Wages and productivity in Argentine manufacturing: a structuralist and distributional firm-level analysis[1]

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Abstract

Is there a link between labour productivity and wages in Argentine manufacturing? Does it vary between different technical and productive categories and wage levels? What factors affect this relationship, in the light of the country's premature deindustrialization? Employing a firm-level dataset for 2010–2021 from the National Survey on Employment and Innovation Dynamics (ENDEI) database, we estimate the link between productivity and wages across the conditional wage distribution among manufacturing firms. Our results confirm a positive but extremely low wage-productivity pass-through that differs between sectors according to their technical and productive capabilities and is robust to alternative estimation strategies. These asymmetrical firm-level distribution patterns carry substantial implications for the macroeconomic trajectory of the country, as they are perpetuating the underdevelopment trap.

Keywords

Industrial enterprises, manufacturing enterprises, employment, labour productivity, wages, economic analysis, econometric models, Argentina

JEL classification

J31, D24, O14

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I. Introduction

Wages and productivity are two of the most important variables in the development process. The extent to which they are coupled or decoupled has substantial implications for the macroeconomic trajectory of a country. In fact, productivity is the ultimate growth engine in the global economy and a challenge for countries that are catching up, as it is a precondition for breaking out of the middle-income trap (Organisation for Economic Co-operation and Development [OECD], 2015; Paus, 2018). In addition, the pass-through of productivity gains to wages represents a crucial dimension for workers' welfare and distributive justice.

However, wage and productivity heterogeneities both between and within production sectors are substantial and growing. Firm-level heterogeneity in productivity means that the aggregate macroeconomic growth path is substantially influenced by the shape of the micro-level productivity distribution, while sector-level heterogeneity means that alternative specialization paths will affect aggregate macroeconomic performance. From the distributive perspective, wage heterogeneity, both between firms and across sectors, produces unjustifiable economic and social disparities between similar workers and weakens internal macroeconomic demand and autonomous growth potential.

The literature has identified a positive relationship between these two dispersions, known as the "great divergence(s)" (Berlingieri et al., 2024), both in advanced economies (Barth et al., 2016) and in emerging countries (Barrera Insua and Fernández Massi, 2017). One issue in these divergences is the extent to which wage dispersion mirrors productivity dispersion, whenever there is a link between the two variables (Card et al., 2018; Dosi et al., 2020; Stansbury and Summers, 2017). So far, little effort has been made to study these relationships in relation to the development stage of a given country. This is one research gap that the present paper helps to fill.

A development obstacle that Argentina faces is the "middle-income trap", whereby middle-income nations are unable to trade internationally in standardized goods, labour-intensive products or both because of their relatively high wage levels, while their poor productivity and limited technological capabilities leave them unable to compete on a large enough scale in higher-value added sectors (Paus, 2017). In a globalized world, developing economies have few options for reducing productivity disparities and improving employment conditions (Dosi, Riccio and Virgillito, 2021; Graña, 2018). Comparative advantages in natural resources in Latin American countries do not appear to favour these processes (McMillan and Rodrik, 2011). Therefore, a country's structural international positioning and dependency relationships influence wage-productivity coupling or decoupling.

Besides the issues of a country's development stage and international positioning, the wage-productivity literature suffers from another limitation. Most studies focusing on wage-productivity pass-through analyse elasticity via the conditional mean (Card et al., 2018; Stansbury and Summers, 2017), but it is essential to explore this link throughout the wage distribution and across sectors with different technological regimes, especially when examining a country such as Argentina that displays persistent productive heterogeneity and large wage disparities, in a structural context of rapid deindustrialization.

Given the research gaps described, this paper addresses three interconnected questions: What is the link between wages and productivity in Argentine manufacturing? Does it vary along the wage distribution and across industries or technology classes? What factors influence this relationship, given that Argentina is a late-industrializing and prematurely deindustrializing middle-income country?

To try and solve this puzzle, we employ a firm-level dataset from the National Survey on Employment and Innovation Dynamics (ENDEI) covering the period 2010–2021. This firm-level dataset is a solid representation of Argentine manufacturing production. Using conditional quantile regression methodologies, we examine wage-productivity pass-through patterns across production sectors and technological classes (Pavitt, 1984). According to our estimates, which are robust to different specifications, the Argentine manufacturing sector is characterized overall by a very low degree of pass-through of productivity gains to wages, which highlights the unequal appropriation of total value generated between profits and wages. As further evidence, we show that low-technology industries that are heavily dependent on external demand are even less likely than others to redistribute productivity gains. Such industries, which are intensively resource-dependent, draw greatly upon informal labour. Lastly, from a sectoral composition perspective, our findings depict a self-defeating cumulative cycle in which the specialization pattern followed until recently has created a dual development trap, impeding both productivity upgrading and wage growth.

The paper is organized as follows. Section II after this Introduction summarizes the theoretical underpinnings of the structuralist and evolutionary literature. Section III focuses on the political and institutional context in Argentina since the late industrialization phase. Section IV gives a picture of the manufacturing sector's development. Section V discusses the database and empirical strategy, section VI sets out our findings, and section VII presents a discussion of their implications and concluding remarks.

II. Theoretical background

To study the wage-productivity relationship in Argentina, we adopt the evolutionary and structuralist perspectives, which link the composition of countries' production to development and growth opportunities (Lewis, 1984; Syrquin, 1988). The approach taken to the relationship between technological progress and economic growth differs from that of neoclassical theory, as it focuses on technology accumulation resulting from endogenously generated capabilities that are influenced by the nature and strength of opportunities for technological progress and the ability of firms to appropriate the returns to scientific research and development (R&D) (Dosi, 1988). These mechanisms highlight the dynamic nature of capitalism (Schumpeter, 1934). This is the context in which firms decide whether or not to bring innovations to market, and microeconomic behaviours are highlighted as fundamental to innovative outcomes (Nelson and Winter, 1982).

Given how idiosyncratically countries move along the trajectories of technological progress, then, there is not one but a variety of highly path-dependent routes to development (Adelman, 2001). In the structuralist view, sectors and products represent heterogeneous learning opportunities and different income elasticities of demand, and choosing which to promote is critical (Dosi, Riccio and Virgillito, 2021), for "today's specializations influence tomorrow's productivity growth, chances to innovate and demand potential" (Cimoli et al., 2009, p.3). In the global context, having proper "bridging institutions" to link science and technology creates the conditions for local, national and regional technological development (Dosi, 1982; Freeman, 1974). Technological progress is thus about interaction between firms, organizations and institutions endogenously determining the path of innovation as a collective process, as an innovation system (Lundvall, 2010; Malerba, 2002) or, if there is a structural break, as the emergence of a new technical and economic paradigm (Dosi et al., 2025).

The long-run process of structural transformation (Syrquin, 1988) involves five dimensions: science, technology, economics, politics and culture, which intermingle through positive or negative interactions (Dosi et al., 2025; Freeman, 2019). Countries' growth does not have a single cause, but is the outcome of the specific conditions under which these dimensions interact. Institutions and policies determine countries' development trajectories and boundaries, both geographically and temporally. Consequently, policies that worked well in igniting economic growth for early industrializers (Britain, Germany, the United States) were generally not appropriate for countries with abundant natural resources that expanded commodity exports at an early stage in their development (Adelman, 2001), in part because of colonial path dependence.

Historically, major technological developments and their impacts on productivity growth have occurred in manufacturing, with a significant link between productivity and wages (Hirschman, 1968; Pavitt, 1984; Prebisch, 1959). Nowadays, although new technologies have blurred the boundaries between manufacturing and services, with all the challenges entailed by automation and digitalization, "manufacturing is still an important contributor to labor productivity and GDP growth" (Palma and Pincus, 2024, p. 333). In short, manufacturing drives growth and knowledge absorption, strengthens the wage-productivity relationship and acts as an economy-wide employment multiplier (Berlingieri et al., 2024; Bogliacino and Pianta, 2011; Cresti and Virgillito, 2025).

The experience of developed countries shows that, in any virtuous industrialization process, the production structure needs to be regarded as critical for the development strategy. Unfavourable production structures, which are typical of underdeveloped countries, reduce development opportunities (Pagés, 2010) and can be understood as part of the middle-income trap framework (Kang and Paus, 2020; Paus, 2018). A seeming paradox arises: natural resource intensity does not improve productive performance because it contributes to a bad strategy of specialization in products that are not demand-elastic (Dosi et al., 2022; Reinert, 1995). Something that is supposedly positive for the country actually impedes any genuine structural change that might improve productivity.

Thus, more complex production processes are associated with greater learning potential and ability to cope with expansions in demand (Dosi et al., 2022). To classify industry composition and inherent complexity, Pavitt (1984) develops a taxonomy that groups sectors and firms into four distinct classes according to their technological content, the quality of their specialization and their position within value chains (Dosi, Riccio and Virgillito, 2021). Taking them from least to most complex, the supplier-dominated class includes firms where innovation is driven by exogenous changes in capital inputs and the process of learning by using (food and beverages, textiles, leather and wood products). The scale-intensive class includes firms which rely on capital-intensive production technologies and where learning is cumulative and reinforced by economies of scale (paper, rubber, plastics and their derivatives, basic metals, trailers and semi-trailers). In the specialized supplier class, firms act as suppliers of capital equipment, instruments and components, and innovation arises from endogenous learning and in-house R&D investment (machinery and equipment, other transport equipment). In the science-based class, lastly, the innovation process is strongly associated with applied and basic research and networking with scientific and technological systems (basic chemicals and pharmaceuticals, medical and optical instruments).

Using the Pavitt taxonomy, Dosi, Riccio and Virgillito (2021) highlight the opportunities deriving from specialization in knowledge-disseminating and specialized supplier sectors and point out the barriers facing developing countries, given the tight appropriability conditions, enforced by intellectual property rights, that have prevailed since the Washington Consensus phase. While developing countries specialize in non-core productive activities, developed countries concentrate on core ones, often relying massively on sectors protected by property rights (Aguiar de Medeiros and Trebat, 2017), such as digital and communication technologies and pharmaceuticals.

Lastly, to foster the generation of crucial technological capabilities, industrialization needs to be coordinated with macroeconomic policies (Syrquin, 1988; Cimoli et al., 2009). National policymakers inevitably apply or forego industrial policies when making decisions about distributive, production and trade patterns or even when accepting their position in the international division of labour and learning opportunities (Hausmann and Rodrik, 2006).

III. The regional background

The industrialization of the Latin American countries represents a major and still under-researched case study, as the process was interrupted in the 1970s, with reindustrialization efforts taking place in the early 2000s. In this context, some economists have developed variants on the concept of deindustrialization (Dasgupta and Singh, 2007; Rodrik, 2016; Tregenna, 2014), speaking of "premature deindustrialization" and emphasizing the economic drivers behind it. The literature focuses on institutional and political factors and the long-term variability of industrial policies vis-à-vis their macroeconomic and fiscal objectives (Cimoli et al., 2019; Peres and Primi, 2009). Contributions from international political economy focus on production structures, firm heterogeneity and exposure to globalization since the neoliberal turn (Graña and Terranova, 2020; Triador and Pinazo, 2021), while other strands concentrate on the factors underlying natural resource dependence and the role of comparative advantage (Castillo and Martins Neto, 2016; Hirschman, 1968; McMillan and Rodrik, 2011; Palma, 2019). In a nutshell, the factors influencing the manufacturing experience of Latin America and the Caribbean can be summarized as: (i) delays and inertia in technological upgrading investment; (ii) excessive specialization in low-value added activities with weak backward linkages; (iii) increasing reliance on the export of resource-intensive manufactured goods; (iv) rising dependence on natural resources; (v) lack of a systematic industrial policy framework; and (vi) growing macroeconomic and social instability.

Thus, the Latin American countries have failed to undertake significant structural transformations in the most recent decades and have missed out on the benefits of technological upgrading and long-term development. The major constraints have been an inability to climb the structural upgrading ladder and overcome their technological and financial dependence on the developed economies (Ormaechea and Fernández, 2020; Santarcángelo, 2019). By contrast with the successful catching-up processes in China and the Asian tigers (Yu et al., 2015), they have remained trapped in a specialization centred on natural resources and low-complexity manufacturing production and export (Chena and Pérez Caldentey, 2020), which has held back productivity growth (Paus, 2018).

This weak productivity performance has been manifested both in productivity gaps relative to international competitors and in domestic heterogeneity (Graña, 2018). Argentine manufacturing now exhibits a clear neo-dualism between firms in the production structure (Dosi et al., 2021). While a limited number of firms in a few manufacturing sectors engage in sustained innovation and attain international productivity frontiers as technological leaders (Raffo et al., 2008), a majority of small and medium-sized enterprises (SMEs) operate in low-productivity, low-technology sectors, remaining competitive by holding down wages and downgrading employment conditions (Graña, 2018).

Against this multifaceted backdrop to deindustrialization in Latin America and the Caribbean, we shall now briefly review some of the key historical and institutional developments that have shaped the current production structure of the Argentine economy. These macroeconomic and institutional factors will inform and guide the microeconomic and industry-level empirical analysis that follows.

1. Incomplete catch-up in Argentine manufacturing

Industrial policies can be defined as a set of instruments that States apply to promote the development of specific industries, technologies or groups of activities in line with national development priorities (Peres and Primi, 2009; Dosi et al., 2025). In Latin America, these policies have not always been formalized, designed or evaluated with long-term considerations in mind. Industrialization "was fact before it was policy, and policy before it was theory" (Love, 1995, p. 395). An explanation for this pattern might be the recurrent macroeconomic and policy swings that many of these countries have experienced for decades. Nevertheless, there is an industrial policy tradition in the larger countries of the region, with Argentina a leading example.

Until the Second World War, Argentina had a highly natural resource-intensive economy and depended on international trade in commodities. In this context, the industrialization process that began in the 1940s was designed to foster traditional manufacturing activities through import substitution (Santarcángelo, 2019). The first industrial promotion regime was implemented in 1944 by the Ministry of Industry and Commerce. An industrial credit bank was also created to strengthen the financial structure of industry and diversify the production structure of the economy. Labour-intensive industries were promoted throughout this decade and the next, with a focus on the domestic market. Employment conditions and wages improved, reducing inequality and urban poverty.

Between 1950 and 1970, with an industry-supporting legal framework in place, the State nurtured a set of development planning and research institutions, and a number of vertical industrial policy instruments were applied (tariffs and import quotas, production, export and financing subsidies, and the creation of public companies) (Bascur and Coviello, 2021). The State played an active role in developing the production fabric, which included the implementation of multi-year industrial plans, in line with the prevailing political consensus about the importance of manufacturing to the economy (Santarcángelo et al., 2018).

