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The Impact of KIBS Agglomeration on Chilean Mining Sector Productivity

Kenneth Castillo-Hidalgo

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Campus de la UAB
08193 Bellaterra
(Cerdanyola del Vallès)
Barcelona · Spain
Tel. +34 93 581 16 80
Fax +34 93 581 22 92
d.econ.aplicada@uab.cat
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Coordinator: Rosella Nicolini (rosella.nicolini@uab.cat)

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The Impact of KIBS Agglomeration on Chilean Mining Sector Productivity

Kenneth Castillo-Hidalgo*

Departament d'Economia Aplicada, Universitat Autònoma de Barcelona, Barcelona, Spain.
Departamento de Ingeniería Comercial, Universidad de Antofagasta, Antofagasta, Chile.

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Abstract

This paper aims to explore the existence and the effects of inter-sectoral agglomeration economies in a developing country like Chile, exhibiting a strong dependence on natural resources, especially mining. We estimate the impact of the spatial concentration of firms that supply knowledge-intensive business services (KIBS) on mining labor productivity by following a multi-level approach, relying upon individual- and aggregate-level data. In addition, a spatial analysis of these interactions is conducted, aiming to explore spatial dependency and potential intra-territorial structures. Results suggest a positive effect of KIBS agglomeration on mining workers' productivity at the individual level. Results from the exploratory spatial analysis suggest evidence of spatial spillovers from KIBS agglomeration. These results yield relevant policy implications for knowledge-intensive firms' location, promotion of a knowledge-based economy linked to natural resources, and sub-national-level development perspectives.

Keywords: KIBS, Agglomeration, Mining, Chile
JEL Classification: R11, R12, R19

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Contents

1 Introduction

The extractive sector in Chile implemented outsourcing services to enhance productivity and competitiveness, aiming to solidify the presence of numerous firms in both national and international markets. Each of these firms became a node within a local productive network, typically involving suppliers of engineering process know-how, public sector institutions, and local communities (Katz & Pietrobelli, 2018). Concurrently, the mining sector has undergone significant organizational restructuring, with a marked increase in technological integration across production processes, spanning from exploration to transportation. This trend toward segmenting various productive stages in companies' processes to boost efficiency has led to the emergence of specialized service providers. Consequently, mining firms are now able to concentrate on their core activities. This strategic shift has also resulted in the consolidation of suppliers for routine services with lower technological demands (e.g., cleaning, maintenance, catering), alongside suppliers offering knowledge- and technology-intensive services. The latter have progressively expanded their presence in the industrial landscape surrounding extractive operations. Consequently, collaboration with knowledge-intensive service providers is anticipated to be pivotal for advancing the mining sector.

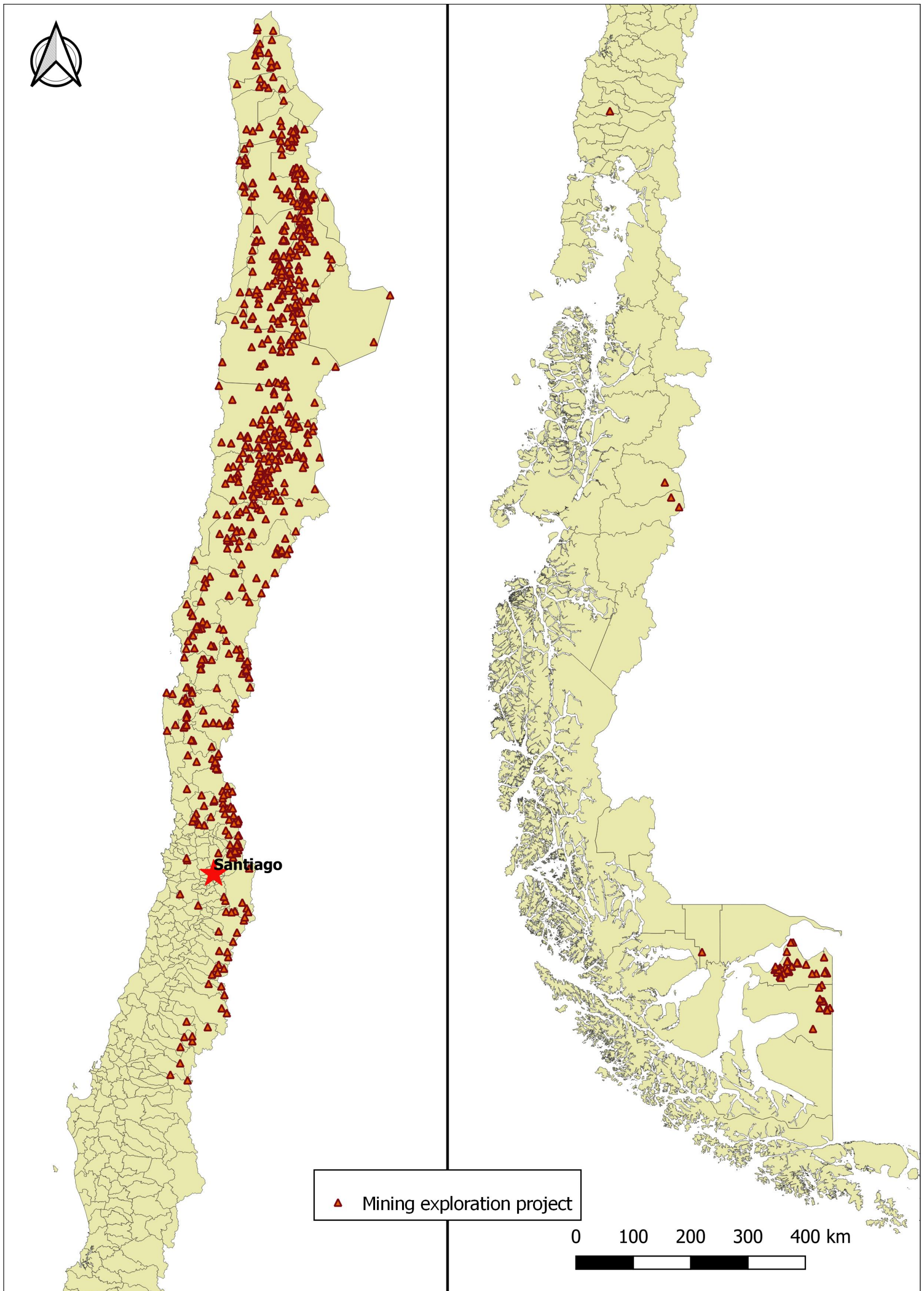
This paper aims to explore the potential effects of the spatial concentration of knowledge-intensive business services (KIBS) on the productivity of the Chilean mining sector. Generally, KIBSs have nurtured great attention in the innovation, development, and economic geography literature. These firms play active roles in regional dynamics as contributors or facilitators of innovative changes and co-producers of innovation (Cooke & Leydesdorff, 2006; Shearmur & Doloreux, 2008). In this context, analyzing both the determinants and the effects of location and agglomeration of KIBS has significant relevance for the Chilean mining industry. In this vein, the literature has suggested that KIBS suppliers tend to cluster in metropolitan areas (Di Giacinto, Micucci, & Tosoni, 2020; Muller & Doloreux, 2009; Zhang, 2016) because of the need for proximity to clients (Keeble & Nachum, 2002), available innovation infrastructure and linkages (Meliciani & Savona, 2015), and the existence of agglomeration economies (Romero de Avila Serrano, 2019). In contrast, studies on the effects of location and agglomeration of KIBS have led to mixed conclusions. Some studies suggest a weak impact of location decisions of KIBS firms on clients' performance (O'Farrell & Moffat, 1995), the quality of the relations with clients' headquarters (Aslesen & Jakobsen, 2007), and the economic development of urban areas (Shearmur, 2010). Nevertheless, KIBS agglomeration has been associated with benefits in peripheral zones or multi-industrial clusters in the form of knowledge spillovers (Liu, Lattemann, Xing, & Dorawa, 2019; Shearmur, 2010), increased regional export levels (Kamp & Ruiz de Apodaca, 2017) and urban productivity (Zhang, 2016).

