The Impact of Intangible Capital on Productivity and Wages: Firm level evidence from Peru*

El impacto del capital intangible en la productividad y los salarios: evidencia a nivel de empresas de Perú

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Abstract

In the past decades, intangibles assets have become an important source of productivity and economic growth in developed countries. Despite the transforming properties of intangibles across economies and the large and dynamic literature on the impact of intangible investments on productivity growth in frontier countries, there is not much evidence for the Latin America context. This paper contributes to the empirical literature on intangible investments along various dimensions. First, we make use of a large firm-level longitudinal data set from Peru, a Latin America middle income country, which contains separated information on intangible assets, which allow us to measure the impact of them on both wages and productivity at the firm level. Second, the analysis at the firm level and the panel structure of the data allows us to control for the endogeneity of variable inputs applying different control function approaches. In addition, the production function estimates provide us with a measure of unobservables, which we include in the wage equation to retrieve consistent estimates for the impact of intangible assets on wages. Third, our data allow us to explore how the impact of intangibles on wages and productivity is affected by the differences in the composition of the bundle of intangibles, changes in the product mix at the firm level and for the presence of imperfect competition in the labor market. We find that an increase in the share of intan-

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gible assets by one standard deviation is associated with 6.8% to 7.2% higher total factor productivity, depending on the model´s specification. We also find that the capital productivity premium of intangible assets over tangible ones is substantial with estimates suggesting that intangibles are up to 2 times more productive than tangible assets. We also find that this capital productivity premium is not entirely offset by an increase in wages. Finally, we conclude that the main channels for appropriability are the specificity of the ideas generated by intangible investments at the firm level and the wage compression due to imperfect competition in the labor market.

Key words: *Productivity; capital; intangible assets; production function; wages; innovation; R&D; firms; spillovers.*

JEL Classification: *D24, E22, O30, O47*

Resumen

En las últimas décadas, los activos intangibles se han convertido en una importante fuente de productividad y crecimiento económico en los países desarrollados. A pesar de las propiedades transformadoras de los intangibles en las economías y la amplia y dinámica literatura sobre el impacto de las inversiones en intangibles en el crecimiento de la productividad en los países más avanzados, no existe suficiente evidencia para el contexto de América Latina. Este estudio contribuye a la literatura empírica sobre inversiones en intangibles en varias dimensiones. Primero, hacemos uso de una amplia base de datos longitudinales a nivel de empresas de Perú, un país de ingreso medio de América Latina, la cual contiene información separada sobre activos intangibles, lo que nos permite medir el impacto de estos en los salarios y la productividad a nivel de empresa. Segundo, el análisis a nivel de empresa y la estructura de datos de panel nos permite controlar la endogeneidad de los insumos variables aplicando diferentes enfoques de funciones de control. Además, las estimaciones de la función de producción nos proporcionan una medida de las variables no observables, la cual incluimos en la ecuación salarial para obtener estimaciones consistentes del impacto de los activos intangibles en los salarios. Tercero, nuestros datos nos permiten explorar cómo el impacto de los intangibles en los salarios y la productividad se ve afectado por las diferencias en la composición del conjunto de intangibles, por cambios en el portafolio de productos a nivel de empresa y por la presencia de competencia imperfecta en el mercado laboral. Encontramos que un incremento de una desviación estándar en la participación de los activos intangibles se asocia con un aumento del 6.8% al 7.2% en la productividad total de los factores, dependiendo de la especificación del modelo. También encontramos que la prima de productividad del capital de los activos intangibles sobre los tangibles es sustancial, con estimaciones que sugieren que los activos intangibles son *hasta 2 veces más productivos que los activos tangibles. Además, encontramos que esta prima de productividad del capital no se compensa completamente con un aumento en los salarios. Finalmente, concluimos que los principales canales para la apropiabilidad son la especificidad de las ideas generadas por las inversiones intangibles a nivel de empresa y la compresión salarial debido a la competencia imperfecta en el mercado laboral.*

Palabras clave: *Productividad, Capital, Activos intangibles, Función de producción, Salarios, Innovación, I+D, Empresas, Externalidades.*

Clasificación JEL: *D24, E22, O30, O47.*

1. Introduction

One important feature of modern economies is the presence of a large and growing gap between tangible assets as reported in corporate annual reports and companies' market values. For example, the ratio between the market value and the accounted value of tangible assets – such as buildings and equipment – in the case of Apple and Microsoft is 5.9 and 7.3 times respectively (Corrado, Haskel, Jona-Lasinio, and Iommi, 2022). However, this gap cannot be explained only by capitalized research and development (R&D). Capitalizing R&D for Apple and Microsoft, reduces the gaps to just 4.9 and 5.2 times respectively. There is a remaining value gap that is explained by other types of knowledge investments that firms do and are not classified as R&D such as software, designs, branding, marketing, business practices, services delivery, after-sale services, and others. These other expenditures should be also considered as investments to the extent that are outlays expected to yield a return in the future. Recent research on national accounts suggests that once these intangible assets are computed as part of domestic gross investment a very different pattern emerges. Indeed, in the US, while tangible (fixed) capital investment drops from about 12.5% of the GDP in 1985 to about 8.5% in 2021, intangible capital investment rises rather dramatically from 4% to 16% of the GDP over the same period. Similar figures are reported in several EU countries (Corrado, Hulten, and Sichel (2005, 2009)). In summary, the global economy has entered into the *age of intangibles*, and it is expected that sooner rather than later similar patterns will be observed also in some Latin American countries.

Investment in intangible assets is basically foregone consumption in the accumulation of ideas, and ideas, unlike physical goods, have some particular properties. First of all, ideas are non-rivals in consumption. This is in the sense that a new idea, once developed, can be used without physical limits in numerous applications both inside and outside the generating firm. The second property of ideas has to do with their control. Ideas don't float around in the air, but generally tend to be associated for use with some kind of physical platform. For example, a chemical formula may be reflected in an article in a journal or in a patent document. A programming code can be written in a copyright document and a dataset can be stored in an external disk. An organizational routine can be compiled into a set of organizational policies sanctioned by a board of shareholders. In all these cases, the generating firm can regulate the access to these ideas by third parties by controlling the physical support on which these ideas are represented, such as when intellectual property rights as patents or copyrights mentioned above are generated. However, it is also true that on numerous occasions the physical support on which the idea is materialized is much more difficult to control. This is particularly the case when new ideas basically rest in the brains of the firm's workers who have participated in their generation and/or internal use. In this case, although there are control procedures such as confidentiality agreements, they are more difficult to implement and as such the human capital of the originating company becomes a physical backup whose control is much more difficult to exercise. In other words, one is certain that an engineer involved in research and development, design or value-chain optimization activities was in the company's floor today, but it is much more difficult to predict whether she will show up for work tomorrow and even more uncertain if she is not going to do it in some rival competitor firm. In short, the ideas that underlie investments in intangible assets are not only non-rivals in consumption, but also suffer from a problem of partial appropriability, particularly when this idea is only attached to the firm's human capital (Romer, 1989). These two characteristics of ideas generate knowledge externalities in the economy, but at the same time they might represent a disincentive to private investment in their generation[1].

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1 There is an emerging literature emphasizing on other characteristics of intangible assets that are beyond the aim of this paper. Indeed, according to Haskel and Westlake (2018), intangible investment has other three characteristics that differentiate it from tangible assets. *First*, an intangible investment is normally sunk, that means, it is a sort of investment that cannot be easily recovered after disbursed; *second*, an intangible investment is easily scaled up after the initial outlay (e.g. the fast growth of Uber after the initial software was developed) and *third*, an intangible investment normally has strong synergies and complementarities with other intangible investments. These three key characteristics have important policy implications. Being a sunk investment normally implies some difficulty to obtain external financing, scalability means that intangible-intensive companies get large very quickly implying competition worries and finally, the presence of synergies impact inequality to the extent that there are potentially large income gains for intangible capital owners. In summary, the rise of intangibles might lead to fast growing economies, if some market failures related to financing and spillovers are tackled, but also to more unequal societies due to the scaling and synergy properties.

However, one way the firm can increase the chances to appropriate the returns of the ideas is by focusing human capital related intangibles on those ideas which are more specific to firm's needs. Ideas that are rather generic in nature and that are difficult to protect using other methods such as intellectual property rights or by exploiting their complementarity with other firms' specific assets such as organizational routines or value chains, are far more likely to spillover to other firms via labor mobility. The presence of intangible assets embedded in human capital can also make appropriability dependent on the degree of competition in the labor market. If the firm enjoys some degree of market power in the labor market could also retain at least part of the returns to intangible assets, even in the case of generic knowledge. In other words, under perfect competition in the labor market firms won't pay for the development of generic ideas that are embedded in their workers who can leave the firm for a better-paid job that compensates them for the higher marginal productivity they obtain thanks to their access to those ideas. The only way a firm might be willing to invest in low appropriability generic ideas is if there is some form of compressed wage structure in the labor market through which marginal productivity increases more than wages.