As a result, having specialized in textiles, food and beverages and tobacco (the supplier-dominated Pavitt class), Argentina became a manufacturer of consumer durables, machinery and equipment, while more dynamic and complex sectors with greater value added took off over the following decades.[2] Although the foreign trade effects of commodity price and foreign currency movements hampered the country's industrialization (Graña, 2018), the post-Second World War period represented a first successful phase in this national policy-led process.

Under Argentina's last military dictatorship (1976–1983), economic policy was radically reoriented towards a model centred on financialization, deregulation and privatization. This led to a structural breakdown in manufacturing, undermining labour conditions and compressing wages (see figures 1 and 3) (Rougier, 2021). Natural resource-intensive manufacturing had been on the increase for two decades (Santarcángelo, 2019), and the situation did not change significantly in the 1980s where industrial policy was concerned, as economic policy focused on resolving inflationary, fiscal and balance-of-payments crises. In Argentina and Latin America more generally, the urgency of these concerns left no space to engage either in debates about long-term strategies or in discussions about intervention and industrialization (Odisio and Rougier, 2021).

A decade later, the Convertibility Plan, a neoliberal stabilization model implemented in the wake of a hyperinflation crisis, reintroduced many of the policies of the 1970s financialization regime. With regard to industry, the State gave preference to neutral interventions that did not discriminate between production sectors, with these taking the form of so-called competitiveness policies (Peres and Primi, 2009)[3] or horizontal industrial policies (Dosi et al., 2025). Specialization in largely resource-based manufactures (see figure 2), coupled with increasing foreign capital flows, gave rise to structural asymmetries, and deindustrialization set in strongly. SMEs had to develop survival strategies (Schorr, 2021) that involved leveraging cost competitiveness, widening income gaps and increasing their use of informal labour (Ghibaudo and Raccanello, 2021).

Argentina experienced a major shift in its accumulation and growth regime in the early twenty-first century. In an effort to rebuild the domestic market and increase exports, economic

[2] Metalworking, chemicals, electronic equipment and automotive products, among others.

[3] The automotive sector was an exception because of the regional policies implemented by the Southern Common Market (MERCOSUR).

stimulus policies and social programmes were implemented, leading to improvements in material living conditions. A new phase of incipient "reindustrialization" and manufacturing job creation began. Despite structural weaknesses (low productivity, technological and productive heterogeneity and premature deindustrialization), manufacturing activity and GDP increased significantly in the 2000s (Graña, 2018). After 2008, however, Argentina was unable to close the productivity gap, in part owing to the rise of new global actors, most notably China, which acquired enormous capacity through productive and technological upgrading and came to dominate international markets for manufactures. Manufacturing and overall macroeconomic performance stagnated from 2011 onward, while new balance-of-payments constraints appeared, reflecting difficulties such as rising price levels, input supply bottlenecks and the rising cost of the national debt.

Industrial policy management varied in intensity, but included: (i) a number of overlapping and sometimes inconsistent regulations and incentives implemented at different levels of intervention and involving heterogenous actors, particularly at the outset; (ii) strong emphasis on the hierarchical structuring of the science and technology system; (iii) non-automatic trade licensing; (iv) specific instruments for high-technology industries (software, biotechnology and nanotechnology); (v) a growing State role as producer and purchaser; and (vi) the creation, at enormous fiscal cost, of a regionally based maquila cluster to serve the domestic market (Rougier 2021; Santarcángelo et al., 2018). This summary reinforces the point made earlier that any productive development policy must be coordinated with macroeconomic policies.

From 2016 to 2019, a new regime of deregulation, trade liberalization and financialization prevailed again, affecting Argentina's trade balance and exchange-rate stability. Financial vulnerability caused by capital outflows also became a major threat (Médici, 2020). Manufacturing activity declined greatly during the period, with sharp falls in output, employment and the number of firms, placing Argentina at the forefront of deindustrialization (Schteingart and Tavosnanska, 2022).

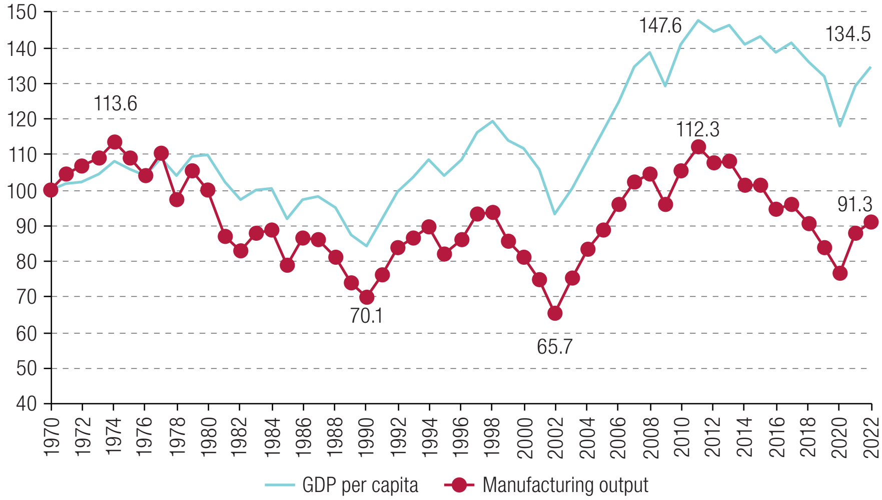
2. Long-term production and export profiles

Figure 1 plots real per capita GDP and manufacturing output, with deindustrialization reflected in their progressive decoupling. Manufacturing output peaked in 1974 before declining until 2002, after which it grew continuously until it reached another peak in 2010. By 2022, per capita manufacturing output was 9% lower than in 1970. Manufacturing and wholesale and retail commerce had accounted for the largest shares of output over the foregoing decade at the ISIC one-digit level, with over 17% of GDP apiece (see annex table A1.1).

Figure 2 plots the export shares of manufactures of industrial origin against those of agricultural origin. The industrial series includes textile, printed and published, chemical and pharmaceutical, rubber and plastic, and fabricated metal products, among others. The agricultural group comprises food and beverages, meat and dairy products, among others. Industrial exports increased between 1983 and 1989 and then declined, while agricultural exports, whose share was consistently higher, expanded between 1985 and 1987 before likewise declining.[4] The industrial share stagnated at about 30% during the 1990s and for the rest of the period, with fluctuations of 5 percentage points either way. As late as 2018, the value of agricultural and industrial exports was almost the same, but a "bad" specialization phase followed, with a gap opening up to the detriment of the latter in the last years of the period. This represents a limitation on the long-term prospects for the Argentine economy, increasingly trapped as it is in an export specialization centred on less complex and more natural resource-intensive products.

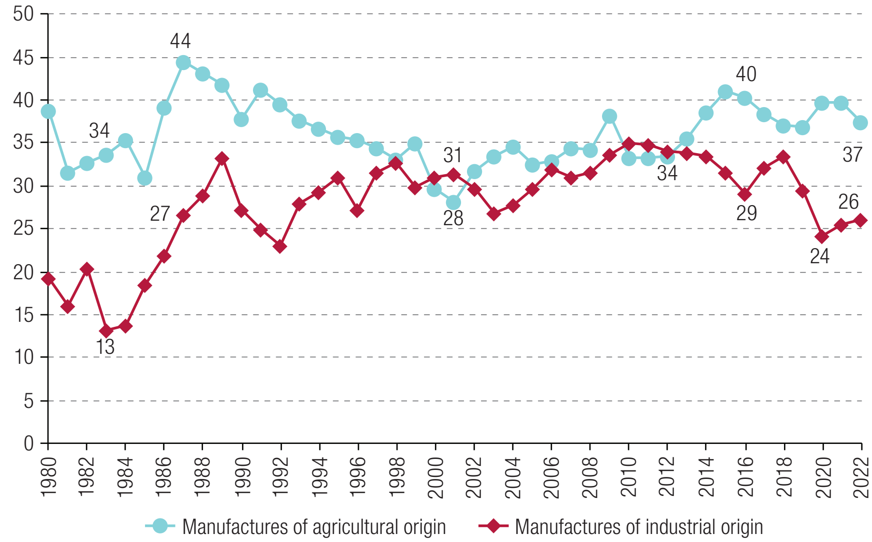
[4] This period was also characterized by a very low level of diversification within groups, with only a narrow range of manufacturing activities taking place (Azpiazu and Kosacoff, 1988).

Figure 1
GDP per capita and manufacturing output, 1970–2022
(Index: 1970 = 100)



Source: Prepared by the authors, on the basis of Ferreres, O. J. (Dir.). (2020). *Dos siglos de economía argentina: historia argentina en cifras*. Fundación Norte y Sur.

Figure 2
Manufacturing share of total exports, 1980–2022
(Percentages)



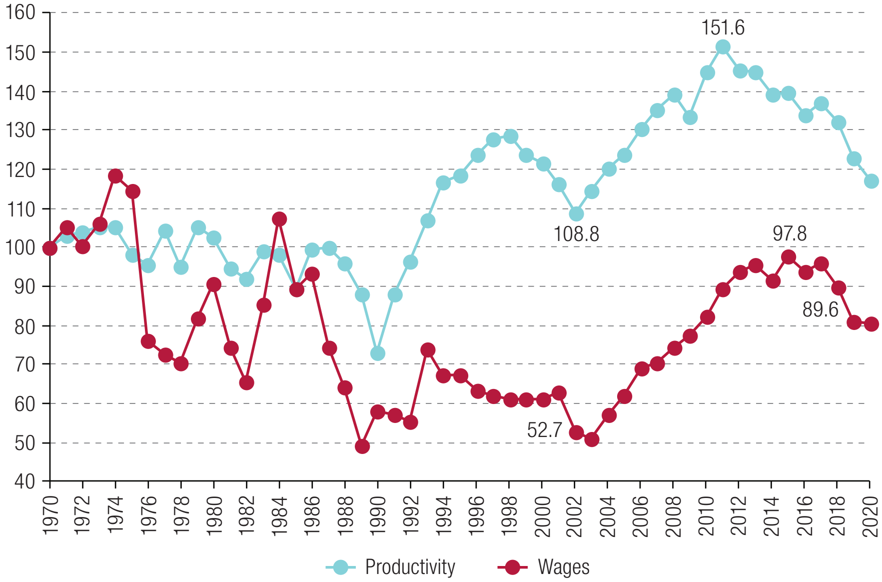
Source: Prepared by the authors, on the basis of Ferreres, O. J. (Dir.). (2020). *Dos siglos de economía argentina: historia argentina en cifras*. Fundación Norte y Sur.

Note: Exports are measured in current dollars. Manufactures of agricultural origin include food and beverages, meat products and the like. Manufactures of industrial origin include textile, printed and published, chemical and pharmaceutical, rubber and plastic and fabricated metal products and the like.

3. Aggregate productivity and wages

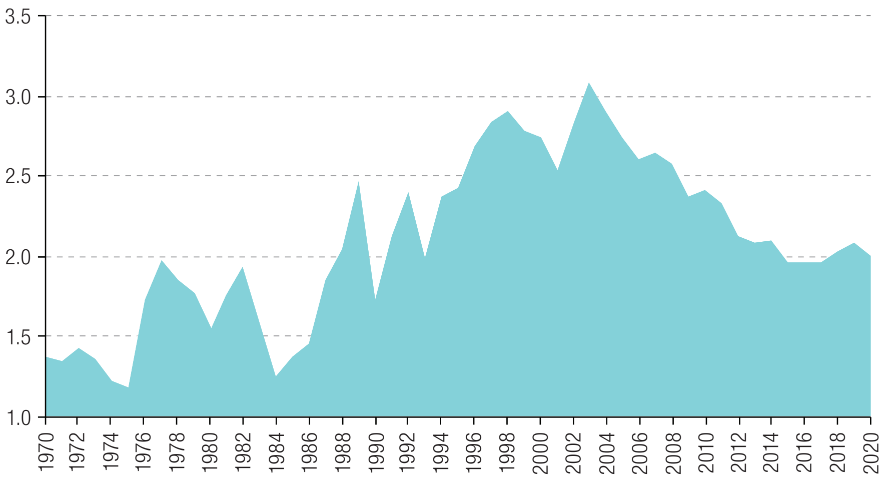
Figure 3 shows real wages and productivity, and figure 4 the productivity to wage ratio. Four phases emerge from the comparison between the two variables. In the first, lasting until 1973, wages and productivity are coupled, with a relatively low ratio. The second (1974–1990) exhibits a constant decoupling trend following a sharp fall in wages in 1976 under the new financialization regime. Productivity stagnated, oscillating by 5% above and below its starting value (figure 3), so that the ratio was left higher, albeit stable (figure 4). Both variables, but especially wages, collapsed with the hyperinflation crisis of the late 1980s. The third phase covers the convertibility stage, which ended with the widest wage-productivity gap of the whole period. Lastly, both variables rose in the 2000s before beginning to decline from 2011 and 2015, respectively.

Figure 3
Average labour productivity and wages in manufacturing, 1970–2020
(Index: 1970 = 100)



Source: Prepared by the authors, on the basis of Graña, J. M. and Terranova, L. (2020). Distribución funcional del ingreso en el sector industrial argentino, 1935-2019: valor agregado, remuneración al trabajo, ocupación y salarios. *Documentos de Trabajo*. (26). Research Centre on Population, Employment and Development.
Note: The analysis is restricted to formal (registered) employment.

Figure 4
Average labour productivity to wage ratio in manufacturing, 1970–2020

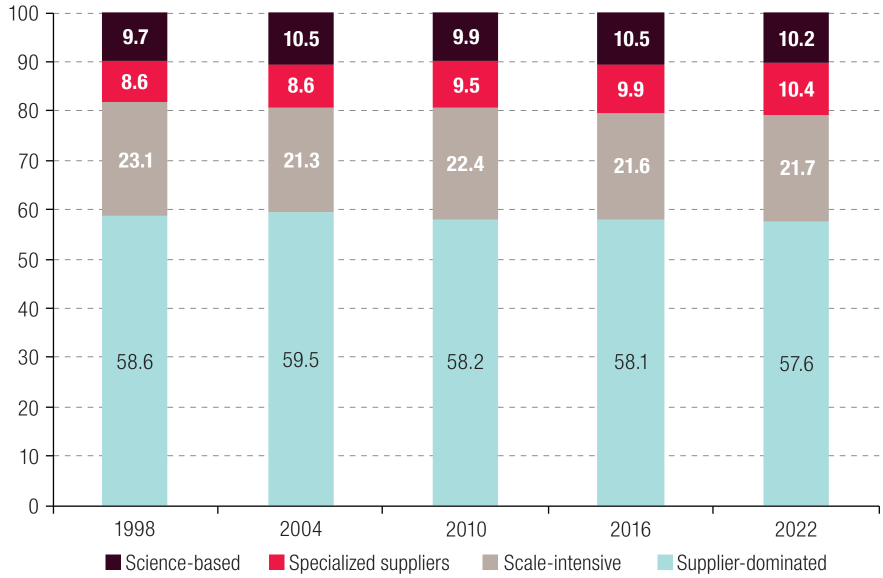


Source: Prepared by the authors, on the basis of Graña, J. M. and Terranova, L. (2020). Distribución funcional del ingreso en el sector industrial argentino, 1935-2019: valor agregado, remuneración al trabajo, ocupación y salarios. *Documentos de Trabajo*. (26). Research Centre on Population, Employment and Development.
Note: The analysis is restricted to formal (registered) employment.