The emergence of specialized knowledge-intensive services for natural resource activities supports the notion that extractive activities can serve as potential sources of growth and development for resource-rich countries. Marin, Navas-Alemán, and Perez (2015) put forward that economic benefits could stem from the coexistence of knowledge-intensive activities and natural resource capabilities. This represents an opportunity for developing countries to progress toward science-based production schemes within the context of natural resource-based activities. This transition can be considered a "major revolution" with a significant long-term impact across Latin America (Crespi, Katz, & Olivari, 2018). However, studies from the economic geography literature proposed a more pessimistic point of view for this natural resource-intensive development strategy, particularly concerning the Chilean mining sector. Whereas suppliers of mining services with high knowledge and technology tend to concentrate in the Metropolitan Region where Santiago is located, mining activity itself is concentrated in the Atacama Desert in northern Chile. The absence of knowledge-generating proximity has resulted in uneven development potential around the mining sector (Atienza, Lufin, & Soto, 2021; Bravo-Ortega & Muñoz, 2021). This scenario raises questions about the sustainability of economic growth in Chilean mining regions (Arias, Atienza, & Cademartori, 2014). Figure 1 illustrates the geographic concentration of mining exploration projects recorded during the period 2018-2021, which predominantly occurred in the Atacama Desert, extending along the Andes range into the South-Central zone.

Current literature has not explored the potential impact, if any, of the agglomeration of KIBS on the natural resource extractive sector, particularly mining. This paper aims to address this research gap by focusing on the Chilean mining sector productivity over the past decade. According to the fundamentals of agglomeration economies (Combes & Gobillon, 2015), it is expected that the geographic concentration of KIBS would have an effect on the productivity of mining sector. The channel is expected to be effective by means of the increasing outsourcing of non-core tasks in the mining industry. Spatial proximity entailed in this process makes it prone to fuel cross-fertilization of ideas between industries, thus enhancing innovation. The scope of this study is to provide new empirical evidence about this channel by analyzing the impact of the municipal level of industrial specialization in KIBS on both the average mining labor productivity of the municipality itself, and on the level of labor productivity of workers from the Chilean mining sector. We anticipate that this approach will offer insights into the extent to which the spatial proximity of KIBS firms contributes to enhancing mining productivity. This analysis is conducted using original panel data spanning the period from 2010 to 2019. Additionally, a spatial analysis will explore possible spatial structures within the Chilean territory and identify potential direct and indirect spillover effects.

Our results suggest a positive association between KIBS agglomeration and workers' productivity in the mining sector at the individual level. However, the results for municipality-level estimations regarding the role of KIBS agglomeration economies are inconclusive. One interpretation of these findings is that the positive externalities generated by KIBS tend to be effective at the individual level, as they primarily focus on enhancing labor productivity within firms. How-

Figure 1: Mining exploration projects recorded in period 2018-2021.