Nevertheless, it is important to keep in mind that intangible assets bundle different components, in which the importance of non-rivalry and control is expected to vary across them. There is widespread consensus that R&D investments generate spillovers from the innovator to potentially rival firms (Hall, Mairesse and Mohnen, 2010). However, the extent to which the potential for knowledge spillovers also extends to other intangibles such as investments in business models, marketing, software, databases, and designs (among other assets) is more uncertain. Some researchers claim that these other intangibles are more tacit and linked to tangible capital investments rather than R&D, suggesting that their returns are more appropriable and so that spillovers might be lower. In fact, studies suggest that the productivity slowdown of the last couple of decades could be explained by the increasing share of these other intangibles vis-à-vis R&D (Haskel and Westlake, 2018). Whether these other intangibles should be subsidized is an empirical fact that is just starting to be tackled as more comprehensive and harmonized data regarding intangibles investments is being collected at the firm level. However, most of this research is still at early stages and mostly focused on the US and EU countries. Indeed, despite the transforming properties of intangibles across the economy, very little is known regarding the impacts of intangible investments in developing countries. A major constraint for this lack of evidence has been the absence of systematic firm level data on intangible capital and investment.

This paper contributes to the empirical literature on intangible investments along various dimensions. First, we make use of a large firm-level longitudinal data set that contains separated information on intangible assets, which allow us to measure the impact of them on both wages and productivity at the firm level. Furthermore, the data is from Peru, which is a Latin America middle income country so it could represent rather well the typical country in this region. Second, the analysis at the firm level and the panel structure of the data allows us to control for the endogeneity of variable inputs applying different control function approaches. In addition, the production function estimates provide us with a measure of unobserved productivity which we include in the wage equation to retrieve a consistent estimate for the impact of intangible assets on wages. Third, our data allow us to explore how the impact of intangibles depends on the composition of the bundle on intangibles and the product mix at the firm level.

We find that an increase in the share of intangible assets on total capital by one standard deviation is associated with 6.8% to 7.2% higher total factor productivity, depending on the model´s specification. We also find that the productivity premium of intangible assets over tangible ones is substantial with estimates suggesting that intangibles are up to 2 times more productive than tangible assets. However, consistent with the theoretical insights about partial appropriability of these investments, this capital productivity premium is not entirely offset by a similar increase in wages. The average wage per worker premium of intangibles is just a fraction of the capital productivity premium of intangibles. Finally, we conclude that the main channels for appropriability are the specificity of the ideas generated by intangible investments at the firm level and the wage compression due to imperfect competition in the labor market.

The paper is structured in the following sections after this introduction. In section 2 a literature review on the impact of intangible assets is carried out, including the main research questions emerging from it. Section 3 introduces the conceptual framework and section 4 outlines the estimation strategy. Section 5 describes the data after which the main results are presented in section 6. Section 7 introduces several extensions, while section 8 elaborates further on policy recommendations. Finally, section 9 closes the paper with the conclusion and recommendations for further research.

2. Literature Review

There is an important literature using growth accounting macro data to explore the contribution of intangibles to economic growth. This literature points out to the problems that exist to capitalize intangible investments trying to correct for several issues related to them such as the lack of price deflators or the uncertainty regarding their economic depreciation. Despite these concerns, the literature suggests that, under relatively reasonable assumptions, intangible assets accumulation has contributed half percent to labor productivity growth in Europe over the last two decades and even a little more in the case of the US (Corrado, et al., 2022). However, to the best of our knowledge, there is no similar evidence expanding national accounts for Latin American countries.

At the micro level, the empirical literature on intangible assets is not new. However, most of it focuses on the effects of particular types of intangibles. The most studied intangible so far is R&D. The literature on the returns (both social and private) to R&D has accumulated over half a century and it is mostly based on the use of a production function framework augmented by R&D[2]. Hall, et al. (2010) summarizes a large set of studies at the firm, industry, and country levels on the returns to R&D. When looking at the studies using firm level data, the major findings are that private returns to R&D are strongly positive and somewhat higher than those for ordinary capital[3]. In the case of Latin America, similar results have also been obtained for Chile (Benavente et al., 2005), but with evidence of important adjustment costs.

A more recent literature on R&D tackles the issue of spillovers which is important as R&D originated in one firm can affect the productivity performance of other firms. Most of the studies on spillovers have been conducted by adding a measurement of external (to the firm, sector, or country, depending on the level of aggregation) R&D to the production function. The empirical results suggest that spillovers are found to be positive and quite large, but rather imprecisely estimated[4]. More complex has been to identify the source or the channel through which spillovers materialize. One channel is researchers' labor mobility (Moen, 2005; Kerr, 2008 and Marilanta, et. al 2009), a second channel is knowledge diffusion among firms located within geographical clusters (Jaffe, 1989) and a final channel is through international spillovers (Coe and Helpman, 1995). Crespi et al. (2008) investigate spillovers by using direct measures of knowledge flows, as they are revealed by the UK Community Innovation Survey and find that flows from competitors, suppliers and plants

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2 More specifically, the residual factor in production that is not accounted by the usual inputs (labor, capital, intermediate materials) is assumed to be the product of R&D that produces technical change.

3 On the whole, although the studies are not fully comparable, it may be concluded that R&D rates of return in developed economies during the past half century have been strongly positive and may be as high as 75% or so, although they are more likely to be in the 20%-30% range (Hall, et al. 2010).

4 In principle spillovers can be also negative if there are market stealing effects. This is the case when a new product renders old products obsolete, when R&D is used strategically to preempt competition or when patent races lead to duplicative R&D. Bloom et.al. (2007) found evidence of market stealing effects for spillovers in the industry segment space as opposed to positive spillovers in the technology space.

that belong to the same group explain half of firm level total factor productivity growth. In this paper, information from competitors is considered to be pure knowledge spillovers. Spillovers can depend on the type of innovation, with product innovations having normally larger spillovers than process innovations (Ornaghi, 2006). In the case of Latin America, previous research has found significant and positive spillovers of R&D due to both researchers' labor mobility (Castillo, et.al., 2019) and geographical proximity, but in this case only for projects carried out in collaboration with universities (Crespi, et.al., 2020). However, the studies reviewed so far only apply to R&D which, according to national accounts estimates, is a rather small component of total intangible investments, and which economic properties cannot be linearly extrapolated to other intangibles.

With regards to other intangible assets, there is a very large but more recent literature regarding to the effects of information and communications technologies (ICT) capital on productivity. Using an ICT capital augmented production function, Bloom et al. (2012) find that US multinationals operating in Europe obtained higher productivity from ICT than non-US multinationals, particularly in the same sectors responsible for the US productivity acceleration. Furthermore, establishments taken over by US multinationals (but not by non-US multinationals) increased the productivity of their ICT capital afterwards. Combining European firm-level ICT data with a survey on management practices, they find that the US ICT capital productivity advantage is primarily due to its better management practices. Crespi, et al. (2007), examines the relationships between productivity growth, ICT investment and organizational change using UK firm panel data. Consistent with other micro studies, they find that ICT investment appears to have high returns in a growth accounting sense when organizational change is omitted; however, when organizational change is included ICT returns are greatly reduced, so ICT investment and organizational change interact in their effect on productivity growth. Finally, they also found that organizational change is affected by competition and the nationality of the owner of the firm. Consistently with Bloom et al. (2012), they found that US-owned firms are much more likely to introduce organizational change relative to foreign owned firms who are more likely still relative to UK firms. Baldwin and Sabourin (2002) examines the relationship between the use of ICT and growth in plant's market share and its relative productivity in Canadian Manufacturing, finding that technology users that were using communications technologies increased their relative productivity the most. Bresnahan et. al (2002) using US firm level data find evidence of complementarities between ICT, organizational change, and new products and services. In addition, firms that adopt these innovations tend to use more skilled labor. The effects of ICT on labor demand are greater when ICT is combined with organizational change. For Latin America, Aboal and Tacsir (2017), find that ICT play a bigger role for innovation and productivity in services than in manufacturing for the case of Uruguay. On the contrary, in the case of Peru and using firm level panel data, no clear effects of ICT on productivity are found (Garcia, 2022).

As for other intangibles, there is large empirical literature on the effects of training on productivity reporting mixed results mostly based on limited samples (Bartel, 1995; Black & Lynch, 2001; Zwick, 2006). For the remaining intangibles, the literature is scanter. One exception is Cereda et al. (2005) that analyses the relationship between design and economic performance by using the third wave of the UK Community Innovation Survey. By estimating a knowledge production function, an output production function, and a design expenditure function, they found that design expenditure also has a positive and statistically significant association with productivity with a return rate of about 20%.

With regards to the evidence of spillovers in the case of other intangibles, the literature is more limited. However, some related research on the productivity impacts of the mobility of key personnel at the firm level suggests that a partial appropriability scenario is the most likely result. For example, Van Reenen (1996) examines the impact of technological innovation on wages using a panel of British firms finding that innovating firms have higher wages, but rival innovation tend to depress own wages, a result which appears consistent with a model where wages are partially determined by a sharing in the rents generated by innovation. More recently, Kline et.al. (2018) link US patent application to US business and worker tax records, causally finding that an initial allowance of an ex-ante valuable patent generates substantial increases in firm productivity and in worker compensation suggesting that on average, workers capture roughly 30 cents of every dollar of patent-induced surplus in higher earnings. Some research makes use of event studies methodologies to assess the relevance of rent sharing of innovative rents. Research tracking executives' performance when they leave a company find that they are often unable of repeating their success, suggesting that the ideas are greatly appropriable at the firm level (Groysberg, McLean, and Nohria 2006). On the contrary, using administrative employer-employee matched data on US startups, Choi, et.al (2023) utilize premature death as a natural experiment that exogenously separates talent from startups. They find that losing an early joiner has large negative effects on employment and revenues that persist for at least ten years. In contrast, losing a later joiner yields only a small and temporary decline in firm performance. The results point to the fact that organizational capital, an important driver of startup success, is embodied in early joiners. Regarding to the literature on training, Konings and Vormelingen (2015), use a Belgium firm-level panel data about on-the-job training to estimate its impact on productivity and wages. After correcting for the endogeneity of input factors and training, they found that the productivity premium of a trained worker is substantially higher compared to the wage premium, thus it seems plausible that to the extent that skills training provided by the firm are firm specific (due perhaps to their combination with firms' specific organizational routines), the appropriability concerns on these investments in training are mitigated.