4. Employment and wage structures: the role of labour institutions

Manufacturing employment and wage structures are illustrative of productive heterogeneity in Argentina. Figure 5 shows the distribution of registered jobs by Pavitt classes for selected years between 1998 and 2022. Throughout the period, the supplier-dominated class was responsible for the bulk (about 58%) of manufacturing jobs. Scale-intensive firms accounted for an average of 22% of formal employment and science-based industries for barely one in ten jobs.

Figure 5
Employment shares by Pavitt manufacturing sector, 1998–2022
(Percentages)

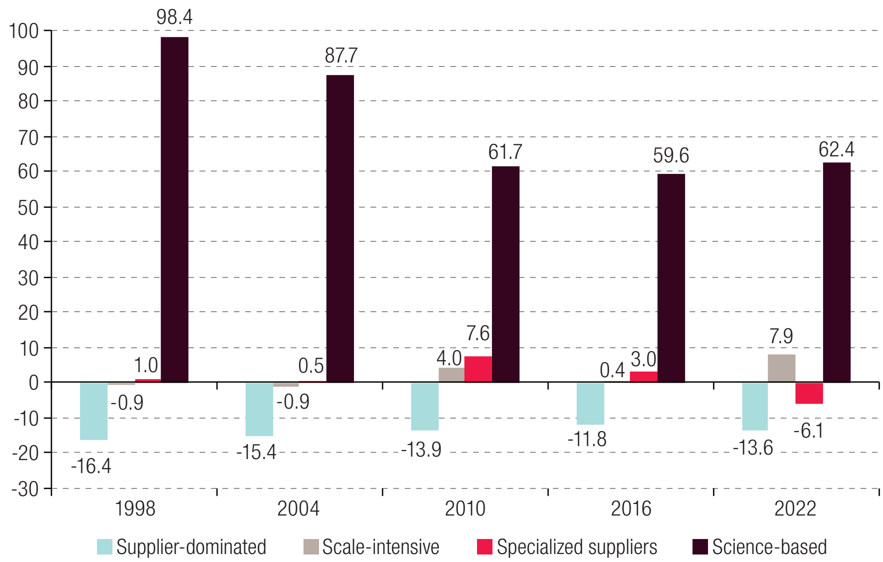


Source: Prepared by the authors, on the basis of Secretariat of Labour, Employment and Social Security.
Note: The analysis is restricted to formal (registered) employment.

Some points deserve consideration. Firstly, the data pertain to formal employment only. Where informal employment is concerned, manufacturing is better placed than other sectors (see annex table A1.1), with the highest rates of informality being mostly associated with the supplier-dominated class (Acosta and Montes-Rojas, 2014). Thus, an analysis that included both registered and unregistered employment would exhibit a greater concentration of informality in low-value added manufacturing sectors. Secondly, there has been lock-in to low-complexity industries (the supplier-dominated and scale-intensive classes) over the years. As expected, the evolution of manufacturing employment closely tracks the per capita GDP trend in figure 1. Taken together, these patterns highlight the absence of the kind of genuine structural shifts towards more complex forms of production that are an essential precondition for sustainable development.

Figure 6 shows the wage gaps between the Pavitt classes and the industrial average, represented by the zero line. Bars above (below) the benchmark represent higher (lower) wages. From 1998 to 2022, the science-based class displays by far the highest wages in manufacturing, while firms in the supplier-dominated class paid the lowest wages (between 12% and 17% below average). The scale-intensive and specialized supplier classes exhibit small negative and positive gaps, respectively, at the beginning of the period, but are close to the average in the following years. The differential between the highest (science-based) and lowest (supplier-dominated) wages shows a slight trend towards compression over time.

Figure 6
Wage gaps between Pavitt manufacturing sectors and the manufacturing average, 1998–2022
(Percentages)



Source: Prepared by the authors, on the basis of Secretariat of Labour, Employment and Social Security.
Note: The zero line represents the manufacturing benchmark. The analysis is restricted to formal (registered) employment.

To conclude this subsection, consideration will be given to trade unions and minimum wages as key institutional determinants of wage-setting regimes that counteract the forces making for wage suppression and the deterioration of employment conditions (Mishel and Bivens, 2021). Where unions are concerned, Argentina has gone in the opposite direction to most advanced Western countries (Acemoglu et al., 2001; Bishop and Chan, 2019). Since 2004, trade unions have been revitalized under a regime of moderately centralized collective bargaining, and a minimum wage policy has been implemented (Morris, 2017), playing an important role in reducing wage inequality (Gómez, 2020a). Collective bargaining is particularly strong in the manufacturing sector, which accounted for more than 34% of all collective agreements negotiated during 2010–2022 (see annex table A1.2). Unfortunately, the dataset used lacks information on union membership at the firm level, but a secondary information source[5] makes it possible to identify collective bargaining coverage in the different Pavitt classes (see table 1). The supplier-dominated class reports the lowest coverage (43.9%) and the specialized supplier class the highest (57.2%).

Table 1
Collective bargaining coverage by Pavitt class, 2010–2021
(Percentages)

Sector	Share of labour that is formal (registered)
Supplier-dominated firms	43.9
Scale-intensive firms	53.1
Specialized suppliers	57.2
Science-based firms	52.7

Source: Prepared by the authors, on the basis of Research Programme on Contemporary Argentine Society. (2015). *National Survey on Social Structure.*
Note: Sectors are classified at the two-digit level of the International Standard Industrial Classification of All Economic Activities (ISIC Revision 4).

[5] National Survey on Social Structure (Research Programme on Contemporary Argentine Society), period 2014–2015.

IV. Data and methodology

1. Data description

We employ a dataset from the National Survey on Employment and Innovation Dynamics (ENDEI). Conducted by the Secretariat of Innovation, Science and Technology of Argentina (MINCyT), this collects information on employment, innovation, production and commercial activities.

ENDEI provides data on manufacturing firms from three waves, 2010–2012, 2014–2016 and 2019–2021, disaggregated at the two- and four-digit ISIC Revision 4 sectoral levels. Although this is not a panel dataset (firms cannot be tracked across periods), it is a statistically representative sample of the universe of Argentine manufacturing firms. The dataset includes only firms with 10 or more registered workers, which means that it does not capture informal employment (see section V).

Firms are grouped at two different aggregation levels: (i) the original database disaggregation using ISIC Revision 4 and (ii) a revised Pavitt (1984) taxonomy including four classes of firms categorized by technological intensity[6] (Bogliacino and Pianta, 2011; Dosi, Riccio and Virgillito, 2021). Each technological class comprises the following manufacturing branches:[7]

- Supplier-dominated: food, beverages and tobacco and textile, leather, wood (including furniture), metal and paper products (ISIC Revision 4, codes 10, 11, 12, 13, 14, 15, 16, 25, 31, 1010, 1050 and 1102).
- Scale-intensive: paper, rubber and plastic, non-metallic mineral and basic metal products and motor vehicles, trailers and semi-trailers (codes 17, 22, 23, 24 and 29).
- Specialized suppliers: machinery and equipment, other transport equipment, domestic appliances, electronic components and boards, computers, and communication and electrical equipment (codes 27, 28, 30, 2610 to 2640, 2750 and 2821).
- Science-based: chemicals and refined petroleum products, pharmaceutical products, measuring, testing and control equipment, and electromedical and optical instruments (codes 19, 20, 21 and 2650 to 2680).

Table 2 presents the descriptive statistics for wages and productivity. The latter registers a modest yearly increase until 2016, with a slight reversal in 2020, while wages display a notably stable pattern throughout the period.

Table 2
Average labour productivity and wage in manufacturing, 2010–2021
(Thousands of 2010 pesos)

Year	Number of firms	Labour productivity	Wage	Log labour productivity	Log wage
2010	3 151	147.07	3.72	11.43	8.09
2011	3 204	169.68	3.85	11.60	8.14
2012	3 215	183.91	3.98	11.72	8.17
2014	3 401	249.48	3.95	11.97	8.21
2015	3 457	272.69	3.96	12.07	8.21
2016	3 431	270.85	3.75	12.06	8.16
2019	2 873	257.47	3.76	11.93	8.13
2020	2 874	230.33	3.56	11.73	8.08
2021	2 875	269.57	3.57	11.92	8.08

Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.
Note: The analysis is restricted to formal (registered) employment.

[6] As measured by R&D intensity, given by the ratio between a firm's R&D expenditure and its sales.

[7] For reasons of statistical confidentiality, ISIC codes 10, 11 and 12 were aggregated in the original database. Sectors 10 and 11 do not include codes 1010, 1050 or 1102, and sectors 27 and 28 do not include codes 2750 or 2821.

2. Wage and productivity distribution trends

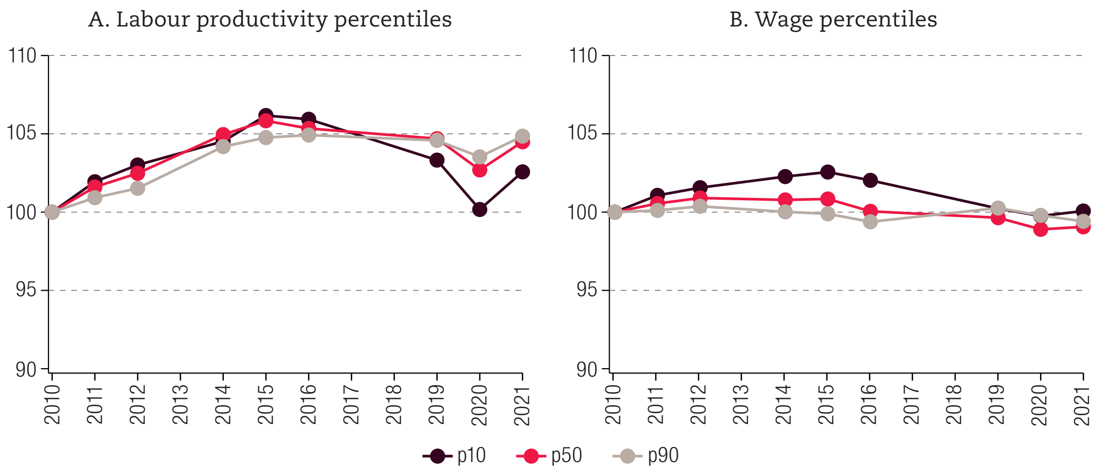
To characterize the evolution of wages and productivity beyond average values, figures 7 and 8 present time trends for selected percentiles and percentile ratios, focusing on the tenth, fiftieth and ninetieth wage and productivity percentiles. In respect of dispersion, the 90/10 ratio (the interdecile gap) captures the widest spread of each distribution. We also calculate the 50/10 and 90-50 wage and productivity ratios to observe inequality in the lower and upper tail of the distributions, respectively. All percentiles and ratios are indexed to 2010 as the base year.

The productivity percentiles in the upper left panel of figure 7 show an upward trend until 2015, followed by a period of stagnation, a decline, and a partial recovery during the coronavirus disease (COVID-19) pandemic. As regards wages (upper right panel), these show a slight rising tendency only among firms in the lowest pay segment (tenth percentile), which anyway is reversed from 2015 (albeit less sharply than in the case of productivity), while the real wages paid by firms in the fiftieth and ninetieth percentiles remain quite steady until 2019. All wage series stabilize during the COVID-19 years.[8]

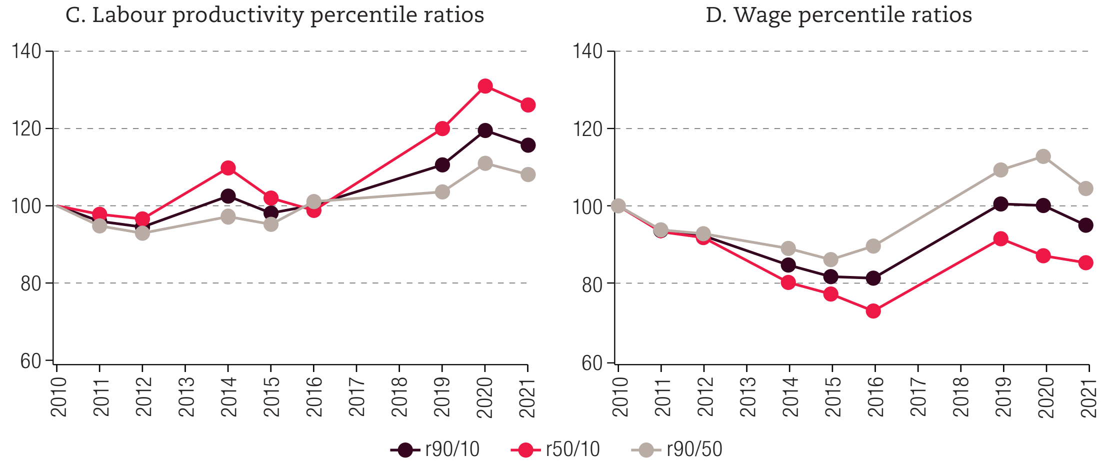
In relative terms, the bottom left panel shows an oscillating pattern for labour productivity ratios between 2010 and 2016 and a divergent trend thereafter. Both the 90/10 and the 50/10 ratios exhibit an initial decline and a subsequent increase (albeit a small one in the case of the 90/50 ratio), reflecting high levels of dispersion. A different pattern emerges for the wage ratios in the bottom right panel, one that is consistent with the percentile trends. Wage inequality displays a clear downward trajectory, with the exception of the 90-50 ratio, which by 2021 had returned to approximately its 2010 level. Conversely, the interdecile (90/10) ratio shows a sharp decline, driven largely by movements in the 50/10 ratio.