Source: Own elaboration. Data retrieved from SIGEX (SERNAGEOMIN).

ever, these effects fade away when observations are aggregated. The latter might be related to the heterogeneous composition of the mining workforce in terms of education and task complexity, blurring the effect of externalities. Furthermore, our results do not allow us to conclude in favor of the existence of localization economies in the mining sector, consistent with previous literature (Arias et al., 2014; Phelps, Atienza, & Arias, 2015). Instead, our findings suggest that the agglomeration of mining activities generates a competition effect in the workforce to obtain available positions. In addition, by augmenting our baseline aggregate-level model we conclude that the agglomeration of KIBS intensifies the competition effects on labor. This result stems from the spatial proximity of KIBS firms that enhance technological processes intensive in physical capital, and by increasing mining workers' productivity at the individual level, they reinforce the competition effect in mining activities.

Regarding the exploratory spatial analysis, results suggest the existence of a heterogeneous spatial structure throughout the country. The influence exerted by Santiago (the national capital) on mining productivity is negligible in the northern and southern zones, while it is a central node influencing productivity in its nearest municipalities. Finally, the estimation of spatial models allows us to conclude in favor of the existence of spatial dependencies between municipalities concerning mining productivity. Following this spatial approach, direct and indirect impacts of KIBS agglomeration at the municipal level are found. Spatial dependencies concerning labor productivity determinants, especially demographic characteristics, are pointed out as well.

This paper's contribution is twofold. First, it estimates the effects of the spatial concentration of knowledge-intensive services on mining productivity within the context of a developing country. The positive impacts of spatially concentrated knowledge-intensive activities on natural resource industries are expected to enhance firm performance. Moreover, this incentive could also stimulate the creation of new specialized services, thereby positioning the extractive sector as a catalyst for economic transformation toward a knowledge-based economy.

The remainder of the paper is structured as follows. Section 2 reviews the current literature on KIBS and the mining sector. Section 3 details database and selected variables. Section 4 describes the empirical strategy. Section 5 presents estimation results. Finally, Section 6 concludes and discusses policy implications, as well as potential future research directions.

2 Literature review

Our study centers around the hypothesis that the agglomeration of knowledge-intensive activities spurs the generation of knowledge spillovers, thereby facilitating the emergence of productivity-enhancing innovations. These externalities might be captured by mining companies through the outsourcing of knowledge-intensive, non-core tasks, fostering cross-fertilization of ideas between industries and increases in productivity in the extractive sector. The agglomeration economics literature labels this as *Jacobian externalities* (Glaeser, Kallal, Scheinkman, & Shleifer, 1992). These are grounded in the notion that denser locations are also more likely to host knowledge-generating institutions. Consequently, the concentration of these institutions fosters the production and absorption of know-how, thereby stimulating innovation and growth (Harrison, Kelley, & Gant, 1996;

McCann & van Oort, 2019). However, knowledge-intensive service suppliers tend to agglomerate toward the top of the urban hierarchy, resulting in uneven spatial economic development (Gallego & Maroto, 2015; Shearmur & Doloreux, 2008). These dynamics are particularly pertinent to the Chilean mining industry, which is predominantly concentrated in areas far from urban metropolitan centers.

2.1 KIBS agglomeration: characteristics and impacts

In recent decades, a growing body of empirical literature has emerged focusing on the study of knowledge-intensive business service (KIBS) suppliers, their spatial distribution, and the implications arising from the agglomeration of these firms (Coffey, Drolet, & Polèse, 1996; Muller & Doloreux, 2009; Shearmur, 2010; Wood, Bryson, & Keeble, 1993; Zhang, 2016). KIBS firms can be defined as entities that provide services with high intellectual value added (Muller, 2012). These companies are characterized by their heavy reliance on professional expertise, their capacity to generate and utilize information and knowledge, and their role in delivering intermediary services to client firms (Miles et al., 1995; Muller & Doloreux, 2009).[1] The most recent classification of KIBS to date encompasses three main types based on the services provided: P-KIBS, involving professional services, such as legal, accounting, or consultancy services; T-KIBS, comprising specialized services closely linked to technological innovation, such as engineering or technical consultancy activities, computer programming, testing, analysis, and research; and C-KIBS, covering creative activities such as advertising, architecture, and design (Miles, Belousova, & Chichkanov, 2018). Shearmur (2010) suggests that, in general, T-KIBS are more responsive to external sources of information and have a greater reliance on exports compared to P-KIBS, which are more oriented toward local markets. Additionally, T-KIBS services tend to evolve more rapidly than those provided by P-KIBS. Moreover, P-KIBS would tend to be more spatially diffuse, i.e., less concentrated at the top of the urban hierarchy and more present in smaller cities. However, T-KIBS may also have an effect on certain local production systems because of its propensity for local collaborations.

Because of their features, KIBS firms contribute to the host region's dynamism through their participation in regional innovation systems, fostering local synergy and thus regional development (Shearmur & Doloreux, 2008; Wei & Toivonen, 2006).[2] The role of KIBS in innovation processes has been extensively studied. These firms generate bilateral knowledge flows between their partners and themselves by means of an "almost symbiotic" relationship with their client firms, turning

[1] International statistical systems, such as the International Standard Industrial Classifications (ISIC) and *Nomenclature Statistique des Activités Économiques dans la Communauté Européenne* (NACE), facilitate the identification and classification of business services industries.