In summary, there is a large and dynamic literature on intangible investments that shows sizable positive effects on productivity growth in frontier countries at the aggregate and micro levels (Haskel and Westlake, 2018, Tambe et al, 2020). Although in Latin America econometric studies are more limited and render mix results, case study-based evidence suggests that intangible based firms such as Mercado Libre, Globant, Despegar, OLX, Auth0, Rappi, dLocal, 99, Nubank, Prisma, GymPass, Softtek and Kio, among others, are able of competing with world leaders in their sectors, and, at the same time, coexist with a large number of firms that lag significantly behind in terms of productivity. However, in a context characterized by poor absorptive capacities, weak institutions, and poor technological infrastructure impacts of intangibles observed in developed countries both in terms of productivity and spillovers cannot be taken for granted. Hence there is need to get a deeper understanding on how the accumulation of intangible capital is affecting productivity at the firm level and if any sort of incomplete appropriability is affecting this impact.

3. Conceptual Framework

Intangible assets can increase productivity by improving product quality or reducing the average production costs of existing goods or simply by widening the spectrum of final goods or intermediate inputs available. So, in order to assess the productivity impacts of intangible assets our methodological starting point is an intangible capital augmented production function written as $Y_{it} = A_{it} F\left(L^*_{it}, M_{it}, K^*_{it}\right)$, where A_{it} is the technology that applies to the entire production function and Mit are intermediate inputs or materials. Here, total capital stock K^*_{it} is a combined variable that includes both tangible and intangible assets weighted by their relative productivities. While L^*_{it} is human capital augmented labor. Assuming a Cobb-Douglas production function and taking natural logs results in the standard (log) linear production function:

(1) $$y_{it} = \beta_0 + \beta_l l^*_{it} + \beta_m m_{it} + \beta_k k^*_{it} + \varepsilon_{it}$$

where lower-case letters refer to natural log and where:

(2) $$a_{it} = \beta_0 + \varepsilon_{it}$$

β_0 measures the mean efficiency level across firms and ε_{it} is the time and producer-specific deviation from that mean, which can then be further decomposed into observable (or at least predictable) and unobservable components. We follow Crepon, et al. (1998) to define a quality augmented total capital function as:

(3) $$K_{it}^{*} = \theta_T K_{T,it} + \theta_I K_{I,it}$$

Where the parameter θ_j captures the different qualities of intangible and tangible capital stocks respectively. Considering that total (non-quality adjusted) capital stock is simply $K_{it} = K_{T,it} + K_{I,it}$, we can use this identity into (3) to obtain $K_{it}^{*} = \theta_T (K_{it} - K_{I,it}) + \theta_I K_{I,it}$. We can rewrite this as $K_{it}^{*} = \theta_T K_{it}\left(1 - \frac{K_{I,it}}{K_{it}} + \frac{\theta_I}{\theta_T}\frac{K_{I,it}}{K_{it}}\right) = K_{it}\left[1 + \rho_I \frac{K_{I,it}}{K_{it}}\right]$ where $\rho_I = \left(\frac{\theta_I}{\theta_T} - 1\right)$ captures the relative productivity premium of intangible capital on tangible capital[5].

Assuming that this premium is relatively small and normalizing $\theta_T = 1$, we can take logs and use the approximation $k_{it}^{*} = k_{it} + \rho_I \frac{K_{I,it}}{K_{it}}$. Following a similar approach for human capital augmented labor we have $l_{it}^{*} = l_{it} + \rho_H \frac{H_{it}}{L_{it}}$ where H_{it} is the number of workers with a given level of human capital and ρ_H captures the relative productivity premium of human capital with regards to headcount labor. Substituting this together with (3) into (1) results in the following equation.

(4) $$y_{it} = \beta_l l_{it} + \beta_l \rho_H \left(\frac{H_{it}}{L_{it}}\right) + \beta_m m_{it} + \beta_k k_{it} + \beta_k \rho_I \left(\frac{K_{I,it}}{K_{it}}\right) + \omega_{it} + u_{it}.$$

and:

(5) $$\omega_{it} = \beta_0 + \vartheta_{it}$$

Where ϑ_{it} is the predictable component of ε_{it} and u_{it} is an i.i.d. component, representing unexpected deviations from the mean due to measurement error,

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5 It measures how quality adjusted capital changes in percentage terms with changes in the intensity of intangible assets $\frac{dk^{*}}{d\left(\frac{KI}{K}\right)} = \rho_I$.

unexpected delays, or other external circumstances. In (4), the main parameter of interest is ρ_I which measures the capital productivity premium of intangibles with respect to tangible capital. The final impact of intangible capital on total output will be given by $\beta_k \rho_I$ which represents the percentage change in output in response to variations in the intangible intensity of total capital, which is also the impact of intangible intensity on total factor productivity. A nice feature of this specification is that it mitigates the collinearity problem between tangible and intangible capital stocks which, as the previous literature on R&D capital suggests, is a source of lack of precision and volatility in the results about R&D returns when using within estimates (Hall, et al. 2010). The key assumption underlying equation (4) is that intangible capital only affects capital productivity[6].

In order to explore the effects of intangible assets on wages, we need to recall from our previous discussion that if intangible assets are, at least partially, linked or stored into the firm's worker's brains, current employees will be imperfect substitutes with new hires, which generates a mechanism to extract rents from the firm in the form of a wage premium. Based on these considerations, innovative firms should share rents with its workers to increase the chances of retaining them (Kline, Petkova, Williams, and Zidar, 2018). The rent sharing mechanism depends on two considerations. First, how specific to the firm are the characteristics of ideas embedded in the intangible assets linked to their workers and second the degree of imperfect competition in the labor market. If ideas are generic, in other words if they can be applied without major adaptation or reverse engineering costs in firm's rivals, workers are expected to receive higher salary offers from competitors and so they will be in a better position to extract rents from the innovative firm. However, on the other hand, if ideas are firm specific, major adaptation or reverse engineering spending could be necessary to implement them in other firms. In this case, the salaries offered from the innovative firm's rivals are expected to be lower (as they should at least internalize adaptation or reverse engineering costs) and so innovative firm's employees will be in a worse position to extract rents from their current employer. In any scenario, innovative firms will be in a better position to retain the rents from their intangible investments whenever there are fewer or no rivals to them, in other words when there is imperfect

6 To the extent that much of intangible capital, in particular organizational capital, could be stored in key employees' talent, we cannot a priori rule out some effect of intangible capital on labor productivity (Crouzet, et.al. 2022). However, under this approach the problem is that we need to be able of separating the effects of intangible assets on total factor productivity among both labor and capital productivities leading to a problem of identification due to the lack of the necessary information in the dataset (for example, information on the number of R&D, design, and engineering workers).

competition in the labor market[7].

The theoretical discussion suggests a reduced-form model for wages of the form $W = W\left(\tilde{W}, S, \frac{K_I}{K}\right)$, where $\tilde{W}$ represents the external offers received by the employee that are independent from the characteristics of the ideas embedded into the intangible assets but that are affected by both employee level attributes (such as education and training) and firm level attributes (such as productivity, working environment, etc.). $\frac{K_I}{K}$ is the intangible assets intensity which effects on wages will depend on how generic the ideas embedded in the assets are. Finally, S captures the bargaining power of the firm relative to the employees which will also affect the effects of intangible assets on wages. So, we expect that the first derivative of the wage function with regards to $\tilde{W}$ and $\frac{K_I}{K}$ will be positive (and, in the last case, increasing with the outside value of intangibles assets related ideas) but that the cross derivative of W with regards to $\frac{K_I}{K}$ and S will be negative, because a higher S increases the bargaining power of the firm. So, following Van Reenen (1996), Konings and Vormelingen (2015) and Castillo et.al (2016), the reduced form model for the average wage at the firm level can be written as:

(6) $$w_{it} = \delta_H \left(\frac{H_{it}}{L_{it}}\right) + \delta_I \left(\frac{K_{I,it}}{K_{it}}\right) + X_{it}\gamma + \varphi_{it} + \varepsilon_{it}$$

Where w_{it} is the average wage at the firm level (in log), X_{it} captures additional control variables including training, location and sector dummies determining average wages. Unobservables determinants of wages (such as labor quality among others) are represented by φ_{it}. Where in first instance we assume that firms are price takers in the labor market $(S = 0)$. The coefficients δ_H and δ_I capture the wage premiums of human capital and intangible assets intensities respectively. 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 $(\rho_I = \delta_I)$.