As an alternative, figure 8 compares these wage and productivity percentiles and ratios across different segments of the distribution. The upper panels display indexed wage-productivity trends for the tenth, fiftieth and ninetieth percentiles. In every percentile, the labour productivity series displays an increasing trend until 2015, with a period of decline or stagnation thereafter. Conversely, wages do not show any significant movement, with the result that a substantial gap opens up between the two variables throughout the distribution, narrowing significantly only during the pandemic period.

Figure 7
Trends in wage and productivity distributions: absolute percentiles and percentile ratios, 2010–2021
(Index: 2010 = 100)



[8] One explanation for this is a national programme that supported formal employment during the pandemic, the Emergency Assistance Programme for Work and Production (ATP).



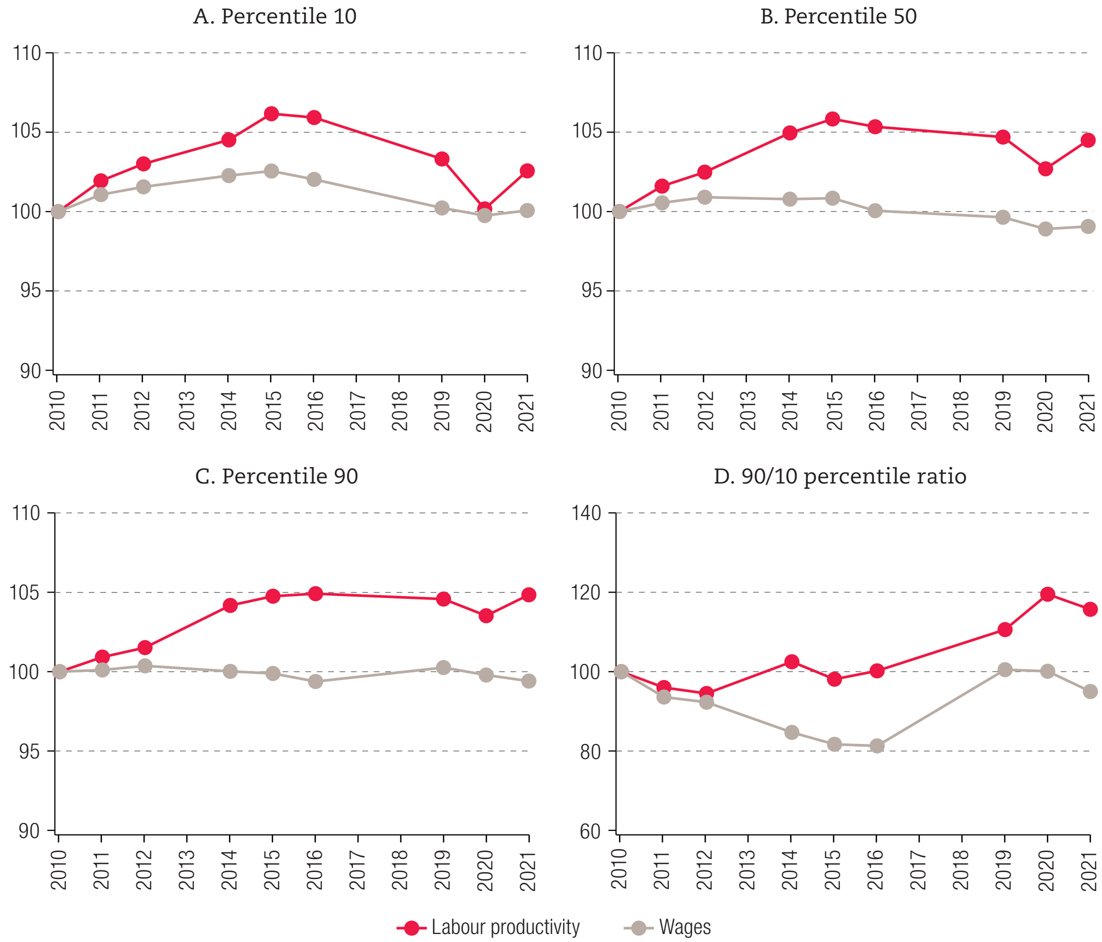
Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.

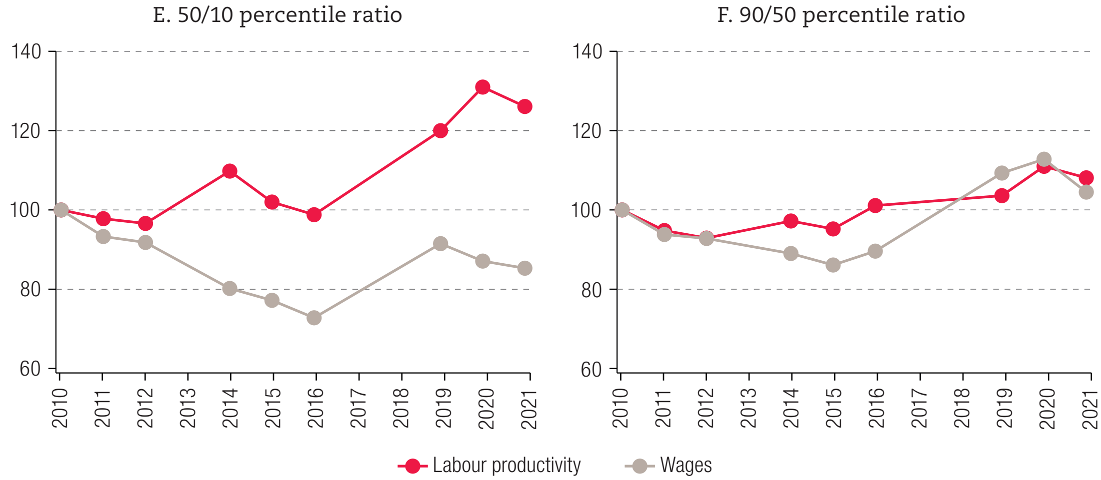
Note: Panels A and B report the tenth, fiftieth and ninetieth percentiles (p10, p50, and p90) of labour productivity and wages, respectively. Panels C and D report percentile ratios (r90/10, r50/10 and r90/50). The analysis is restricted to formal (registered) employment. No observations are available for the years 2013, 2017 and 2018.

Figure 8

Trends in wage and productivity distributions: selected percentiles and percentile ratios, 2010–2021

(Index: 2010 = 100)





Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.

Note: The analysis is restricted to formal (registered) employment. No observations are available for the years 2013, 2017, and 2018.

The percentile ratio shows the evolution of the indexed percentile ratios for wages and productivity, considered separately. They reveal contrasting patterns across the distributions. Whereas productivity dispersion increased during the period (with a small decline in 2021), the wage gap steadily narrowed until 2016, widening very slightly again thereafter. Similar differences appear in the panel displaying the 50/10 ratios. In the right-hand panel, although the 90/50 wage ratio does not follow the same trend as the productivity ratio, both measures dip slightly at the end of the period.

From figures 7 and 8, we can infer that the evolution of wages and productivity has been very uneven. While productivity gaps exhibit small downturns but large upturns, especially in the lower tail of the distribution, most wage gaps shrank between 2010 and 2021. Moreover, productive heterogeneity proves to be substantially greater than wage inequality. This is manifested not only by their relative values, as labour productivity percentile ratios are higher in 2021 than in 2010 whereas wage ratios are lower (see figure 7), but by their distinct evolution, with a substantial gap opening up between productivity and wages for the 50/10 and 90/10 percentile ratios (see figure 8). These results are consistent with findings from Barrera Insua and Fernandez Massi (2017).

3. Export composition by Pavitt class

The final descriptive analysis deals with firms' export profile. The first column in table 3 shows the proportion of firms in each Pavitt class that are exporters. Firms in the science-based and specialized supplier classes exhibit the strongest propensity to export, with about 53% and 43%, respectively, of them doing so. The second column shows the distribution of exporting firms by Pavitt class, with supplier-dominated industries (46.4%) accounting for the largest share, followed by scale-intensive ones (20.6%). Conversely, the science-based and specialized supplier classes, despite their greater technological intensity, complexity and export propensity, each account for less than 18% of exporting firms. In light of the concepts of "quality of specialization" and "quality of exports" (Hidalgo et al., 2007; Dosi et al., 2022), this distribution is indicative of a weak specialization strategy.

Table 3
Exporting firms, by Pavitt class, 2010–2021
(Percentages)

Pavitt class	Share of firms exporting	Distribution of exporters by Pavitt class
Supplier-dominated firms	22.4	46.4
Scale-intensive firms	30.2	20.6
Specialized suppliers	43.4	17.5
Science-based firms	52.7	15.5
Total		100.0

Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.

V. Empirical strategy

Our empirical strategy evaluates the wage-productivity relationship along the wage distribution, in line with Dosi et al. (2020). The structural heterogeneity and associated wage inequality described above reveal that productivity and wage levels are highly dispersed within each Argentine manufacturing sector (Gómez and Borrastero, 2018). This prompted us to adopt the quantile regression method (Koenker and Bassett, 1978). An advantage of quantile regression is that it allows the relationship between variables to be examined across different points of the conditional distribution, rather than focusing on a single summary measure of inequality such as the mean.

Equations (1) and (2) show the conditional quantile regression structure proposed for the estimates:

$$y_{it} = Q_\tau (y_{it} / x_{it}) + u_{\tau it} = x'_{it} b_\tau + u_{\tau it} \quad (1)$$

with

$$b_\tau \equiv argmin_b E[\rho_t(y_{it} - x'_{it} b)] \text{ and } \rho(u) = \begin{Bmatrix} \tau|u| & for\ u \geq 0 \\ (1-\tau)|u| & for\ u < 0 \end{Bmatrix} \quad (2)$$

where y_{it} represents the response variable, Q_τ is the τ-th conditional quantile of y_{it} given x_{it} (covariates), b is the vector of parameters at each quantile τ, and u is a vector of residuals. The τ-th quantile, as defined in equation (2), solves a minimization problem by linear programming.

Using a quantile regression approach, our analysis examines firm-level wage elasticities of labour productivity and other relevant covariates across the conditional wage distribution. This empirical strategy does not seek to establish any causality. Indeed, given the analytical framework presented here, any attempt to do so might obscure the full picture of dependencies between the variables analysed.

Two alternative specifications are estimated, reflecting different wage equation structures. First, the baseline quantile regression model, estimated by equation (3), is intended to identify the basic link between productivity and wage levels:

$$w_{it} = \alpha + \beta_\tau \pi_{it} + y_t + \epsilon_{\tau it} \quad (3)$$

where w_{it} is the log of the real average wage for firm i at time t, deflated by the consumer price index (2010 = 100); π_{it} is the log of labour productivity, proxied by the log of real value added per worker[9] and

[9] Both wages and labour productivity are annual average measures per firm.

deflated by the producer price index (2010 = 100); y_t introduces year dummies to capture seemingly unrelated macroeconomic shocks; and β_τ and $\epsilon_{\tau it}$ are the coefficients for productivity and standard errors, respectively.[10]

The second quantile regression model, estimated by equation (4), includes a set of covariates that are specific to individual firms, reflecting their internal structure and international position, and that potentially affect the level of wages.

$$w_{it} = \alpha + \beta_{\tau 1}\pi_{it} + \beta_{\tau 2}exporter_{it} + \beta_{\tau 3}foreign_{it} + \beta_{\tau 4}size_{it} + y_t + \epsilon_{\tau it} \quad (4)$$

The *exporter* variable is a binary indicator equal to 1 if the firm reports export activity, reflecting evidence for wage premiums at exporting firms (Brambilla et al., 2017; Dosi et al., 2023). Firm ownership structure, expressed by *foreign*, equals 1 if the firm has at least 1% foreign-owned capital; according to Schorr (2021), multinational firms pay the highest wages in Argentine industry. Lastly, firm size is proxied by log employment (*size*), capturing the elasticity of wages with respect to this variable (Cobb and Lin, 2017).[11]

Because there are no data available on informality, it is important to consider the possibility of biases in both sets of estimations. They may be of two types: (i) biases arising from the sorting of firms into the proposed classes and (ii) biases associated with the pass-through between labour productivity (or the other firm covariates) and wages. To our knowledge, there are no current firm-level databases covering informality in Argentina. Further studies and broader datasets, which are beyond the scope of this paper, would make it possible to carry out an in-depth evaluation of the nature and sign of these biases and would shed new light on the formal and informal sectors of Argentine manufacturing industry.

To examine the nature of the pass-through between productivity and wages, we estimate each quantile regression model at the sectoral level using the pooled data. We also estimate regressions for the 0.05, 0.10, 0.25, 0.5, 0.75, 0.9 and 0.95 quantiles to evaluate whether the wage-productivity relationship displays any increasing or decreasing trend over the conditional wage distribution. These estimates are combined with sectoral disaggregation based on both the ISIC Revision 4 codes and the Pavitt classes.

In the first case, we present violin plots for each wage quantile. These plots include the median, the interquartile range and the kernel density distribution of the estimated coefficients, capturing both the sectoral and quantile distributions of the dependent variable (Dosi et al., 2020), as an extension of standard ordinary least squares violin plots (Dosi et al., 2015). In the second case, we explore the relationship across different industry types by estimating quantile regression coefficients for each Pavitt class. As an additional exercise, we briefly introduce the results of an alternative model in which the model with control variables is supplemented by the log of the skill ratio (defined as the ratio between workers with professional skills and other workers).[12]

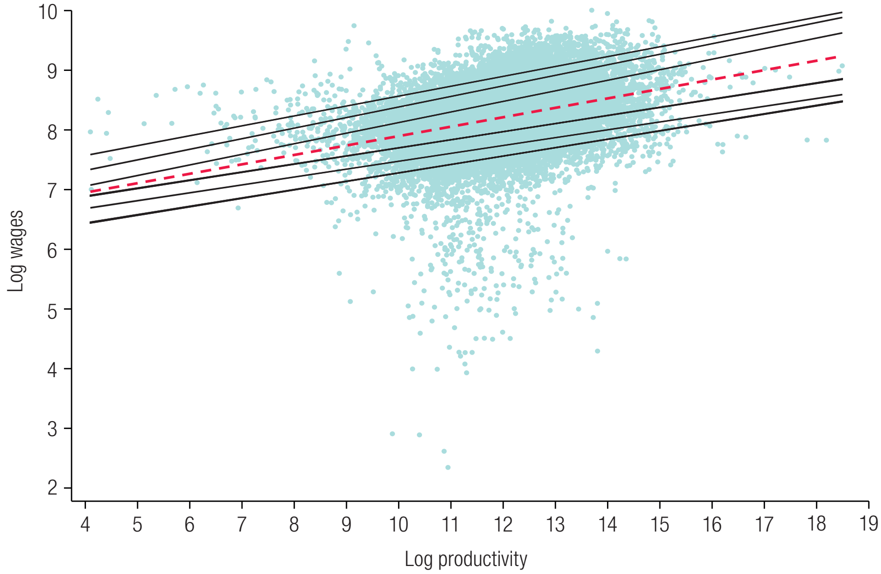
Figures 9 and 10 are scatter plots that show how the conditional quantile regression estimates fit our data at the industry level and by Pavitt class, respectively. The black lines represent the quantile regression estimates, and the dashed red line plots the standard pooled ordinary least squares estimate. These plots show pronounced heterogeneity and the presence of outliers in both wage and productivity levels. In the disaggregation by Pavitt classes (figure 10), we find higher dispersion in the supplier-dominated class but a better fit to the data in the science-based industries.