[2] Citing Asheim and Gertler (2006, p. 9), a regional innovation system "*...can be thought as the institutional infrastructure supporting innovation within the production structure of a region.*"

them into co-producers of knowledge and innovation (den Hertog, 2000). KIBS firms contribute to the innovation of their client firms by acting as external sources of knowledge. However, they also introduce internal innovations based on new knowledge acquired from their interaction with clients (Muller & Zenker, 2001). In this sense, KIBS act both as knowledge intermediaries and knowledge users (Shearmur & Doloreux, 2019). One strand of the literature has been devoted to the study of the relationship between KIBS firms and their client firms based on outsourcing, most notably from the manufacturing sector, and the role that this interplay has on developing and revitalizing regional competitiveness (Amancio, de Sousa Mendes, Moralles, Fischer, & Sisti, 2021; Liu et al., 2019). Lafuente, Vaillant, and Vendrell-Herrero (2017) conclude that "territorial servitization," that is, the mutual dependency between KIBS firms and manufacturing businesses, has a positive effect over employment creation in the manufacturing sector and regional competitiveness. Baines et al. (2017) offer an extended review of the literature referring to this issue.

From a spatial perspective, the literature presents heterogeneous evidence regarding the relevance of location and geographic proximity. In the 1980s, the locational behavior of producer service suppliers emerged as a primary focus in research on service industries (Coffey et al., 1996; Harrington, 1995). Similarly, the study on KIBS firms' location decisions gave rise to strong evidence suggesting that these activities are more likely to concentrate in large metropolitan areas (Muller & Doloreux, 2009; Shearmur & Doloreux, 2008). Keeble and Nachum (2002) concluded for London and southern England that KIBS firms cluster as a result of the need for proximity to client firms. For European regions, Meliciani and Savona (2015) found that the locations of business services are determined not only by the classical agglomeration economies, but also by the structure of linkages to users and the region-specific innovation and knowledge infrastructure, highlighting ICT intensity. Romero de Avila Serrano (2019) stressed that the urban spatial structure is associated with the location of KIBS, as these firms take advantage of both urbanization and localization externalities. These results were confirmed by Di Giacinto et al. (2020) for Italian KIBS firms.

On the other hand, literature has examined the impacts of these location decisions on the local milieu, leading to mixed conclusions. Some studies have indicated a weak impact of location on client firms' performance (e.g, O'Farrell and Moffat (1995) for Scotland and England), which is associated with the possibility of remotely accessing to these services (Antonelli, 1999). For Norway, Aslesen and Jakobsen (2007) stated that geographic proximity was not a decisive factor for successful relations between KIBS and clients' head offices, but that an agglomeration of KIBS does provide positive externalities. For Canada, Shearmur (2010) concluded that T-KIBS can be conceived as key components of successful local innovation systems in peripheral areas, but metropolitan urban areas do not seem to benefit from the presence of KIBS. Spatial concentration of KIBS may also impact the rest of the local economy. The agglomeration of KIBS firms generates knowledge spillovers on multi-industry clusters, alleviating local knowledge gaps (Liu et al., 2019).

Kamp and Ruiz de Apodaca (2017) found a positive association between KIBS consumption and the overall regional turnover and exports. Results from Zhang (2016) suggest a positive association between KIBS agglomeration and urban productivity.

Zhang (2016) put forward an extension of the micro-foundations for agglomeration economies proposed by Duranton and Puga (2004) to elucidate the contribution of KIBS agglomeration to urban productivity. The author suggests that large cities provide highly skilled labor force and knowledge-generating environments (presence of universities, research laboratories, and so on) that are shared by KIBS firms, boosting their productivity. Likewise, other local firms share a higher endowment of specialized services as well, being able to focus on core functions and thus becoming more productive. As innovation intermediaries, KIBS firms might also increase the quantity and quality of matches between their clients and other relevant organizations. Finally, the nature of KIBS activities inherently fosters local creation, accumulation, and dissemination of knowledge, thereby stimulating regional endogenous growth and development (Shearmur & Doloreux, 2008).

2.2 KIBS and the Chilean mining sector

Although often characterized as a latecomer (Morris, Kaplinsky, & Kaplan, 2012), the landscape of mining production has undergone a significant transformation in recent decades, shifting from high integration to notable de-integration and reliance on outsourcing (Marin et al., 2015). This evolution has been accompanied by a global technological upgrade within the mining industry. Consequently, there has been a surge in innovation rates, productivity growth, and the emergence of suppliers offering specialized services covering various stages of the mining process, from exploration to mine planning and environmental engineering. These specialized services are commonly referred to as *knowledge-intensive mining services* (KIMS) (Urzua, 2012).

According to Bartos (2007), the mining sector has a long-lasting common reputation of being a slow innovator. Using productivity statistics, the author stated that metal mining firms have held innovation rates comparable with those from general manufacturing over the last fifty years. Still, these rates are far lower than those from high-tech manufacturing. However, mining nowadays counts on a high degree of technological sophistication, derived from innovation in artificial intelligence, big data, and robotics. This has allowed the mining industry to embed automatized heavy machinery throughout the production process (Arboleda, 2020). According to Daly, Valacchi, and Raffo (2019), mining innovation has been rapidly increasing since 2005, fueled by innovations in exploration and transport technologies, along with increases in automation. In this vein, mining equipment, technology, and service suppliers play a role in developing innovative solutions (Valacchi, Raffo, & Daly, 2019). These firms show a higher average R&D expenditure than mining firms (Daly et al., 2019), turning them into key contributors of the innovation process. For Australia, Martinez-Fernandez (2010) concluded that knowledge-intensive service activities performed by mining technology services firms play a crucial role in the transformation of the mining industry, where the interaction between client firms and suppliers is a key process in innovation.