7 Of course, although important, specificity of ideas and the degree of imperfect competition in the labor market are not the only factors affecting the sharing of innovation rents. Other determinants are related with firm's amenities such as geographic location or work environment, the duration of the relationship between the workers and the firm, involvement of workers in intangible assets intensive activities, hiring and separation costs, etc. Unfortunately, we lack enough detail information to control for these other factors which will be treated as unobservables in our study. However, we are confident that our identification strategy is robust enough as to control for their omission.

We discuss below how the results are affected if the firms are not price takers in the labor market.

4. Estimation Strategy

To have meaningful results for policy recommendations is critical to have unbiased estimates of intangible premiums for both equations. With regards to (4), unfortunately, OLS or fixed effects estimates do not provide a proper answer. Standard OLS techniques suffer from at least 2 problems. In first place, to the extent that (unobserved) productivity is partially anticipated by the firm, variable inputs hiring decisions will internalize productivity, so inputs will be endogenous and OLS estimates biased (Marschak and Andrews, 1944). Second, as firms enter and exit the panel, and given that firms make also exit decisions based on anticipated productivity shocks, exit won't be at random so, not taking the exit decisions into consideration, will lead to a problem of selection bias (Olley and Pakes, 1996).

To deal with these problems, we estimate the production function using different versions of the control function approach as suggested by Olley and Pakes (1996); Levinsohn and Petrin (2003), and Ackerberg, Caves and Frazer (2015), among others. The three approaches explicitly model unobservable productivity as a function of some observable control variable highly correlated with the anticipated productivity shock, thus the anticipated productivity shock can be eliminated from the production function by inverting this function into observable variables. For example, if we follow Olley and Pakes (1996), investment decisions at the firm level can be shown to depend on capital and productivity $i_{it} = i_t\left(k_{it}, \left(\frac{K_{I,it}}{K_{it}}\right), \omega_{it}\right)$. Provided investment is strictly increasing in productivity, conditional on capital, this investment decision can be inverted allowing us to express unobserved productivity as a function of observables $\omega_{it} = h_t\left(k_{it}, \left(\frac{K_{I,it}}{K_{it}}\right), i_{it}\right)$, where $h_t(.) = i_t^{-1}(.)$. However, given that firms make also exit decisions based on anticipated productivity shocks, exit won't be at random so, not taking the exit decisions into consideration, will affect the consistency of the estimates (Olley and Pakes, 1996). Intuitively, the bias emerges because the firms' decisions on the allocation of inputs in a particular period are made conditional on its survival. If firms have some knowledge about their productivity ω_{it} prior to their exit, this will generate correlation between ω_{it} and the fixed input capital, conditional on being in the data set. This correlation has its origin in the fact that firms with a higher capital stock will (ceteris paribus) be more able to survive with lower ω_{it} relative to firms with a lower capital stock. This generates a negative correlation between the error and the capital stock $\left(E(k_{it}\omega_{it}\right) < 0)$ leading to a downward biased in the capital coefficient and to a further underestimation of returns rates of capital. To correct for this, we follow Olley and Pakes (1996) by including the survival probability into the control function (P_{it}) . Based on the discussion in this paragraph, equation (4) can be rewritten as:

$$y_{it} = \beta_l l_{it} + \beta_l \rho_H \left(\frac{H_{it}}{L_{it}} \right) + \beta_m m_{it} + \beta_k k_{it} + \pi_k \left(\frac{K_{I,it}}{K_{it}} \right) + h_t \left(k_{it}, \left(\frac{K_{I,it}}{K_{it}} \right), i_{it}, P_{it} \right) + u_{it} \tag{7}$$

Where $\pi_k = \beta_k \rho_I$. Equation (7) can be estimated by using a polynomial in capital stock, intangible assets share, investment, and survival probability. The method proceeds in two steps. In the first step, only the parameters of the free inputs are estimated (labor and materials) while the rest of the parameters are estimated in a second step assuming a Markov process for the productivity shocks. Levinsohn and Petrin (2003) argue that the Olley and Pakes (1996) method fails when investment cannot be inverted (for example, when firms report zero investment), and they propose using materials instead of investment in the proxy function for productivity. Ackerberg, Caves and Frazer (2015), instead, notice that when using materials none of the free inputs coefficients is identified in the first step, so they propose an adjustment to the methodology by which the parameters of all the inputs (free and predetermined) are identified in the second step.

Estimating the wage equation (6) suffers from the same problems as estimating the production function since human capital and intangibles intensity are likely to be correlated with unobservables. To correct for this, we follow Frazer (2001) and Konings and Vormelingen (2015) and use the productivity estimates from the productivity equation to control for the unobserved factors affecting wages. The assumption here is that the main component of the productivity shock after controlling for industry and year effects is unobserved labor quality. So, we estimate the following wage equation at the firm level:

$$w_{it} = \delta_H \left(\frac{H_{it}}{L_{it}} \right) + \delta_I \left(\frac{K_{I,it}}{K_{it}} \right) + X_{it}\gamma + \widehat{\omega_{it}} + \varepsilon_{it} \tag{8}$$

Where we assume that $\omega \approx \varphi$. Finally, in the specifications, all the regressions include year and industry dummies. Industry dummies are at ISIC two-digit level. Standard errors for all coefficients in both the production function and the wage equation are obtained using bootstrapping. After this we can derive the capital productivity premium of intangible assets from the estimated coefficient of intangible assets in (7). In other words:

$$\widehat{\rho_I} = \frac{\widehat{\pi_k}}{\widehat{\beta_k}} = \frac{\widehat{\beta_k \rho_I}}{\widehat{\beta_k}} \tag{9}$$

5. Data Description and Variables

Intangible investments are understood as a composite of three categories of assets: computerized information (software development, database development); innovative property (R&D, mineral exploration, copyright development, design, and other product development costs) and economic competences (market research & advertising, business process investment and training & skill development) (Corrado, Hulten and Sichel, 2005, 2009). In this paper, we use the National Enterprise Survey (ENE) of Peru which collects firm level information on firm's characteristics, infrastructure, human resources, management practices, information and communication technologies, financial products, production, sales, value added and assets.

The ENE produces an unbalance panel for 2015-2019. The total number of observations is 79,372. From this set, there are 43,821 firms observed for one year, 7,143 firms observed for two consecutive years, 2,818 firms tracked over three years, 1,779 firms followed over four years and 1,139 observed during the five years of the time setting. Overall, 12,879 firms are observed over two or more years. Unfortunately, the panel data structure strongly biases the sample composition towards large firms (7,883 of 12,879 firms). In terms of sectors, ENE is representative at two digits ISIC code (rev. 4). From this database, we obtain the main variables needed for the estimation of the production function such as total income, number of employees, fixed capital investments, and inputs (materials) expenditure and for the estimation of wage equation variables such as average wages, training provision and employees' education level[8].

The ENE survey also includes a module regarding fixed capital and intangible assets[9]. The production and asset section of the ENE survey has a specific question about the value of intangible assets which is defined as "*the representation of immaterial values, such as rights and privileges for the use of the firm with respect to its capacity to produce revenues and costs for goods and services that can generate future profits. For example, patents, concessions, trademarks, R&D expenditures, feasibility studies, among other*". The average ratio of intangible assets over total capital investments is 2.7% for the 2016-2019 period. In all the cases we use beginning of the period intangible capital stocks as the previous literature on R&D has found higher elasticities with end

8 All nominal variables are expressed in natural logarithm (ln) except ratios.

9 2015 ENE does not include this information, so the values for this year were imputed based on information from the following years at firm level.

of the period R&D due to simultaneity because of the feedback from output to current levels of intangible investments (Mairesse and Hall, 1994). We proceed in the same way with tangible capital stocks.

In order to adjust employment for labor quality we use the ratio of employees with tertiary education (undergraduate or graduate education) over the total number of employees[10]. To estimate the wage equation, we also include training provision as determinant of average wages. Training provision is a dummy variable that captures if an employee receives any training during the year of the survey. The average educational level for the 2015-2019 period is 30%.

Nominal variables were deflated by using different price indices deflators. We use the gross value-added deflator by ISIC code for total revenues, materials (inputs) are deflated using the wholesale price index, tangible capital was deflated using the gross private fixed capital formation price deflator and average wages are deflected by consumer price index. All deflator data is available at the National Institute of Statistics and Informatics of Peru (INEI).

Finally, we apply the blocked adaptive computationally efficient outlier nominator algorithm to identified multiple outliers in the 2015– 2019 ENE database. This technique uses the Mahalanobis distance from a basic subset of observations to separate outliers from non-outliers based on a specific threshold which is by default 0.15 percentile (Weber, 2010). We applied this technique to each ENE survey database. The final sample size to estimate the production and wage function is 27,654 observations.

Table 1 provides the descriptive statistics for the final working dataset. A Peruvian typical firm in the private sector employs on average 127 employees, generates around S/.26 million in output per year (equivalent to US$8 million) and has an average labor cost of around S/.3.9 million (equivalent to US$1.2 million). The largest average firm operates in the oil and gas and metal mining sectors, while the smallest ones are in the veterinary services and libraries and museums services.