[10] Alternative specifications using one-year lagged productivity levels revealed strong persistence and autocorrelation, validating the choice of a contemporaneous specification. These results are available upon request.

[11] In the last wave (2019–2021), the firm age variable is absent, preventing it from being used as a control variable.

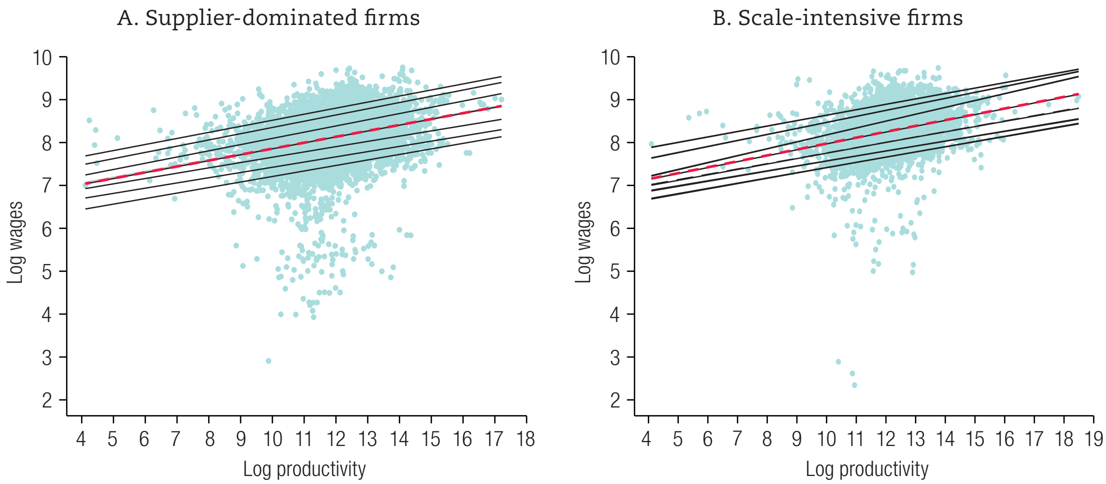
[12] This variable has a great number of observations missing, preventing estimation at the two-digit level. We have therefore included a graphic analysis in annex figure A1.4; the estimates are available upon request.

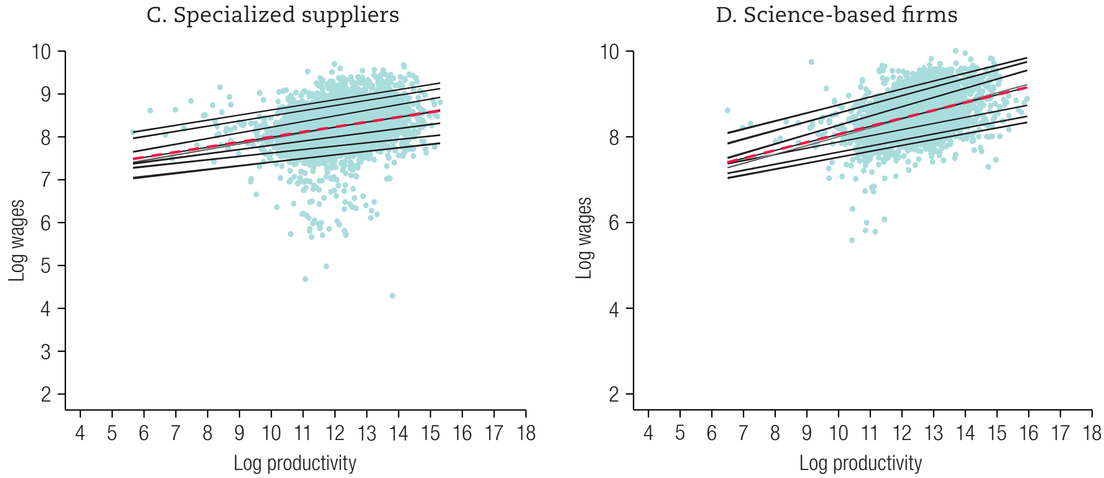
Figure 9
Scatter plot with quantile regression fit for log wages and log productivity, all sectors (baseline model), 2010–2021



Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.
Note: Black lines show the quantile regression fits at the 0.05, 0.10, 0.25, 0.50, 0.75, 0.90 and 0.95 quantiles. The red dashed line shows the ordinary least squares regression fit. The analysis is restricted to formal (registered) employment.

Figure 10
Scatter plot with quantile regression fit for log wages and log productivity, by Pavitt class (baseline model), 2010–2021





Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.

Note: Black lines show the quantile regression fits at the 0.05, 0.10, 0.25, 0.50, 0.75, 0.90 and 0.95 quantiles. The red dashed line shows the ordinary least squares regression fit. The analysis is restricted to formal (registered) employment.

VI. Results

1. The relationship between wages and productivity in the baseline model

Table 4 shows the regression results for the baseline model (equation (3)). The quantile regression estimates confirm significant and positive pass-through between labour productivity and wages in Argentine manufacturing firms, regardless of technological class or production sector. Most of the interquantile results show this relationship strengthening along the intra-industry wage distribution. In the supplier-dominated and science-based classes, the interquantile regressions confirm a strengthening trend in different segments of the distribution, while in the scale-intensive and specialized supplier classes, the median interquartile range (0.25–0.75) and the interdecile range (0.10–0.90) likewise exhibit upward trends.

An analysis at the branch level (ISIC Revision 4 codes) finds significant coefficients for these elasticities in most cases (94% of the estimates) (see table A1.3 and figures A1.1 to A1.3 in the annex).

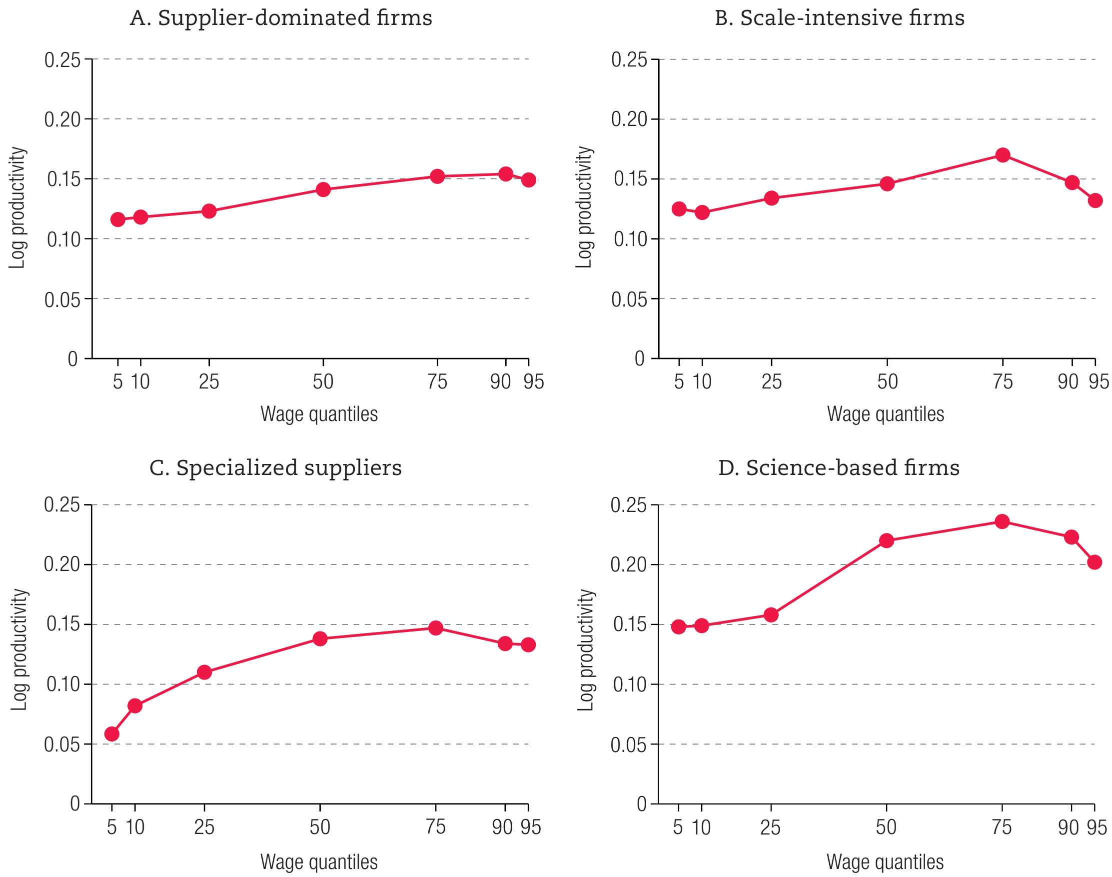
Figure 11 plots the distribution of quantile regression coefficients by Pavitt class, showing a slight rising trend in pass-through up the wage quantiles, indicative of a stronger link between wages and productivity among firms with higher wage levels. Technological classes also differ in the magnitude of the coefficients, with specialized suppliers and science-based firms recording the highest coefficients for the upper quantiles of the conditional wage distribution, while supplier-dominated and scale-intensive firms record the lowest.

Table 4
Quantile coefficients for log productivity in formal manufacturing, by Pavitt class (baseline model), 2010–2021

Pavitt class	Ordinary least squares	Quantile regressions							Interquantile regressions		
		5	10	25	50	75	90	95	$\beta i{,}95 - \beta i{,}05$	$\beta i{,}90 - \beta i{,}10$	$\beta i{,}75 - \beta i{,}25$
All firms	0.162***	0.128***	0.133***	0.139***	0.163***	0.188***	0.195***	0.182***	0.054***	0.062***	0.049***
Supplier-dominated firms	0.140***	0.114***	0.113***	0.122***	0.139***	0.156***	0.163***	0.163***	0.050***	0.050***	0.033***
Scale-intensive firms	0.164***	0.138***	0.130***	0.140***	0.161***	0.193***	0.188***	0.170***	0.032	0.057***	0.053***
Specialized suppliers	0.126***	0.076**	0.081***	0.120***	0.149***	0.155***	0.143***	0.141***	0.066	0.062**	0.035**
Science-based firms	0.201***	0.149***	0.132***	0.142***	0.192***	0.263***	0.260***	0.239***	0.090***	0.127***	0.121***

Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

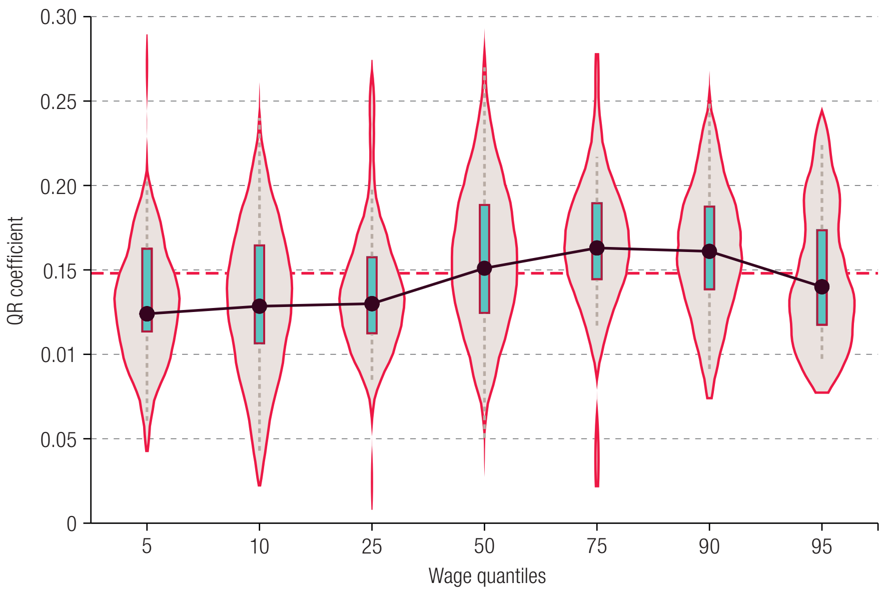
Figure 11
Relationship between wages and log productivity, by Pavitt class (baseline model), 2010–2021



Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.
Note: The analysis is restricted to formal (registered) employment.

Drawing on the quantile regression estimates in the baseline model, figure 12 illustrates the wage-productivity relationship by means of a violin plot, combining the kernel density distribution of the estimates by ISIC code (vertical dimension) and the wage quantile distribution (horizontal dimension). The figure shows a pattern of moderate strengthening in the wage-productivity relationship. The lowest productivity coefficients are observed in the lower quantiles, with a 10% increase in labour productivity being associated with a 1.3% increase in wages in the fifth quantile and a 1.4% increase in the first quartile (all sectors). The relationship is somewhat stronger in the upper tail of the distribution, where a 10% increase in productivity is associated with a 1.8% increase in wages.

Figure 12
Distribution of quantile regression (QR) coefficients for log productivity across wage quantiles (baseline model), 2010–2021



Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.

Note: The figure shows the distribution of QR coefficients for log productivity, estimated using the baseline QR specification. The QR is estimated separately for each sector of the International Standard Industrial Classification of All Economic Activities (ISIC Revision 4). The analysis is restricted to formal (registered) employment. The horizontal dashed line indicates the median of the corresponding ordinary least squares coefficient estimates. The pseudo-R^2 of the median regression across all sectors is 0.082.

To test for interquantile differences, we run two non-parametric tests. First, we use the Kruskal-Wallis test to evaluate overall median differences across the distributions of the 0.05–0.95 quantile estimates (Kruskal and Wallis, 1952). Second, we perform Dunn's test, conducting multiple pairwise comparisons to identify stochastic dominance or median differences between pairs of estimates (Dinno, 2015). Consistently with the foregoing analysis, we identify only minor differences between quantile estimates. Although the Kruskal-Wallis tests reject the null hypothesis that all estimates originate from the same population, Dunn's test shows no statistically significant dominance in the multiple pairwise comparisons, except that there is a significant difference between the seventy-fifth and fifth quantile estimates in the baseline model using the ISIC Revision 4 taxonomy.