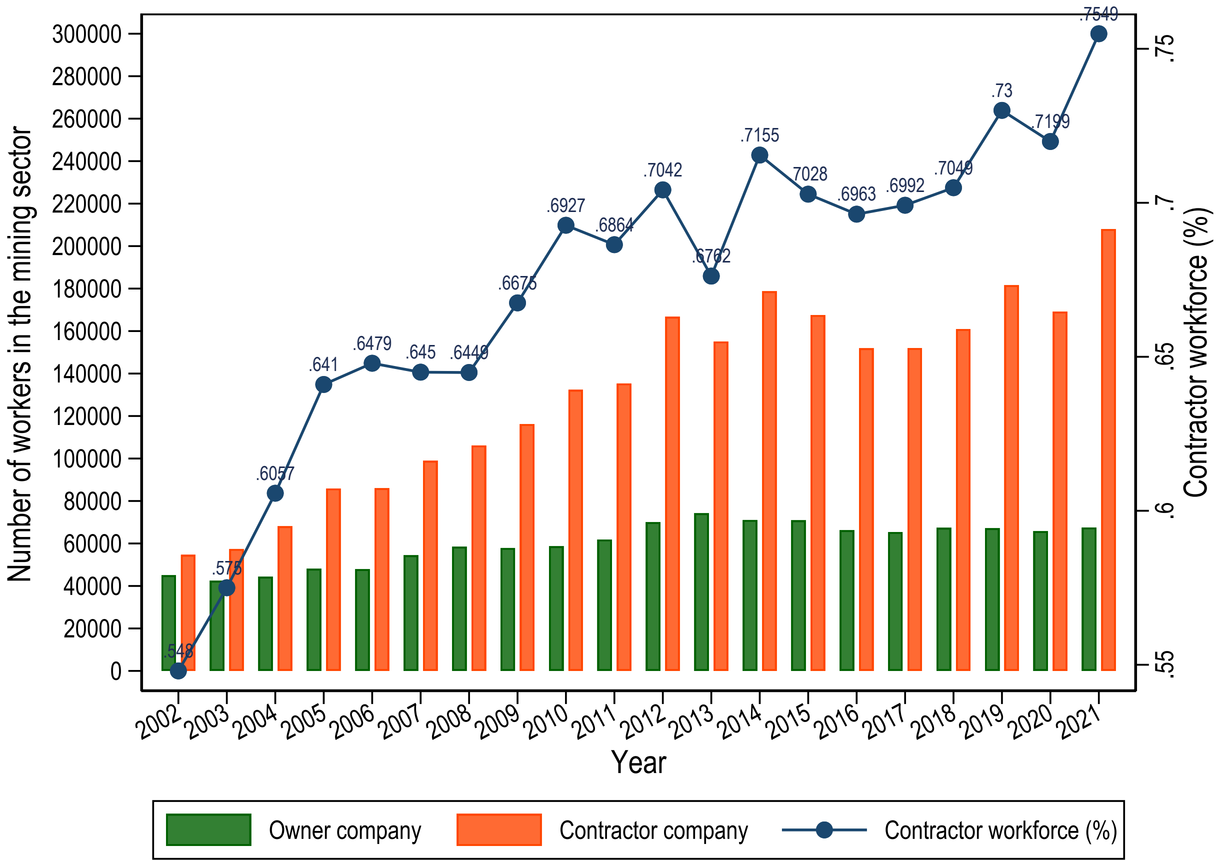
In the case of Chile, the copper mining industry has always had a historically relevant role in the national economy. It had a role in shaping the location of economic activities (Badia-Miró, 2015), and it has been a key activity for national growth rates registered in Chile since the beginning of the 20th century (Atienza, Lufin, Soto Díaz, & Cortés, 2015; Meller, 2000). During 2011-2020, the average share of the Chilean mining sector in the GDP was approximately 10.7%, reaching 12.5% in 2020. Chile is the world's leading copper producer, with a production of 5.77 million fine metric tons in 2020, equivalent to 28.5% of global production. Other mining products for which Chile has relevant shares in the global production are molybdenum (20.2%), iodine (69%) and lithium (26.5%) (SERNAGEOMIN, 2021). As for copper mining, about 72% of the national production is conducted by private companies, whereas the rest is produced by the state-owned company CODELCO. Mining exports represented 59.7% of total national exports in 2020, of which roughly 87% correspond to copper exports (COCHILCO, 2021a). From a geographical perspective, Chilean mining is not evenly distributed; rather, it is highly concentrated, particularly in the northern regions. In the specific case of cooper production, this is strongly localized in the Antofagasta Region, from which more than 53% of the national copper production comes (COCHILCO, 2021a).

Outsourcing plays a relevant role in the mining sector. The share of workers hired by contractors or third-party providers of mining firms has significantly increased over the last decades. Figure 2 shows the evolution of the mining sector workforce by type of hiring company, as well as the share of the workers hired by third-party firms on the total mining sector workforce. This share increased from 55% in 2002, to roughly 76% of the total mining sector workforce in 2021. This depicts the disintegration of mining processes and the considerable reliance on external firms for the execution of non-core tasks. This organizational setting is primarily the result of cost reduction pressure from international competition (Urzua, 2012).