The average fraction of intangible capital on total capital (or intangible capital intensity) is 2.7% being financial services, electricity, oil and gas, metal mining and insurance and pension funds the sectors with the largest intensities and traditional services such as residential care, accommodation, crop production and repair of domestic appliances those with the lowest (table 2). The proportion of firms that do not invest in intangibles is 63.2%. The intensity of intangibles of firms that do invest in intangibles is 7.3%, which implies that the main reason for the low share of intangibles in total capital stock in the total sample is that few firms actually do invest in intangibles.

[10] 2019 ENE does not include data on employees' education level. For 2019, this variable is calculated as 2015-2018 average.

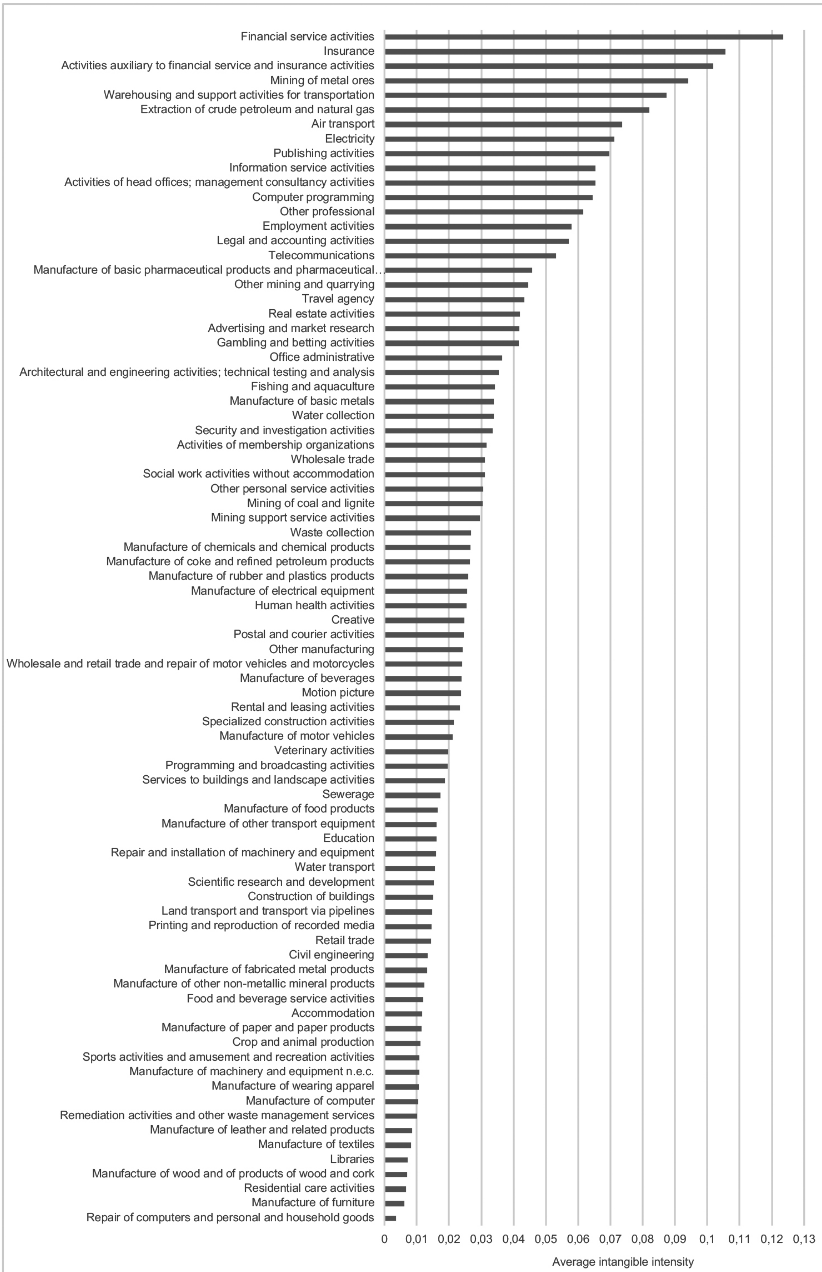
TABLE 1
SUMMARY STATISTICS

VARIABLES	Mean	Std. Dev.	10th Perc.	50th Perc.	90th Perc.	N
Employees	127	472	3	15	264	27,654
Labor cost (S/)	3,964,000	18,270,000	10,200	207,334	8,494,000	27,654
Labor cost (USD)	1,204,863	5,553,191	3,100	63,019	2,581,763	27,654
Labor cost per employee (S/)	30,759	193,050	2,400	13,127	55,777	27,654
Labor cost per employee (USD)	9,349	58,678	729	3,990	16,953	27,654
Education	0.299	0.276	0	0.296	0.750	27,654
Output (S/)	26,600,000	108,900,000	53,190	1,514,000	58,040,000	27,654
Output (USD)	8,085,106	33,100,304	16,167	460,182	17,641,337	27,654
Value added (S/)	22,040,000	98,330,000	0	664,260	47,330,000	27,654
Value added (USD)	6,699,088	29,887,538	0	201,903	14,386,018	27,654
Ratio labor cost over output	0.149	0.168	0.137	0.146	0.192	27,654
Intangible assets over total capital (for total number of firms)	0.027	0.100	0	0	0.038	27,654
Intangible assets over total capital (only firms that invest in intangibles)	0.073	0.154	0.002	0.030	0.184	10,179

Source: ENE (2015-2019).

TABLE 2

INTANGIBLE INTENSITY BY SECTOR (CIIU REV. 4)



Source: Authors' elaboration based in ENE (2015-2019).

6. Econometric Results

In the empirical estimates our main dependent variable is value added (output minus materials). There are several reasons to prefer value added over sales when using firm level data. *First*, the materials-output ratio can vary greatly across firms because different degrees of vertical integration; *second*, proper modelling of the demand for intermediate inputs would probably require modelling adjustment costs related to the stock of materials; and *third*, data on materials are prone to measurement errors when using accounting data (Hall et al., 2010). We do not impose constant returns to scale in the production function because the previous empirical literature on R&D suggests that doing this tends to overestimate the returns to R&D (Hall and Mairesse, 1995). So, using value added deflated data, we first estimate the impact of intangible assets on the productivity (equation 4) and on average wages (equation 6). For the estimation of equation (6) we included as control variable the total factor productivity (TFP) estimated from equation (4) among other control variables which are determinants of wages such as firm provided training and education level of labor force. Our estimation strategy includes the results obtained by applying the control function approach-based methodologies suggested by Olley and Pakes (1996); Levinsohn and Petrin (2003), and Ackerberg, Caves and Frazer (2015) always including the selection bias correction. The results from Table 3 suggest that the control function corrections work in the expected direction as the coefficient of labor decreases with respect to the OLS benchmark (for the OP and LP methods) and the coefficient of capital increases (for the OP and ACF specifications). Using as benchmark the ACF results, labor elasticity (0.72) and capital elasticity (0.34) are within expected values based on the inherited literature on production function estimates. Also, the findings suggest that there are constant returns to scale. The coefficient that captures the impact of intangibles intensity is very similar across the different control function results (with the only exception of the fixed effects results that are rather poorly estimated). Given that this coefficient captures the contribution of intangibles to total factor productivity, by focusing on the ACF result, we can infer that one standard deviation increase in intangible assets intensity (0.10) produces an increase of 6.8% in total factor productivity. Using the estimated results for input elasticities together with equation (9) we calculate that the productivity premium of intangibles on tangible capital is 1.93 (based on the ACF results). In other words, the productivity premium of intangible assets is almost two times the marginal productivity of tangible investments. Additional results suggest that education has also a strong premium on the productivity of labor with a coefficient of 0.57. Such large productivity premium is consistent with the findings by Benavente et.al. (2006) for R&D returns in Chile which

TABLE 3

IMPACT OF INTANGIBLES ON PRODUCTIVITY AND WAGES

(BASELINE MODEL – VALUE ADDED)

VARIABLES	**OLS**	**FE**	**OP**	**LP**	**ACF**
		PRODUCTION FUNCTION			
LABOR (β_l)	0.704***	0.414***	0.573***	0.613***	0.727***
	(0.0096)	(0.0385)	(0.0059)	(0.0024)	(0.0348)
Education ($\beta_l \rho_H$)	0.805***	-0.0960	0.423***	0.558***	0.591***
	(0.0394)	(0.0990)	(0.0047)	(0.0565)	(0.0273)
Capital (β_k)	0.268***	0.179***	0.362***	0.262***	0.345***
	(0.0050)	(0.0224)	(0.0375)	(0.0327)	(0.0063)
Intangibles ($\beta_k \rho_I$)	0.658***	0.411*	0.833***	0.706***	0.683***
	(0.0950)	(0.2450)	(0.0355)	(0.1490)	(0.0148)
WAGE EQUATION					
INTANGIBLES (δ_I)	0.804***	0.299*	0.681***	0.834***	0.832***
	(0.0725)	(0.1680)	(0.0704)	(0.0684)	(0.0687)
TFP (ω_{it})			0.321***	0.308***	0.303***
			(0.0059)	(0.0049)	(0.0050)
TRAINING (γ)	0.395***	0.00770	0.288***	0.346***	0.350***
	(0.0155)	(0.0347)	(0.0147)	(0.0147)	(0.0148)
EDUCATION (δ_H)	0.598***	-0.0829	0.453***	0.564***	0.570***
	(0.0290)	(0.0651)	(0.0284)	(0.0277)	(0.0278)
OBSERVATIONS	23,480	7,348	21,595	26,884	26,884
SECTOR	YES	YES	YES	YES	YES
REGION	YES	YES	YES	YES	YES
YEAR	YES	YES	YES	YES	YES

Source: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses. All control function models correct for attrition of firms. To estimate the production function regressions, we include as control variables: years of establishment functioning, a dummy variable for the location of the firm (1 if Lima, 0 otherwise), two digits sector dummies and time effects. The estimation of the wage equation includes training and educational level as determinants of average wages and control variables such as TFP, location (dummy), two-digit sector dummies and time effects. Where OLS = Ordinary Least Squares, FE= Fixed Effects, OP = Olley and Pakes, LP = Levinsohn and Petrin and ACF = Ackerberg, Caves and Frazer method. For the corrections that control for attrition of firms we follow Rovigatti and Mollisi (2018).

finds that in a balanced sample of firms the rates return to R&D are almost 3 times larger than in the case of fixed capital (0.54 vs. 0.18)[11].