2. The relationship between wages and productivity in the model with control variables

The estimates from the model with control variables reveal that the inclusion of covariates related to firms' characteristics (exporting activity, foreign ownership and firm size) reduces the pass-through between wage and productivity levels, as expected. The quantile regression coefficients in the baseline model at the industry level range from 0.13 to 0.20 in the fifth and ninetieth quantiles, respectively, while in the model with control variables they range from 0.11 to 0.12, respectively (see table 5). The reduction in pass-through occurs across all Pavitt classes.

Table 5
Quantile coefficients for log productivity in formal manufacturing, by Pavitt class (model with controls), 2010–2021

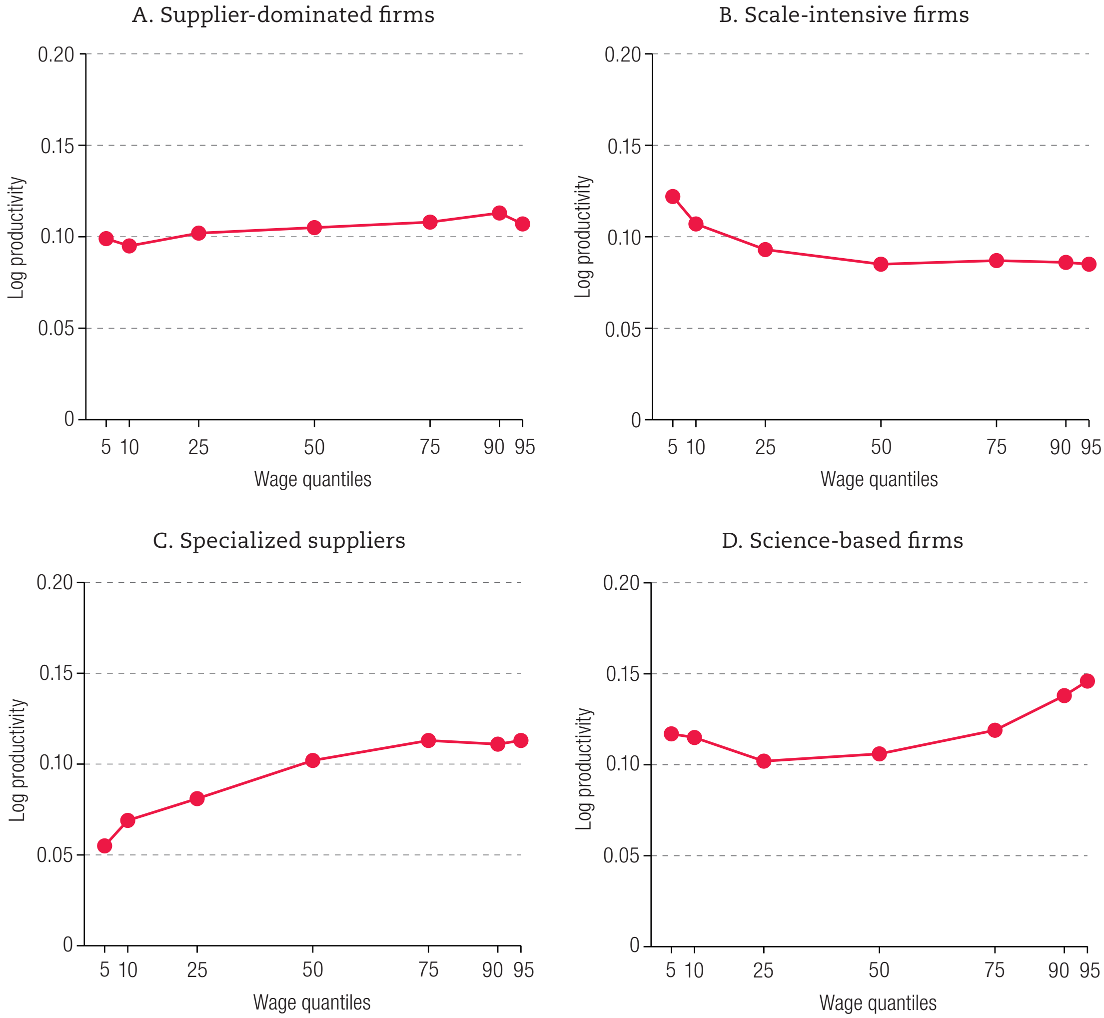
Pavitt class	Quantile regressions								Interquantile regressions		
	Ordinary least squares	5	10	25	50	75	90	95	βi,95 -βi,05	βi,90 -βi,10	βi,75 -βi,25
All firms	0.111***	0.111***	0.115***	0.111***	0.117***	0.122***	0.123***	0.123***	0.013	0.008	0.010***
Supplier-dominated firms	0.103***	0.099***	0.095***	0.102***	0.105***	0.108***	0.113***	0.107***	0.008	0.018**	0.006
Scale-intensive firms	0.090***	0.122***	0.107***	0.093***	0.085***	0.087***	0.086***	0.085***	-0.037**	-0.022**	-0.006
Specialized suppliers	0.090***	0.055***	0.069***	0.081***	0.102***	0.113***	0.111***	0.113***	0.058***	0.042***	0.033***
Science-based firms	0.117***	0.117***	0.115***	0.102***	0.106***	0.119***	0.138***	0.146***	0.03	0.023	0.016

Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Thus, this model delivers a flatter interquantile pattern than the baseline model. We used interquantile regressions to test the upward trend in different segments of the conditional wage distribution and found that only in the seventy-fifth quantile did the coefficient show higher pass-through than in the twenty-fifth quantile. The same was true in the specialized supplier class, while in the scale-intensive group a modest decreasing trend was found for the fifth to ninety-fifth and tenth to ninetieth quantile ranges. For science-based industries, lastly, the relationship between wages and productivity was found to be constant across the different quantiles.

Figure 13 shows wage-productivity pass-through for each Pavitt class in the model with control variables. Most of the classes do not display significant differences in this relationship at different distribution points. The specialized supplier class is the exception, with a slight upward trend. Thus, wage dispersion is found to be significantly lower than productive heterogeneity, and both are found to be lower than technological heterogeneity (Gómez, 2020b). In addition, the estimates of the alternative model including the log of the skill ratio do not change significantly (see annex figure A1.4).

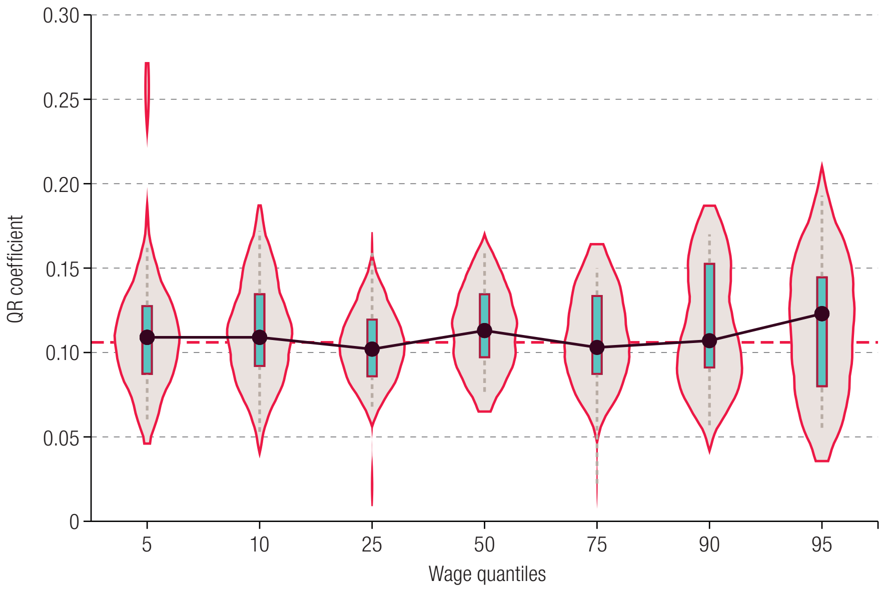
Figure 13
Relationship between wages and log productivity, by Pavitt class
(model with controls), 2010–2021



Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.
Note: The analysis is restricted to formal (registered) employment.

The constant pattern in the wage-productivity relationship for the model with control variables is confirmed at the ISIC Revision 4 level of disaggregation. The violin plot in figure 14 reveals no significant differences in pass-through at different wage levels. Accordingly, while the Kruskal-Wallis test rejects the null hypothesis of equal distributions for the estimates in general, Dunn's test does not identify significant differences in most of the pairwise comparisons. A deeper level of disaggregation between firms likewise shows a constant wage-productivity relationship.

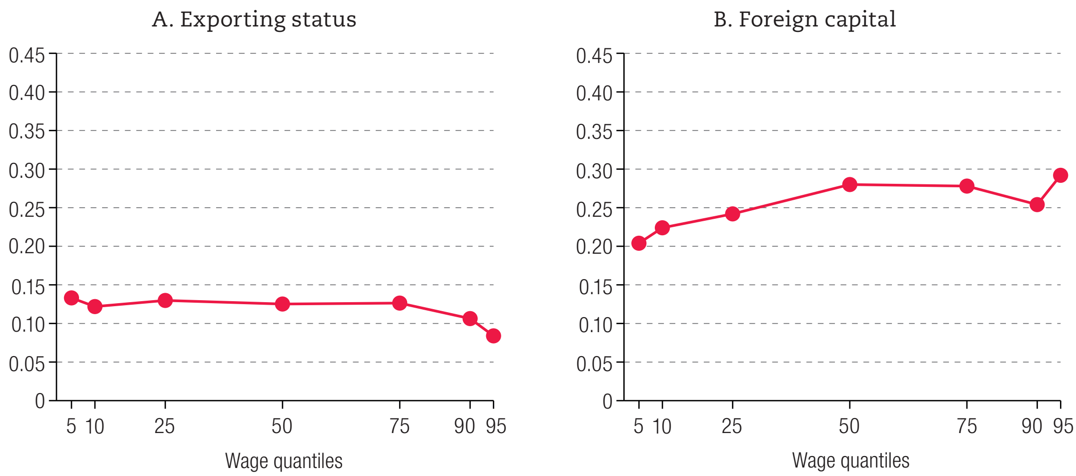
Figure 14
Distribution of quantile regression (QR) coefficients for log productivity across wage quantiles (model with controls), 2010–2021

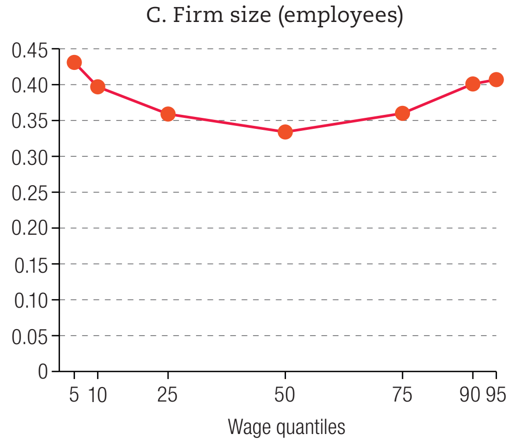


Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*; Secretariat of Labour, Employment and Social Security.
Note: The QR is estimated separately for each sector of the International Standard Industrial Classification of All Economic Activities (ISIC Revision 4). The analysis is restricted to formal (registered) employment. The pseudo-R^2 of the median regression across all sectors is 0.084.

To identify how the control variables relate to wage levels, figure 15 plots the corresponding quantile regression coefficients. We also tested interquantile differences with interquantile regressions. The estimates reveal a slight downward trend in wage premiums for exporting firm status (with non-significant interquantile differences). Foreign ownership displays a gently increasing pass-through trend that is statistically significant over the fifth to ninety-fifth quantile range. Lastly, the firm size proxy displays a U-shaped pattern across the distribution.

Figure 15
Quantile regression (QR) coefficients for additional covariates (model with controls), 2010–2021





Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.
Note: Only statistically significant QR coefficients are reported. The analysis is restricted to formal (registered) employment.

VII. Implications and concluding remarks

Following a structuralist and distributional firm-level approach and employing a dataset for the 2010–2021 period, this study examined the relationship between wages and productivity in Argentine manufacturing industry. The distributional perspective allowed us to examine pass-through effects at different points of the conditional wage distribution. Applying the Pavitt taxonomy, we evaluated whether pass-through differed according to the technical and production characteristics of firms. Overall, the empirical analysis was designed to capture firm-level wage bargaining processes and ascertain the extent to which technical and organizational capabilities influenced the distribution of productivity gains. The structuralist perspective connects micro-level findings with the country's context-dependent development trajectory, highlighting the influence of institutional and policy factors on the deindustrialization trend.

The study confirms the existence of mildly positive pass-through between productivity and wage levels in manufacturing industry when a baseline model is used, and constant patterns in a model including the most important control variables. Analysis by ISIC Revision 4 codes and Pavitt classes confirms the findings, but the pass-through values estimated are extremely low (ranging between 0.02 and 0.27), which is consistent with other estimates for developing countries. There is a non-trivial difference between supplier-dominated firms and those in more complex Pavitt classes, with values for the latter, particularly in science-based industries, being somewhat higher. The slight upward trajectory seen in the baseline model disappears when controls are included. This means that pass-through, although present, is very low and does not differ between high-paying and low-paying firms.

Our findings may be summarized as follows. First, wage-productivity pass-through is positive in all specifications and uniform across the conditional wage distribution when control variables are included, although values are dramatically lower than in advanced countries (Stansbury and Summers, 2017). Second, natural resource-intensive branches and basic manufacturing (the supplier-dominated and scale-intensive classes) account for a substantial portion of Argentina's sectoral and technological structure. This composition affects the results, particularly since pass-through by supplier-dominated firms, the largest component, is particularly weak. These firms are also characterized by stagnant productivity and higher level of informality. The existing production structure thus offers little scope for structural change and constrains both productivity growth and the distribution of its gains, consigning the country to a middle-income trap. Third, pass-through at foreign-owned enterprises shows a rising trend across the wage distribution, albeit of a moderate magnitude, making foreign ownership the only firm characteristic to affect the pass-through patterns observed.