In 2017, 83% of the mining suppliers in Chile were domestic capital firms, of which 78% were small firms (in terms of the number of workers) (Fundación Chile, 2019).[3] Regardless of the specific task, the majority of the workforce has tertiary education, while only 9% of these workers have a postgraduate degree. Mining supplier firms tend to concentrate first in the Metropolitan Region (where the national capital Santiago is located), and then in the Antofagasta Region. This geographical distribution could be detrimental for the knowledge-generating proximity. Referring to Duranton and Puga (2005), the fact that headquarters of mining service suppliers are located

[3]According to the criteria employed in Fundación Chile (2019), small, medium, and large firms correspond to those having 1–50, 50–200, and more than 200 workers, respectively.

Figure 2: Evolution of workforce in owner and contractor companies in the Chilean mining sector, 2002-2021.



Source: Own elaboration, employing data from COCHILCO, 2022.

in the capital city whereas mining peripheral regions host branches, implies weaker territorial networking. This uneven distribution of firms has relevant effects from a geographical development perspective (Atienza, Arias-Loyola, & Lufin, 2020; Atienza et al., 2021). Arias et al. (2014) conclude against the existence of localization economies in the mining sector in the Antofagasta Region, stating that the zone is closer to the ideal type of mining enclave than to a cluster. Linkages between offshore mining companies and local suppliers tend to be feeble. Labor markets in mining regions predominantly specialize in routine tasks. In addition, job structures often prompt workers to choose commuting over residential living, typically over long distances. Furthermore, the limited capacity of local firms to assimilate new knowledge diminishes the likelihood of knowledge spillovers within the mining sector (Phelps et al., 2015). This scenario casts doubts on the sustainability of regional economic growth and long-term developmental prospects.

3 Empirical strategy

In this study we estimate the impact of agglomeration of KIBS firms at the municipal level on the productivity of the mining sector labor. We measure this by the industrial specialization in KIBS for each municipality. In order to do so, a two-dimensional approach is followed. First, we assess the impact of KIBS agglomeration on the labor productivity of mining sector at the aggregate level, in order to evaluate the existence of average effects of spatial concentration of knowledge-generating firms on their client firms' workforce. Next, we estimate the impact of the municipality-level agglomeration of KIBS on individual labor productivity of mining sector workers. In order to explore the potential direct and indirect impact of KIBS agglomeration under a territorial perspective, we ran a set of spatial models based on different weight matrices, taking into consideration the heterogeneity of the Chilean territory. The agglomeration of KIBS firms at the municipal level is represented by the industrial specialization or concentration (Henderson, Kuncoro, & Turner, 1995) in KIBS (ξ_{ct}) for each municipality c in period t. This is approximated by the share of KIBS companies over the total local companies in municipality c at a given year t. The labor productivity in the mining sector is approximated by the level of (real) wages. The underpinning idea for this decision is that mining sector wages are often associated with production levels. This is especially true in large mining companies, where workers benefit from productivity bonuses, mostly derived from union negotiation resolutions (Aguirre-Jofré, Eyre, Valerio, & Vogt, 2021; Carrasco & Muñoz, 2018). Hence, it is plausible to put forward that the potential effects from agglomeration might be reflected as changes in wages.

3.1 Aggregate level effect estimation

In order to assess the potential average impact of industrial specialization in KIBS in the municipality, a set of models was estimated referring to panel data on mining sector wages.[4] We computed the municipality-level average wages of mining sector workers, as explained in the next section, proxying for productivity. In an effort to avoid endogeneity issues associated with contemporaneity between the proxy for labor productivity and the agglomeration measure, the latter was computed using data lagged by one period. When performing the empirical estimations, we were also concerned about the potential influence of the metropolitan area of Santiago. In order to control for it, we produced estimations with and without the Santiago province. Equation 1 presents the baseline estimation.

[4] In order to define the proper framework of analysis we tested to see if fixed rather than random models were more suitable to fit our data. Statistical tests assessed that fixed effects models were the best framework. Tests are available upon request.

$$lnW_{ct} = \alpha + \beta^{\xi}\xi_{ct-1} + \beta^{\mu}\mu_{ct-1} + \boldsymbol{\beta^{MC}MC}_{ct} + \boldsymbol{\beta^{DC}DC}_{ct} + T_t + \nu_c + \varepsilon_{ct}; \\ c = \{1, ..., 317\},\ t = \{2010, ..., 2019\} \tag{1}$$

In Equation 1, lnW_{ct} represents the logarithm of the municipality-level monthly average wage of mining workers. ξ_{ct-1} represents the municipality-level industrial specialization in KIBS. With the aim of controlling for potential localization economies, the measure for industrial specialization in mining for each municipality, μ_{ct-1}, was also incorporated. This was calculated as the local share of mining industry firms over the total firms in each municipality. $\boldsymbol{MC}_{ct}$ is a vector of meso-level controls, including the regional-level employment-to-population ratio, the province-level export-to-import ratio, and the municipality-level share of firms with 200 or more employees. $\boldsymbol{DC}_{ct}$ is a vector for demographic characteristics for the mining workforce at the municipal level, including the mean age of workers, the share of highly educated workers, the share of female workers, and the share of foreign workers. All independent variables are log-transformed.[5] T_t is the time-specific effect; ν_c stands for the unobservable municipality-specific effect; and ε_{ct} represents the idiosyncratic error term.