When examining the wage equation, we obtain that the intangible assets intensity shows a coefficient of 0.83 on the (ln) wages at the firm level. Firms that provide training also pay higher average wages (35%), while more productive firms also pay higher average wages with an elasticity of 0.30 (in other words, about one third of a total productivity increase at the firm level translates to average wages). The large gap we found between capital productivity and wage premiums suggest that only 43% of the productivity premium goes to workers' wages. Although this figure is relevant and it could suggest some policy intervention to compensate firms, still the majority of the returns from intangibles are appropriated by the firms. Although lower than in the case for intangibles, we also found a large wage premium for human capital (0.59). Table 3 suggest that the productivity premium of human capital is 0.80 (0.59/0.73), which indicates that about 60% of the productivity premium of human capital is shared by the firm with its workers.

To check the extent that our results are robust to different definitions of the dependent variable, we also estimated the basic model using total output as the main dependent variable due to the concern that measuring errors in material could also affect value added measurements. In fact, when using value-added if materials are poorly measured (considering that value added is the difference between total output and materials) this could affect the precision of the results. So, instead of using value-added, we also estimate our baseline model using output as dependent variable. The results are summarized in Table 4.

If we take as reference the ACF results, we obtain production function coefficients which are very similar to the ones when using value-added. Indeed, labor elasticity (0.70) and capital elasticity (0.30) are within the expected based on the inherited literature on production function estimates. Also, the findings suggest that there are constant returns to scale. When analyzing the effects of intangible capital on total factor productivity, Table 4 suggests a little higher total effect (0.72 vs 0.68). The main message is similar as before, intangibles are a driving force underlying total factor productivity growth. With regards to the wage equation the results are similar to the ones in Table 3. Indeed, the estimated wage premium of intangibles is 0.88 with important wage effects of productivity, training, and education.

However, the results in Table 4 suggest some changes in the estimated productivity premium of intangible capital. Indeed, a slightly higher coefficient of intangibles intensity combined with relatively lower output elasticities of capital (0.30 vs 0.34) leads to an increase in the computed productivity pre-

11 In the unbalanced sample the productivity premium is lower (1.79)

mium of intangibles on the productivity of capital (2.40 vs 1.93)[12]. In other words, although the results seem to be robust to the main parameters of both the production function and the wage equation, given the high nonlinearity of the parameters of equation (9), small changes in the estimated parameters increases the estimated premium of intangible assets on the productivity of capital. However, we believe, the main conclusions of the previous results are not altered. Intangible capital is a powerful driving force for total factor productivity growth at the firm level and about 64% of the capital productivity premium is appropriated by the firm. Despite this, still 36% is shared with the workers.

Summing up, if intangibles are embedded in labor, this creates concerns at the firm level to the extent that investors can appropriate the results of their investments in intangible capital, and if this knowledge is general, to the extent that it can be used in other firms (labor mobility could also benefit rival firms). Perhaps this is the main reason why, despite the potentially huge impact of intangibles on total factor productivity, very few firms carry out significant investments in it (with many firms with zero intangibles investment overall).

12 Based on the ACF results and using equation 9.

TABLE 4

IMPACT OF INTANGIBLES ON PRODUCTIVITY AND WAGES

(BASELINE MODEL - OUTPUT

VARIABLES	**OLS**	**FE**	**OP**	**LP**	**ACF**
Production function					
Labor (β_l)	0.688***	-0.00454	0.573***	0.613***	0.701***
	(0.0088)	(0.0471)	(0.0059)	(0.0024)	(0.0250)
Education ($\beta_l \rho_H$)	0.740***	0.836***	0.423***	0.558***	0.592***
	(0.0354)	(0.1170)	(0.0047)	(0.0565)	(0.0046)
Capital (β_k)	0.264***	-0.122***	0.362***	0.272***	0.308***
	(0.0046)	(0.0257)	(0.0375)	(0.0338)	(0.0099)
Intangibles ($\beta_k \rho_I$)	0.660***	-0.668**	0.833***	0.729***	0.720***
	(0.0872)	(0.3020)	(0.0355)	(0.0052)	(0.0170)
Wage equation					
Intangibles (δ_I)	0.848***	0.288*	0.704***	0.882***	0.880***
	(0.0731)	(0.1660)	(0.0690)	(0.0676)	(0.0679)
TFP (ω_{it})			0.445***	0.456***	0.453***
			(0.0066)	(0.0064)	(0.0065)
Training (γ)	0.399***	-0.008	0.278***	0.330***	0.334***
	(0.0155)	(0.0341)	(0.0143)	(0.0145)	(0.0146)
Education (δ_H)	0.606***	-0.020	0.445***	0.550***	0.559***
	(0.0293)	(0.0640)	(0.0279)	(0.0274)	(0.0275)
Observations	27,654	9,429	21,595	26,884	26,884
Sector	YES	YES	YES	YES	YES
Region	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES

Source: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses. All control function models correct for attrition of firms. To estimate the production function regressions, we include as control variables: years of establishment functioning, a dummy variable for the location of the firm (1 if Lima, 0 otherwise), two digits sector dummies and time effects. The estimation of the wage equation includes training and educational level as determinants of average wages and control variables such as TFP, location (dummy), two-digit sector dummies and time effects. Where OLS = Ordinary Least Squares, FE= Fixed Effects, OP = Olley and Pakes, LP = Levinsohn and Petrin and ACF = Ackerberg, Caves and Frazer method. For the corrections that control for attrition of firms we follow Rovigatti and Mollisi (2018).

7. Model Extensions

In this section, we introduce several additional experiments because the results presented in section 6 could be affected by several factors. *First*, the effects could depend on the actual composition of the vector of intangible assets. Not all intangibles are expected to suffer from partial appropriability in the similar extent, so controlling for this is important in order to correct more precisely for market failures. *Second*, real firms most of the time are also multiproduct firms. This implies that the production function should be estimated at the product line level which is impossible due to lack of information on the allocation of inputs (and intangible assets) across the different product lines. Moreover, in the case of intangible assets this is important because intangibles are also non-rival in use within firms, which means that the same intangible could be use at the same time across the different product lines. Therefore, it is expected that the productivity premium of intangibles will be higher in multi-product firms compare to single product firms. *Third*, the baseline results could also be affected by the influence of imperfect competition. If there is imperfect competition in the product markets, the estimated elasticities are a mixed between the factor shares and the mark-up. Although exploring the extent to which firms deviate from perfect competition might be interesting, we show that this problem is not relevant to untangling the relative premiums of intangible assets on capital productivity (to the extent that the mark-up parameter factors into the production function). More important, however, is to explore whether the results in the wage equation could be affected by distortions in the labor markets. In particular if there is monopsonic competition in the labor markets, mark-downs could affect the estimated wage premium of intangibles. In this section, we assess the extent to which our results are affected by these problems.

7.1 R&D vs Other Intangible Assets

The main model in section 6 estimates the capital productivity premium of intangible assets as a whole, without differentiating between types of intangibles as this information is not available in the ENE survey. Unfortunately, ENE lacks enough detail as to identify the sample of firms that do R&D. So, to examine the impact of intangible assets on productivity and wages depending on its type, we grouped companies in high and low R&D intensity sectors. For this split, we follow the OECD's taxonomy of economic activities based on R&D intensity developed by Galindo-Rueda and Verger (2016) in which R&D intensity is defined as the ratio of R&D to value added within an industry and economic activities are clustered into 5 groups: high, medium-high, medium,

medium-low, and low R&D intensity industries. Considering the limited sophistication of the Peruvian economy and its low levels of R&D investment, we include medium, medium-high, and high intensity industries in the high R&D intensity sectors group while low and medium-low R&D intensity industries are included under the low R&D intensity sectors group.

Table 5 summarizes the main results of this exercise. Following this classification, we found that the impact of intangibles on total factor productivity is much higher in the case of R&D intensive sectors (0.72 vs 0.61). The intangible assets capital productivity premium is also slightly higher in R&D intensive sectors (2.28 vs 1.79)[13]. In both subsamples we do not observe major departures from constant return to scales, which is reassuring of our previous findings. With regards to the wage premium, we also found that intangible assets impact is slightly higher in the case of R&D intensive sectors (0.84 vs 0.81). Based on these results the share of the capital productivity premium which is captured by labor is 36% in high R&D intensive sectors and 45% in the low R&D intensive sectors. If we interpret this as a signal of a market failure, it seems that the share of the capital productivity premium that goes to labor is more important in low R&D intensive sectors (perhaps this is the main reason of the low R&D intensity in these sectors).