These micro- and industry-level findings have major implications at the macroeconomic level and highlight the path-dependent consequences of the early deindustrialization "choice" made during the dictatorship period. Macroeconomic implications span three domains, namely production, redistribution and external constraints, both financial and material, consistently with the logic of cumulative causation and Gunnar Myrdal's vicious cycle (Myrdal,1974). These consequences range from the micro effects that we have presented to further-reaching macroeconomic dimensions.

First, the limited technological and productive upgrading of domestic firms represents the main constraint on the growth prospects of the Argentine economy, which has progressively shifted towards servitization and financialization. If the finance-led accumulation strategy followed in developed countries tends to dampen growth, this is even more the case for countries experiencing early deindustrialization. The financialization turn has also been coupled with an increasing reliance on resource-based export strategies. Therefore, the first macroeconomic implication of our study is the need to reassert manufacturing as a growth-promoting strategy, particularly in a context marked by an energy transition that is heavily dependent on mineral resources, since otherwise Argentina, like many other countries in Latin America and the Caribbean, risks falling prey to new colonial appetites.

Second, the progressive rentification of the economy (Dosi et al., 2024) entails the accumulation of rents, wealth and inequality. Our paper clearly demonstrates that weak labour productivity in manufacturing, quite apart from the problem of productive composition, means weak wage growth and poor redistribution of the already modest value added generated. Stable growth derives from good jobs, and manufacturing, broadly speaking, provides better jobs than many service industries. A manufacturing specialization strategy centred on low-emission industries might represent a potential route towards the productive, social and environmental benefits of a renewed phase of industrialization.

Third, in relation to external constraints, reindustrialization in selected industries, possibly science-based ones with a strong connection to the education and research systems, which are still quite robust in the country, might help alleviate the current structural dependence on external finance and natural resource-intensive exports. Generating value from manufacturing could ease the debt constraint and reposition the country's economy within international trade regimes.

More broadly, Argentina, like many other countries of Latin America and the Caribbean, needs to liberate the competences and capabilities that still very much exist there but are currently repressed as domestically based growth strategies go through a vicious cycle of dismantling. To attain this objective, a renewed industrial policy framework in association with redistributive policies is the place to start. Market forces alone will hardly make the difference.

Some avenues for future research emerge from this analysis. First, there is a need for a micro-level study of trade unions and their influence on the wage-productivity relationship; our findings indicate that intra- and inter-industry wage heterogeneity has been declining in a period characterized by increasing adherence to collective bargaining agreements. Second, more research is needed on the role of production and export specialization as a factor in sustainable development prospects. Lastly, the gender composition and pay structure of manufacturing employment should be assessed to ascertain whether "good" jobs are available irrespective of workers' gender, or whether decent pay and working conditions are the preserve of the male workforce.

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Annex A1

Table A1.1
Sectoral shares of GDP and formal (registered) labour, 2010–2021
(Percentages)

Sector	GDP share	Registered labour share (private sector)
Manufacturing	20.6	19.2
Wholesale and retail trade, accommodation and food services	17.5	21.9
Real estate and business services	12.5	14.5
Community and human health and education services	11.9	18.5
Agriculture, forestry and fishing	8.8	5.6
Transport, storage and communication	9.2	8.7
Public administration and defence	5.4	-
Financial	4.5	2.5
Construction	3.7	6.7
Mining	3.8	1.3
Utilities	2.1	1.1
Total	**100.0**	**100.0**

Source: Prepared by the authors on the basis of National Institute of Statistics and Censuses (INDEC) and Secretariat of Labour, Employment and Social Security.

Note: Sectors are classified at the one-digit level of the International Standard Industrial Classification of All Economic Activities (ISIC Revision 4). GDP is calculated in constant 2010 pesos).

Table A1.2

Private sector collective bargaining agreements, by economic sector, 2010–2022

(Percentages)

Sector	Share of collective agreements
Manufacturing	34.2
Transport	18.9
Services	15.6
Wholesale and retail trade	9.8
Utilities	9.1
Financial	5.5
Mining	2.9
Construction	2.6
Agriculture	1.5
Total	100.0

Source: Prepared by the authors on the basis of National Institute of Statistics and Censuses (INDEC) and Secretariat of Labour, Employment and Social Security.

Table A1.3

Median of the distributions, by Pavitt class, 2010–2021

	Pavitt manufacturing sector	ISIC codes	Median coefficient across sectors	Pseudo-R^2 (median)
All		-	0.166***	0.082
Supplier-dominated	Food, beverages and tobacco	10-11-12[a]	0.171***	0.120
	Meat products	1010	0.051***	0.025
	Dairy products	1050	0.234***	0.117
	Wines	1102	0.208***	0.121
	Textiles	13	0.115***	0.066
	Wearing apparel	14	0.099***	0.070
	Leather products	15	0.107***	0.071
	Wood products	16	0.125***	0.074
	Fabricated metal products	25	0.202***	0.098
	Furniture	31	0.124***	0.091
Scale-intensive	Paper products	17	0.189***	0.071
	Rubber and plastic products	22	0.185***	0.080
	Other non-metallic mineral products	23	0.148***	0.069
	Basic metals	24	0.166***	0.109
	Motor vehicles, trailers and semi-trailers	29	0.149***	0.063
Specialized suppliers	Electronic components and boards, computers, consumer electronics, communication and electrical equipment	2610-2620-2630-2640-27[b]	0.125***	0.050
	Domestic appliances	2750	0.199***	0.102
	Machinery and equipment	28[c]	0.148***	0.077
	Agricultural and forestry machinery	2821	0.122***	0.063
	Other transport equipment	30	0.151***	0.064
Science-based	Chemical and refined petroleum products	19-20	0.174***	0.079
	Pharmaceutical and medicinal products	21	0.270***	0.133
	Measuring, testing and control equipment, electromedical and optical instruments	2650-2660-2670-2680	0.175***	0.080

Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.

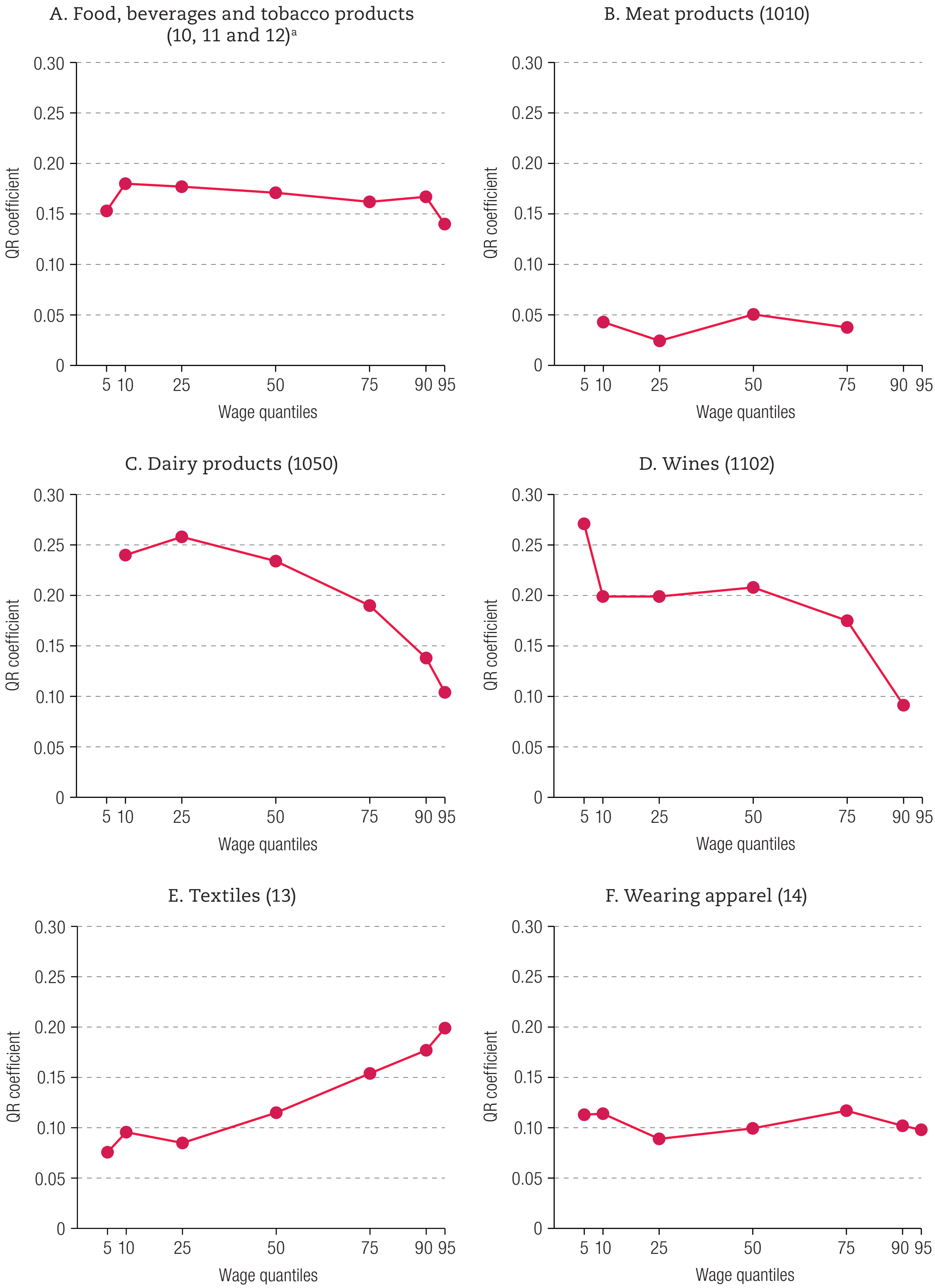
Note: Sectors are classified at the two-digit level of the International Standard Industrial Classification of All Economic Activities (ISIC Revision 4). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

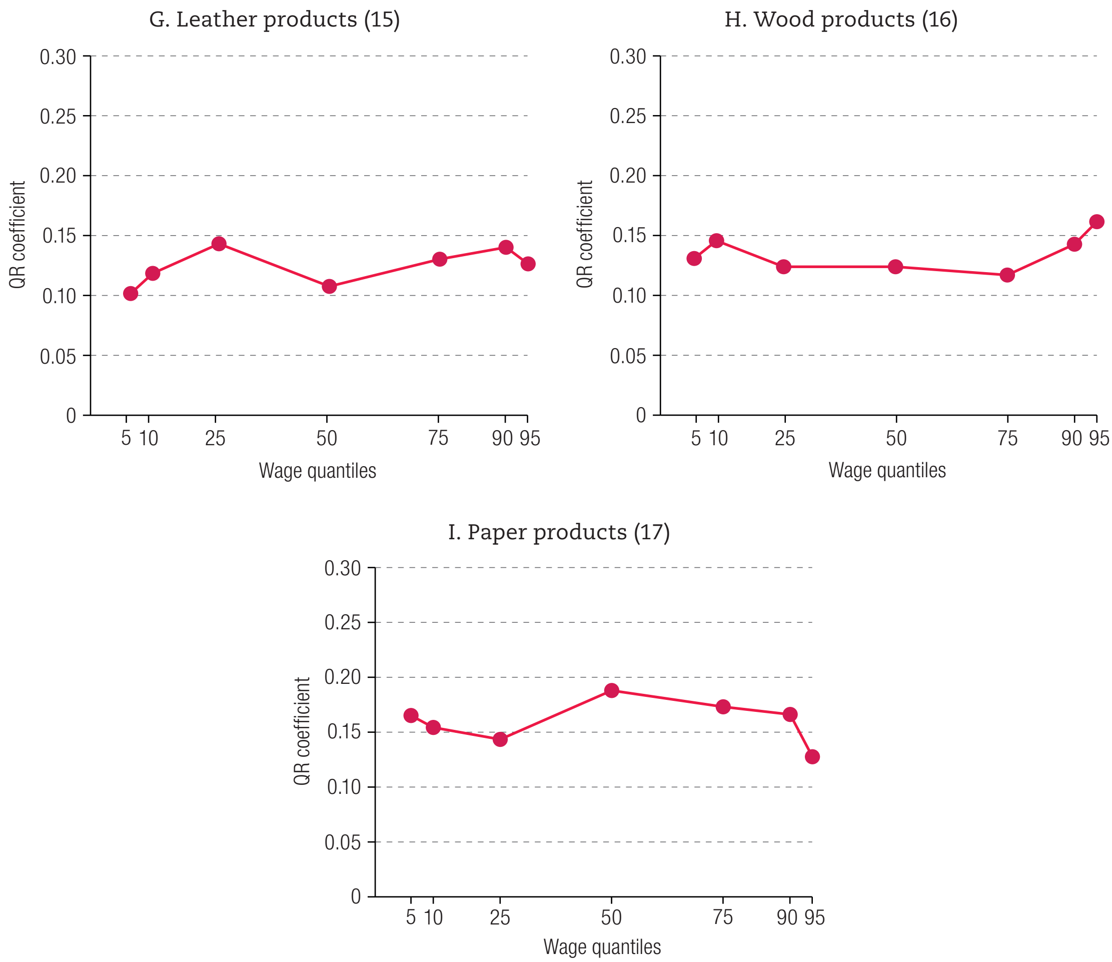
[a] Sector 10 does not include codes 1010 or 1050, and sector 11 does not include code 1102.

[b] Sector 27 does not include code 2750.

[c] Sector 28 does not include code 2821.

Figure A1.1
Distribution of quantile regression (QR) coefficients by ISIC sector (baseline model), 2010–2021





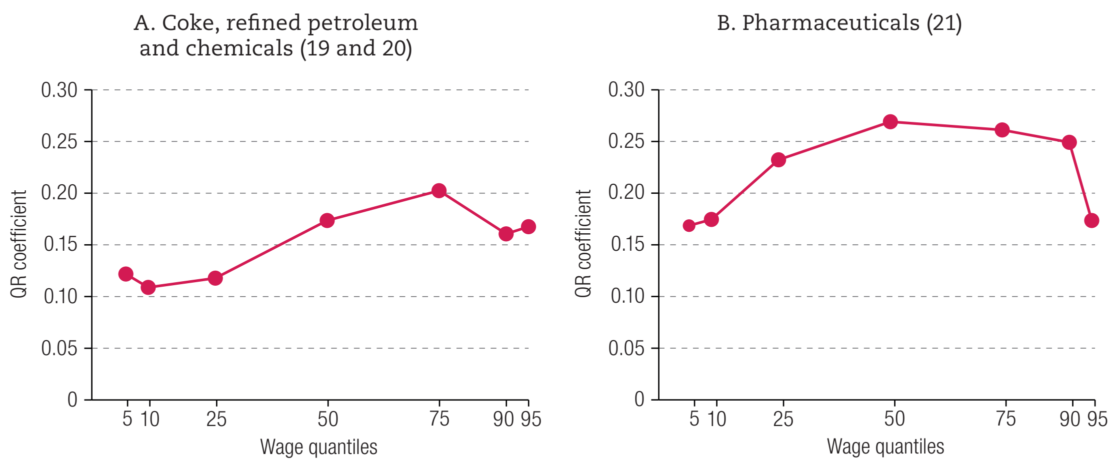
Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.

