
2 – R&D (I+D)	0.1	0.3
3 – Mining exploration and evaluation	0.0	0.0
4 – Entertainment, literary and artistic originals	0.0	0.1
5 – Other	1.8	6.5

Notes: Percentages correspond to the share of investment in each intangible category over total investment (intangible investment + physical capital investment). The second column restricts the sample to firms with positive intangible investment. Source: Authors' calculations based on the EAAE and the EAAE intangible asset classification.