[13] Based on the ACF results and using equation 9.

TABLE 5

IMPACT OF INTANGIBLES ON FIRMS FROM HIGH AND LOW R&D INTENSITY SECTORS

VARIABLES	High R&D intensity sectors (High R&D=1)			Low R&D intensity sectors (Low R&D=0)		
	OLS	**OP**	**ACF**	**OLS**	**OP**	**ACF**
Production function (value added)						
Labor (β_l)	0.757***	0.641***	0.785***	0.692***	0.565***	0.725***
	(0.0422)	(0.0148)	(0.218)	(0.0102)	(0.0134)	(0.0064)
Education ($\beta_l \rho_H$)	0.771***	0.281	0.337***	0.828***	0.462***	0.643***
	(0.1620)	(0.2150)	(0.0194)	(0.0426)	(0.0373)	(0.0112)
Capital (β_k)	0.268***	0.729*	0.320**	0.270***	0.366***	0.342***
	(0.0220)	(0.400)	(0.135)	(0.0053)	(0.0212)	(0.0138)
Intangibles ($\beta_k \rho_I$)	0.914***	2.619***	0.728***	0.604***	0.805***	0.615***
	(0.3330)	(0.6910)	(0.0586)	(0.1010)	(0.0335)	(0.0076)
Wage equation						
Intangibles (δ_I)	0.841***	0.463*	0.845***	0.787***	0.689***	0.815***
	(0.2740)	(0.2660)	(0.2600)	(0.0768)	(0.0746)	(0.0726)
TFP (ω_{it})		0.412***	0.371***		0.318***	0.303***
		(0.0294)	(0.0223)		(0.0061)	(0.0052)
Training (γ)	0.366***	0.188***	0.335***	0.405***	0.297***	0.357***
	(0.0651)	(0.0681)	(0.0618)	(0.0164)	(0.0154)	(0.0156)
Education (δ_H)	0.936***	0.726***	0.898***	0.605***	0.469***	0.585***
	(0.1290)	(0.1380)	(0.1230)	(0.0310)	(0.0303)	(0.0297)
Observations	1,520	1,116	1,696	20,740	19,560	23,953
Sector	YES	YES	YES	YES	YES	YES
Region	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES

Source: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses. All control function models correct for attrition of firms. To estimate the production function regressions, we include as control variables: years of establishment functioning, a dummy variable for the location of the firm (1 if Lima, 0 otherwise) and two digits sector dummies. The estimation of the wage equation includes training and educational level as determinants of average wages and control variables such as TFP, location (dummy) and two-digit sector dummies. Where OLS = Ordinary Least Squares, OP = Olley and Pakes, and ACF = Ackerberg, Caves and Frazer method. For the corrections that control for attrition of firms we follow Rovigatti and Mollisi (2018).

7.2 Scope Economies and Multiproduct Firms

In the basic model, we do not consider the product mix of the firm. If firms produce multiple products, potentially differing in their production technology; failure to estimate the production function at the appropriate product level, rather than at the firm level, will introduce biased input elasticities and productivity premiums (Bernard, Redding and Schott (2005)). In the case of intangibles assets, considering that the firm can have multiple product lines is important due to the non-rival nature of intangible assets (Corrado, et.al. 2022 and Bronnenberg, et.al. 2022). For example, a company can deploy a marketing campaign that affects the demand of the whole mix of products fabricated by the firm. In the same extent, process innovation, such as the adoption of just-in-time, could increase the efficiency of the different production lines of a car manufacturer. So, if non rivalry is important, we should expect a higher productivity effect of intangibles in multiproduct vs single product firms. Fortunately, in the survey we can differentiate between firms producing single or multiple products, so we can split the sample of firms between these two groups. The results of this exercise are presented in Table 6.

Table 6 summarizes the main results of this exercise. Following this classification, we found that the impact of intangibles on total factor productivity is slightly higher in the case of multiproduct firms (0.65 vs 0.60). The intangible assets capital productivity premium, however, is higher in single product firms (2.77 vs 2.32). With regards to the wage premium, we do not find differences between both subsamples (0.82 vs 0.83). Based on these results the share of the capital productivity premium which is captured by labor is 35% in multiproduct firms and 30% in single product firms. If we interpret this as a signal of a market failure, it seems that is more important in multiproduct firms (perhaps the new product designs are more easily transferred and imitated by other firms), however the overall results differences between both samples are rather small.

TABLE 6

IMPACT OF INTANGIBLES ON MULTI-PRODUCT AND SINGLE-PRODUCT FIRMS

VARIABLES	Multi-product firms (Multiproduct=1)			Single-product firms (Multiproduct=0)		
	OLS	OP	ACF	OLS	OP	ACF
Production function (value added)						
Labor (β_l)	0.691***	0.499***	0.689***	0.761***	0.558***	0.733***
	(0.0170)	(0.0087)	(0.0078)	(0.0195)	(0.0140)	(0.0225)
Education ($\beta_l \rho_H$)	0.713***	0.112	0.584***	0.652***	0.121***	0.428***
	(0.0760)	(0.0704)	(0.0042)	(0.0769)	(0.0398)	(0.0108)
Capital (β_k)	0.285***	0.240**	0.283***	0.234***	0.265***	0.216***
	(0.0086)	(0.1200)	(0.0147)	(0.0098)	(0.0622)	(0.0365)
Intangibles ($\beta_k \rho_I$)	0.569***	0.752*	0.652***	0.644***	0.613*	0.604***
	(0.1610)	(0.4070)	(0.0090)	(0.1850)	(0.3660)	(0.0078)
Wage equation						
Intangibles (δ_I)	0.771***	0.700***	0.825***	0.810***	0.513***	0.838***
	(0.123)	(0.122)	(0.116)	(0.138)	(0.136)	(0.1300)
TFP (ω_{it})		0.364***	0.309***		0.311***	0.287***
		(0.0103)	(0.0081)		(0.0111)	(0.0091)
Training (γ)	0.513***	0.309***	0.445***	0.365***	0.236***	0.311***
	(0.0270)	(0.0245)	(0.0255)	(0.0317)	(0.0283)	(0.0299)
Education (δ_H)	0.617***	0.169***	0.594***	0.326***	0.123**	0.302***
	(0.0542)	(0.0532)	(0.0509)	(0.0577)	(0.0542)	(0.0545)
Observations	10,696	8,389	10,662	8,153	6,641	8,127
Sector	YES	YES	YES	YES	YES	YES
Region	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES

Source: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses. All control function models control for attrition of firms. To estimate the production function regressions, we include as control variables: years of establishment functioning, a dummy variable for the location of the firm (1 if Lima, 0 otherwise) and two digits sector dummies. The estimation of the wage equation includes training and educational level as determinants of average wages and control variables such as TFP, location (dummy) and two-digit sector dummies. Where OLS = Ordinary Least Squares, OP = Olley and Pakes, and ACF = Ackerberg, Caves and Frazer method. For the corrections that control for attrition of firms we follow Rovigatti and Mollisi (2018).

7.3 Imperfect Competition

Imperfect competition can operate in both product and input markets. We first focus on the influence of imperfect competition in product markets. Following Klette (1996) if we assume a model of profit maximizing producer behavior, imperfect competition in output market and perfect competition in input markets, the marginal revenue product of an input will be equal to its marginal cost. So, as noted by Hall (1988) and others, it follows that:

(10) $$\beta_h = \mu\theta_h = \frac{\sigma}{1+\sigma}\theta_h$$

Where θ_h is the cost share of factor h as a share of revenues and μ is the mark-up given as $\frac{\sigma}{1+\sigma}$. Where σ is the elasticity of substitution (demand) between differentiated goods in the industry $(-\infty < \sigma < -1)$. A nice feature of (10) is that deviations from product perfect competition can be assessed by simply ratio between the estimated elasticity and the factor cost share, which normally is an observed variable in industrial surveys. However, we claim that deviations from product perfect competition do not affect the relative premium of intangible assets on capital productivity, which can be deducted immediately from the way this premium is obtained in equation (9):

(11) $$\rho_I = \frac{\pi_k}{\beta_k} = \frac{\beta_k\rho_I}{\beta_k} = \frac{\frac{\sigma}{1+\sigma}\theta_k\rho_I}{\frac{\sigma}{1+\sigma}\theta_k} = \frac{\theta_k\rho_I}{\theta_k}$$

In other words, the mark-up parameter (μ) scales-up input elasticities both in the numerator and denominator of equation (11). So, the intangible premium could be estimated by using the capital cost shares (θ_h) that in principle could be computed from the data. The situation becomes more complex if there is imperfect competition in the labor market.