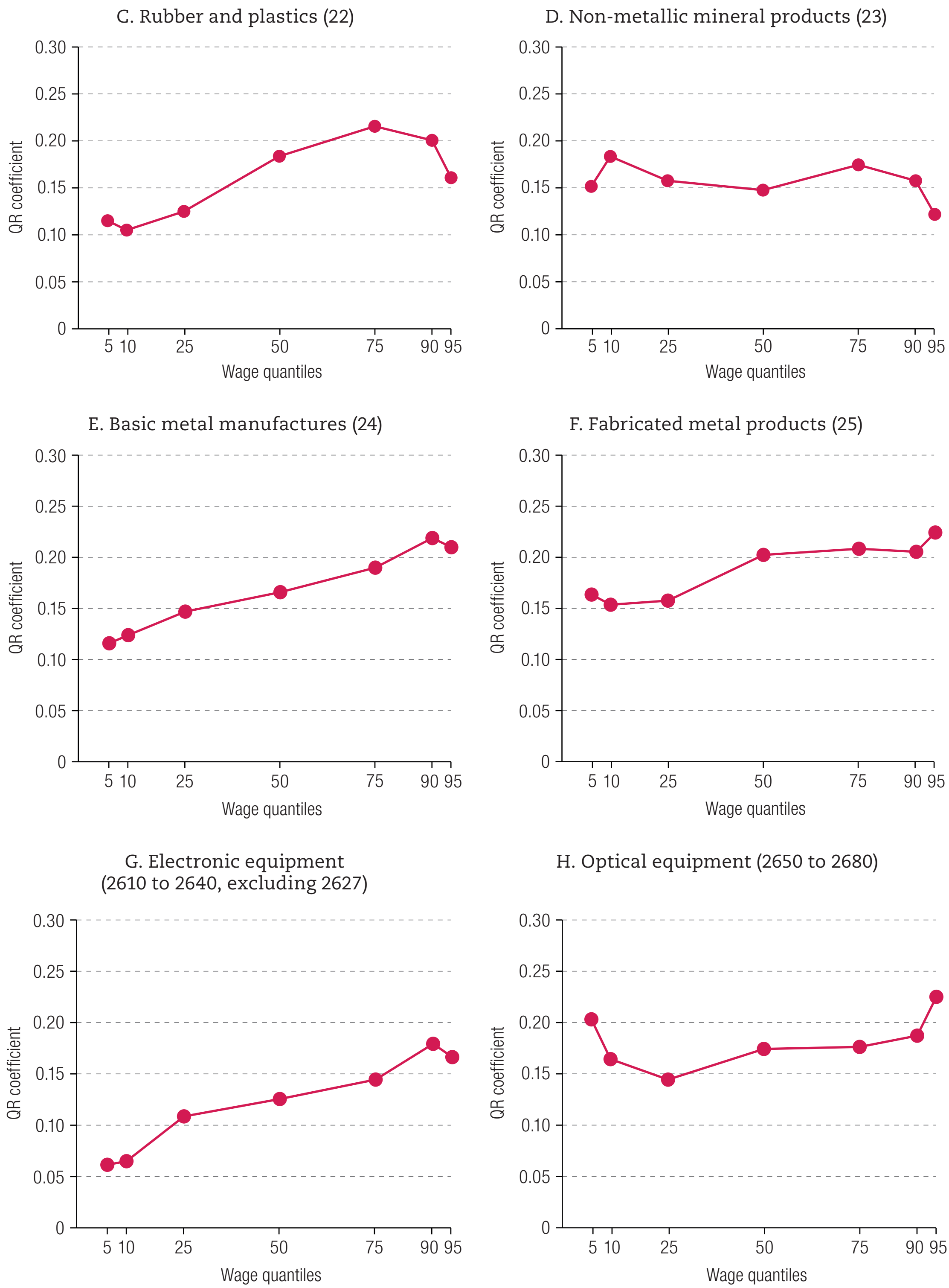
Note: Sectors are classified according to the International Standard Industrial Classification of All Economic Activities (ISIC Revision 4), with 94% of coefficients being statistically significant. The analysis is restricted to formal (registered) employment.

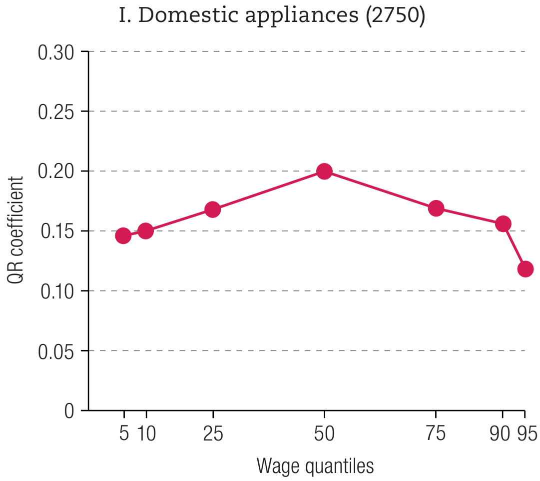
[a] Sector 10 does not include codes 1010 or 1050, and sector 11 does not include code 1102.

Figure A1.2

Distribution of quantile regression (QR) coefficients by ISIC sector (baseline model), 2010–2021




C. Rubber and plastics (22)
D. Non-metallic mineral products (23)
E. Basic metal manufactures (24)
F. Fabricated metal products (25)
G. Electronic equipment
(2610 to 2640, excluding 2627)
H. Optical equipment (2650 to 2680)
QR coefficient
0.30
0.25
0.20
0.15
0.10
0.05
0
5 10 25 50 75 90 95
Wage quantiles

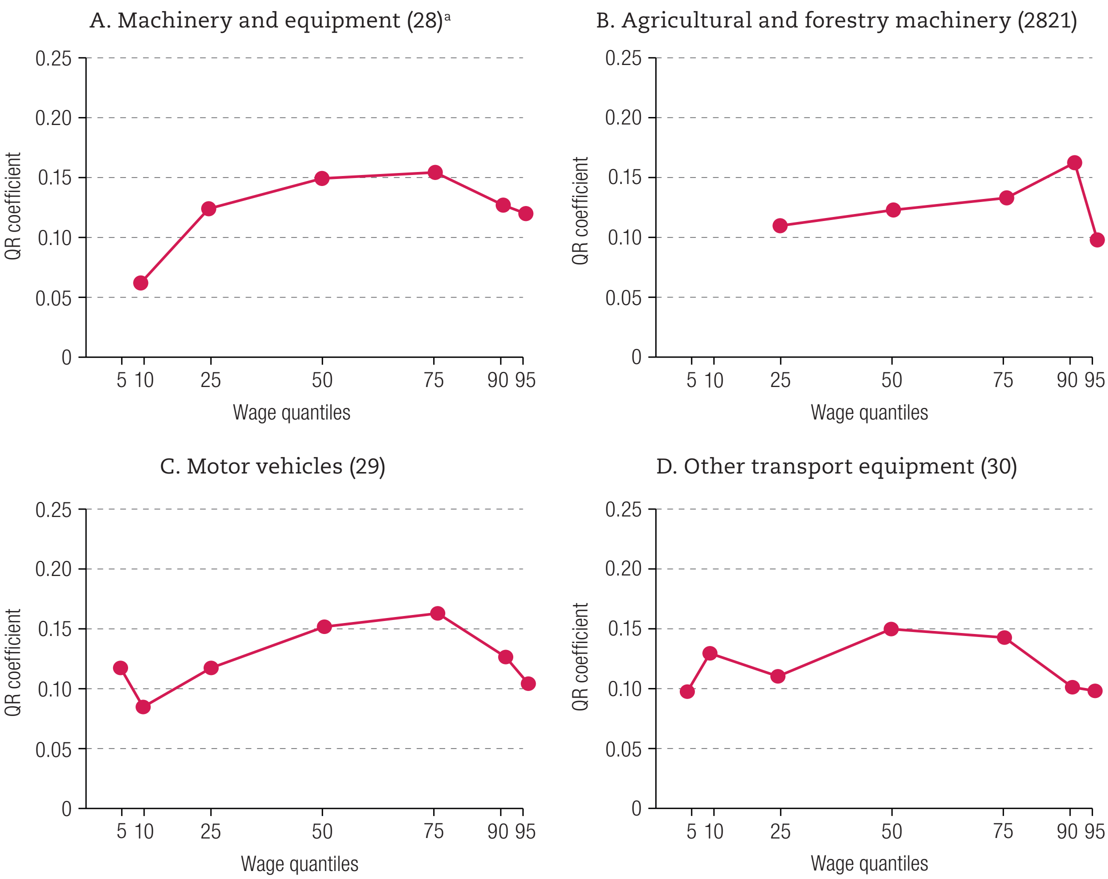


Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.

Note: Sectors are classified according to the International Standard Industrial Classification of All Economic Activities (ISIC Revision 4), with 94% of coefficients being statistically significant. The analysis is restricted to formal (registered) employment.

Figure A1.3

Distribution of quantile regression (QR) coefficients by ISIC sector (baseline model), 2010–2021



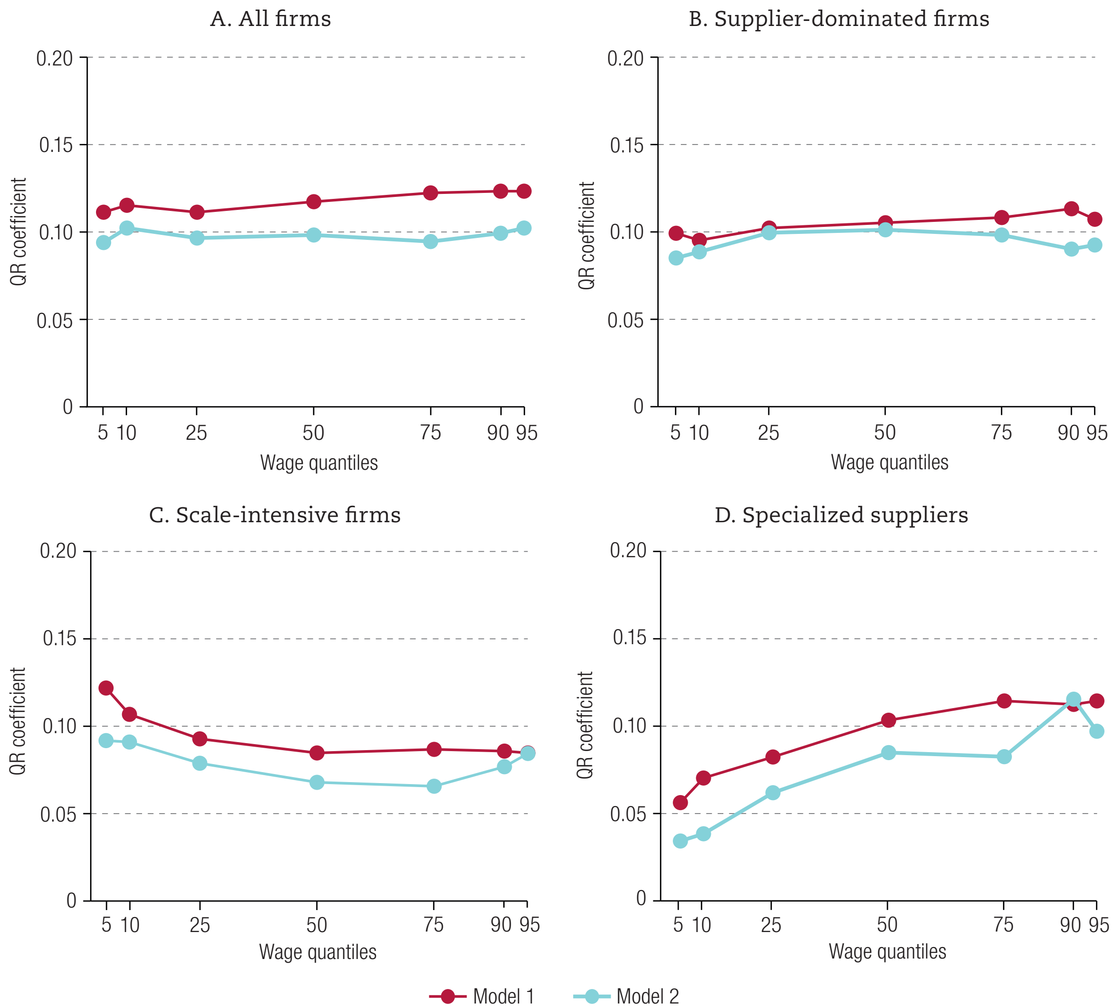
Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.

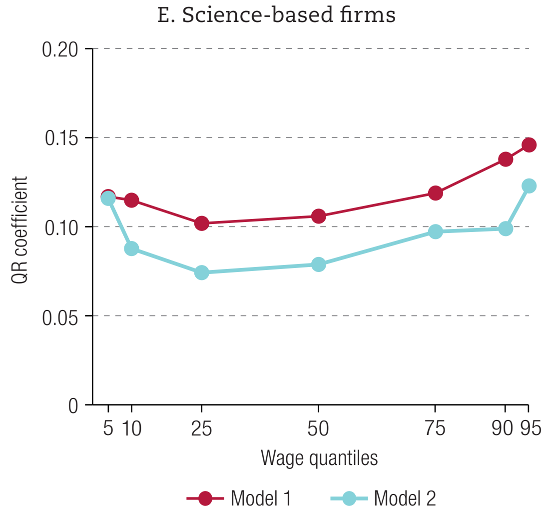
Note: Sectors are classified according to the International Standard Industrial Classification of All Economic Activities (ISIC Revision 4), with 94% of coefficients being statistically significant. The analysis is restricted to formal (registered) employment.

[a] Sector 28 does not include code 2821.

Figure A1.4

Quantile regression (QR) coefficients for log labour productivity, 2010–2021





Source: Prepared by the authors, on the basis of Secretariat of Innovation, Science and Technology. (2021). *National Survey on Employment and Innovation Dynamics*.

Note: Model 1 is the standard model with control variables, while model 2 includes the human capital proxy (log of skill ratio). The analysis is restricted to formal (registered) employment.