3.2 Individual-level effect estimation

The estimation of the impact of KIBS agglomeration on individual productivity was conducted by proxying productivity by the annual income of mining sector workers for each year. As detailed in the next section, the employed data source reports taxable monthly incomes, which correspond to the maximum salary values on which workers' taxes are computed. Therefore, the values are right-censored in cases where salaries are excessively high. As a consequence, it is necessary to consider the upper limits to which the real values are subjected. In order to do this, a set of random-effect Tobit models for panel data was estimated. The model to be estimated is shown in Equation 2. Once more, estimates with and without taking into account the Santiago province are performed.

$$lnW_{it} = \alpha + \beta^{\xi}\xi_{ct-1} + \beta^{\mu}\mu_{ct-1} + \boldsymbol{\beta^{MC}MC}_{ct} + \boldsymbol{\beta^{IC}IC}_{it} + T_t + \nu_i + \varepsilon_{ict}; \\ i = \{1, ..., 35, 302\},\ c = \{1, ..., 317\},\ t = \{2010, ..., 2019\} \tag{2}$$

In this expression, lnW_{it} stands for the logarithm of annual wage of mining sector worker i. Following the previous modeling, all the variables of interest, the measure of industrial specialization in mining, and the rest of the meso-level controls incorporated in the $\boldsymbol{MC}_{ct}$ vector are

[5] The logarithm of independent variables originally expressed in values between 0 and 1 are computed as $ln(1+X)$, where X is the independent variable in levels.

log-transformed. The vector $\boldsymbol{IC}_{it}$ contains controls for individual characteristics, such as age, education level, gender, and civil and migratory status.

3.3 Spatial analysis

For our exploratory spatial analysis, we first assessed the existence of relevant spatial structures for the Chilean territory. The underlying hypothesis to test was the centrality of Santiago. We shaped the spatial structure of the territory by incorporating two different distance variables to the aggregate-level models to check for the existence of a monocentric structure either around the regional capitals or Santiago, the national capital. The distance between each municipality and its corresponding regional capital is represented by $Dist^R$. The distance between each municipality and Santiago City is $Dist^N$. The estimations were conducted following a LSDV approach for the municipalities and splitting the sample into three *macrozones* (North, Center, and South), to capture heterogeneity among territorial units.[6] To avoid collinearity, the measures of distance were not included in Model 3 simultaneously.

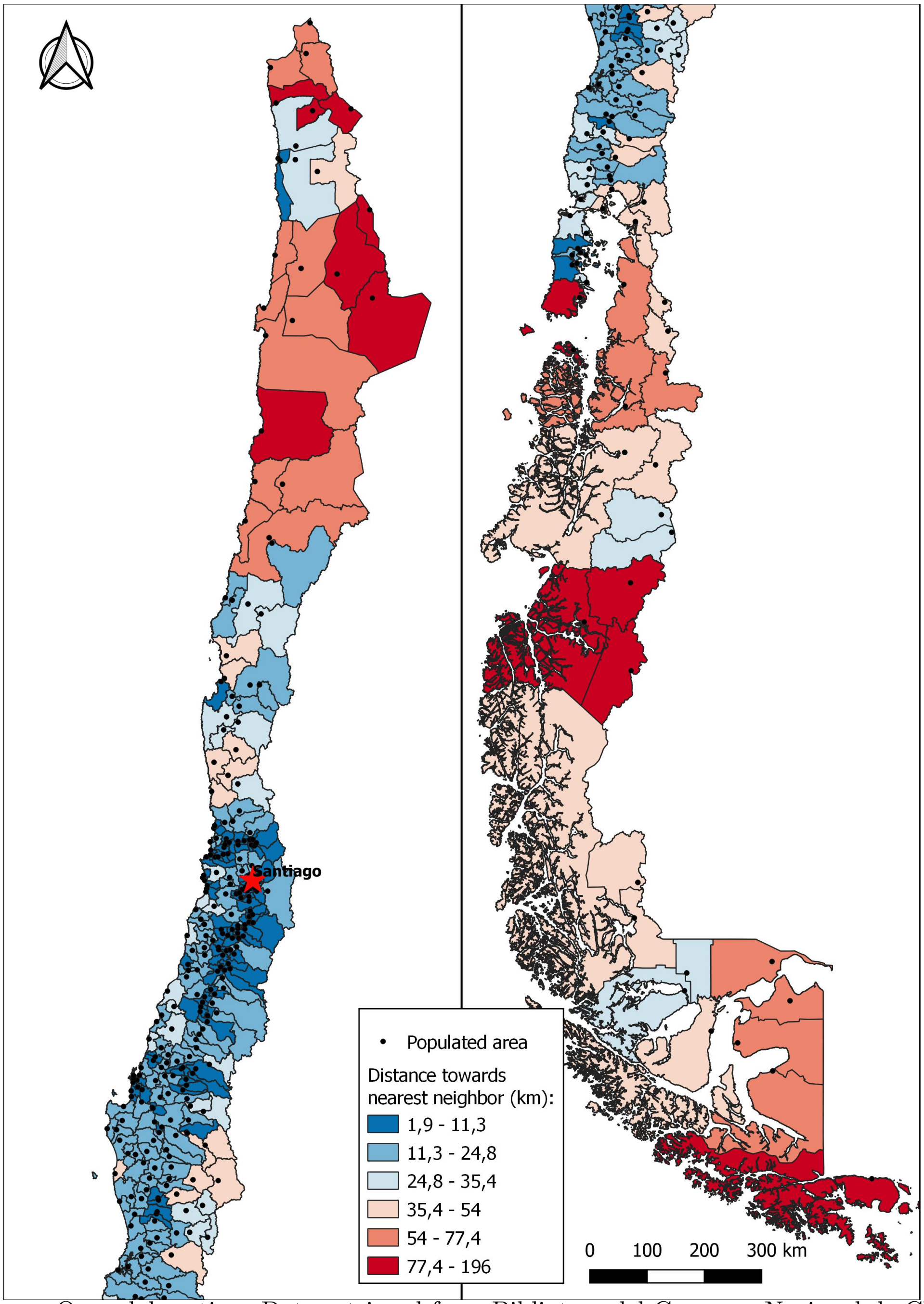
$$lnW_{ct} = \alpha + \beta^{\xi}\xi_{ct-1} + \beta^{\mu}\mu_{ct-1} + \beta^{R}Dist^{R}_{c} + \beta^{N}Dist^{N}_{c} + \boldsymbol{\beta^{MC}}\boldsymbol{MC}_{ct} + \boldsymbol{\beta^{DC}}\boldsymbol{DC}_{ct} + T_t + \nu_c + \varepsilon_{ct};$$
$$c = \{1, ..., 317\},\ t = \{2010, ..., 2019\} \tag{3}$$