If there is imperfect competition in the labor market firms could pass less of the increase in capital productivity due to intangible assets investments to their workers' wages. If this is the case, the intangible assets wage premium (δ_I) in (9) will be a mix of how generic the ideas embedded in human capital are and the mark down due to imperfect competition. So, estimating the mark down in the labor market due to imperfect competition is important in order to property compute the share of intangible assets effects on capital productivity that goes to labor. The issue is how to obtain a reliable estimate of this mark down at the firm level. Our approach rests on the idea of estimating monopsony market power at the labor market level (Bunting, 1962). This approach uses a simple location-based measure of market power as follows. We construct an overall measure of the percentage of the industry-specific labor market that each firm employs (which is the number of workers at firm i divided the number of workers in firm i's region and in firm i's industry or sh_{ijt}). While this variable is far from a perfect measure of an employer's power to set wages, it has the advantage that is a measure that can be constructed transparently from the data and that endogeneity problems are of a less concern. After constructing this variable, we added it as an additional control in equation (6) where we also interact this variable with both human capital and intangible assets intensities. If the interaction terms are negative, we can claim that there is imperfect competition in the labor market and firms are using it to reduce the effect of intangible assets on wages (in other words firms are using market mechanisms to appropriate the effects of intangible assets on productivity).

Table 7 summarizes the results. We found that the wage premiums of intangible assets and human capital are negatively affected by market power in the labor markets (although the results are significant only in the case of human capital). However, if we take as valid the results in the last column of the table (ACF), we obtain that the wage premium of intangible assets in the case of monopsony is much lower than in the case of perfect competition in the labor market (0.35 vs 0.85). The difference in the wage premium between monopsony and perfect competition is also observed in the case of human capital (0.17 vs 0.59). The results suggest that wage compression due to imperfect competition is a channel through which firms could increase their control of innovation rents.

TABLE 7

IMPACT OF IMPERFECT COMPETITION IN THE LABOR MARKET

VARIABLES	OLS	OP	ACF
Intangibles (δ_I)	0.851***	0.695***	0.854***
	(0.0760)	(0.0738)	(0.0721)
Market power*Intangibles ($sh_{ijt}*\delta_I$)	-1.032**	-0.329	-0.500
	(0.446)	(0.449)	(0.420)
Education (δ_H)	0.630***	0.471***	0.591***
	(0.0304)	(0.0298)	(0.0292)
Market power*Education ($sh_{ijt}*\delta_H$)	-0.674***	-0.369**	-0.412**
	(0.179)	(0.171)	(0.171)
Market power (sh_{ijt})	0.150**	-0.0329	0.135*
	(0.0759)	(0.0717)	(0.0722)
TFP (ω_{it})		0.321***	0.303***
		(0.00587)	(0.0049)
Training (γ)	0.397***	0.291***	0.350***
	(0.0155)	(0.0147)	(0.0148)
Observations	23,480	21,595	26,884
Sector	YES	YES	YES
Region	YES	YES	YES
Year	YES	YES	YES

Source: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses. All control function models correct for attrition of firms. To estimate the production function regressions, we include as control variables: years of establishment functioning, a dummy variable for the location of the firm (1 if Lima, 0 otherwise) and two digits sector dummies. The estimation of the wage equation includes training and educational level as determinants of average wages and control variables such as TFP, location (dummy) and two-digit sector dummies. Where OLS = Ordinary Least Squares, OP = Olley and Pakes, and ACF = Ackerberg, Caves and Frazer method. For the corrections that control for attrition of firms we follow Rovigatti and Mollisi (2018).

8. Policy Implications

Estimating the effect of intangible capital investment on average wages is important to understand the extent to which the returns of these investments are appropriated either by the firm or by the workers. To the extent that the contribution of intangible investments to capital productivity is higher than the effect of intangible investments on average wages we can assume (partial) appropriability of these investments by the firms. This can help us investigating whether there are some market failures (in terms of externalities) that can merit public policy intervention. Several possibilities can be explored.

If there is perfect competition in the labor and $\rho_I > 0$ and $\delta_I = 0$ we can assume that the firm appropriates all the returns market from intangible investments or equivalent that intangible related knowledge is firm specific, so there is no room for policy intervention. On the other hand, if $\rho_I = \delta_I > 0$ it implies that all the returns on intangibles are internalized in wages and so that intangible related knowledge is generic. To the extent that workers can leave the company and move to other competitors of the firm there will be a market failure that will require government subsidizing the accumulation of intangible investments. Finally, if $\rho_I > \delta_I > 0$ we have a problem of partial appropriation by the firm, and some degree of policy intervention might be needed.

In this context $\frac{\delta_I}{\rho_I}$ could be considered as proxy of the subsidies to be provided to compensate the firm for the lack of appropriability of its investments in intangibles. In other words, public policies should be subsidizing the share of innovation rents that goes to workers only. Our findings of the baseline model for value added in Table 3 suggest that there is partial appropriability of intangible investments in Peru by contrasting the effects of intangibles on wages with the effects on capital productivity. This result holds for most of extension models which indicates that the conclusions drawn are robust. Therefore, our findings suggest that policy interventions might be needed to compensate firms for spillover effect of intangible assets in Peru.

TABLE 8

SUMMARY RESULTS AND POLICY RECOMMENDATIONS

Intangible Assets	ρ_I	δ_I	$\frac{\delta_I}{\rho_I}$
Perfect competition in the labor market		0.854	43.4%
Average competition in the labor market	1.97	0.604	30.7%
Monopsony in the labor market		0.354	18.0%
Human Capital	ρ_H	δ_H	$\frac{\delta_H}{\rho_H}$
Perfect competition in the labor market		0.591	51.8%
Average competition in the labor market	1.14	0.385	33.8%
Monopsony in the labor market		0.179	15.7%

The results in Table 8 suggest that in a scenario of perfect competition in the labor market, about 43% of the capital productivity premium of intangible assets is shared with the workers (52% in the case of human capital). This implies that the ideas associated with intangible assets are in great part firm specific. In the case of monopsony in the labor market the proportion of the capital productivity premium that is shared with the workers declines to just 18% (15% in human capital). This implies that wage compression due to monopsony is a major source of intangible assets appropriability (and also of education investments). So, at the moment of deciding whether intangible investments should be subsidized by public policies is critical to have some idea of the degree of imperfect competition in the labor market. A flat subsidy rate across firms from different sectors could imply a waste of limited fiscal resources because it would be too low for firms operating in labor markets close to perfect competition and it will be too high for firms with high monopsonic power.

9. Conclusions

The global economy is entering the age of intangibles, in which intangible capital investment, including R&D and other expenditures, has risen dramatically compared to the tangible capital one and has become a major source of productivity growth in developed economies. However, there is not much evidence in emerging economies mostly due to the lack of information. This paper closes this knowledge gap by using a large firm-level panel data set with information on intangibles from Peru for the period 2015-2019. With a per capita GDP of US$13.000, Peru is a middle-income country in the LAC region, so its findings can be somehow considered as representative of the whole region. We use a control function approach to estimate production functions and wage equations at the firm level to infer the capital productivity and wage premiums of intangible assets.

Our results indicate that the capital productivity premium associated with the intensity of intangible assets at the firm level is larger than the wage increase. More precisely, the results suggest that the capital productivity of intangibles is around twice the productivity of tangible assets, which is in line with the previous research by Benavente et.al. (2006) on both the returns to R&D and to fixed capital investment. Moreover, intangible assets accumulation is a major determinant of total factor productivity as an increase of one standard deviation in the intensity of intangible assets (0.10) leads to a 7% higher total factor productivity at the firm level. Moving to labor market related results, our research points out that there is a wage premium associated with intangible assets which suggests that firms are sharing the rents of their innovations with their workers, which creates appropriability concerns leading to a potential need for policy intervention. Our research also extends the basic model to examine how different factors such as the type of intangible assets, multi-product mix and imperfect competition in the labor market have an impact on the results. After separating the sample in different groups according to these factors (firms that pertain to R&D intensive sectors vs firms that do not or multi-product firms vs single-product firms) the findings remain consistent, suggesting that the conclusions drawn are robust. For instance, total factor productivity impacts of intangibles are higher for firms in R&D intensive sectors and multiproduct product firms. We also found that intangibles rent sharing depends on the degree of monopsonistic power of the firm in the labor market. Firms that enjoy labor market power are able to retain a significatively larger fraction of intangibles rents. This has important policy implications for innovation policy design. For example, when making intangible assets investment decisions firms might not be able to appropriate the full rents of their investments which opens the possibilities for the government to implement intangible subsidies, however the subsidy rate should decline with the degree of monopsonistic power of the firm. This is important as most of the support to innovation in Peru (and other countries in the region) does not internalize in the policy designs the importance of market power leading to flat subsidy rates across firms and sectors, potentially leading to subsidy rates that are lower than it is needed by firms that operate in an environment close to perfect competition in the labor market and otherwise higher than it is needed by firms that enjoy monopsonistic power.

Although our results shed lights on the impact of intangibles on productivity and wages for a Latin America country such as Peru, there are potential limitations in our study particularly with the composition of the ENE survey which may affect the results. First, the ENE survey sample is heavily biased towards large firms considering that in Peru these companies only account for no more than 3% of the total number of firms in the economy. Second, there are only around a thousand firms for all five years of the survey which limited our capacity of analyzing the effects of intangibles over time. Third, and final, there is not a consistent definition to measure R&D investment among all the different survey periods, which does not allow us properly analyzing the potentially different effects of R&D in comparison with other intangibles. Improving upon these shortcomings is part of the future research agenda.

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