Furthermore, we were interested in exploring the existence of spatial spillover effects between municipalities using cross-sectional data at the aggregate level. In order to define the spatial structure, in our analysis we georeferenced all the municipalities by referring to their urban centers i.e. populated areas as *centroids*. The rationale behind this is the fact that the municipalities' centroids may differ greatly from the actual points where economic activity is settled, especially for municipalities in extreme regions. Another relevant aspect is the heterogeneous distribution of these cities across the territory, as depicted in Figure 3. On the one hand, cities in central regions are very concentrated and close to each other. On the other hand, populated areas in northern and austral regions are more scattered, with a greater distance between each city and its nearest neighbor. To address this feature, in our analysis we alternated two different k-nearest neighbors matrices: a matrix where $k = 3$, reflecting the median number of neighbors in extreme regions according to contiguity; and a matrix with $k = 5$, as the median number of neighbors in

[6] The northern macrozone is composed of the regions Tarapacá, Antofagasta, Atacama, and Coquimbo; the center macrozone comprises the Metropolitan Region of Santiago, and the regions Valparaíso, O'Higgins, and Maule; the southern macrozone includes the regions Biobio, Araucanía, Los Ríos, Los Lagos, Aysén, and Magallanes.

contiguity within central regions.[7] The empirical approach proposed by Elhorst (2010) was applied for each matrix to find the most appropriate spatial model. The test results indicated that the SAR specification was preferred when employing any of the matrices.

Figure 3: Centroids for urban center and populated areas in Chile.



Source: Own elaboration. Data retrieved from Biblioteca del Congreso Nacional de Chile.

[7] The regions considered as extreme are Arica y Parinacota, Tarapaca, Antofagasta, Copiapo, Aysen, and Magallanes. Non-extreme or central regions include Coquimbo, Valparaiso, Santiago, O'Higgins, Maule, Ñuble, Biobio, Araucania, Los Rios, and Los Lagos.

4 Data and variables

4.1 Data sources and samples

An original dataset was built using information gathered from several public institutions to carry out the empirical analysis. Longitudinal data on income and individual characteristics, i.e. municipality of residence, education level, among others, were obtained from the database of workers affiliated with the Public Unemployment Insurance (PUI),[8] released by the *Superintendencia de Pensiones*. Data on companies by economic sector and sub-sector and geographic location were extracted from the database provided by the Chile's internal revenue service, *Servicio de Impuestos Internos* (*SII*), available for the period 2005-2020. Data on meso-level controls were taken from the national statistics institute (*INE*), national customs service, *Servicio Nacional de Aduanas*, and the *SII*. Geographic information was delivered by the library of the National Congress, *Biblioteca del Congreso Nacional* (*BCN*).

Regarding the geographical dimensions, from 2018 onward Chile was administratively divided into 16 regions (the highest order division), 56 provinces, and 345 municipalities (the basic administrative division), excluding Antarctica. The final sample includes data on mining sector workers for the period 2010–2019, corresponding to 31,423 individuals and 145,211 observations, and encompassing 314 out of 345 municipalities that compose the Chilean territory.

4.2 Dependent variables

This study employs data on real wages as a proxy for labor productivity in the Chilean mining sector. Databases provided the *Superintendencia de Pensiones* report monthly taxable income and individual-level characteristics from workers affiliated with the PUI during different spans between 2002 and 2021. Since October 2002, registration with PUI has been compulsory for dependent, over 18 years old, private-sector workers with a contract regulated by the Labor Code, whereas this is voluntary for those with tenure from a previous period.[9] The final dataset encompasses up to 20% of the total affiliation. Monthly taxable income has a top-capped income value, which is defined on a yearly basis. However, such top value is expressed in *Unidad de Fomento* (UF), and it

[8]Called in Chile "Seguro de Cesantía".

[9]This excludes trainee and underage employees, pensioners, autonomous workers, and public sector employees. Private house clerks were excluded from the PUI until October 2020. However, these categories do not have a significant share in the mining sector. According to data obtained from the National Socioeconomic Characterization Survey (*CASEN*), during the period 2006-2020, the share of mining sector workers in occupational categories subject to PUI was between 91% and 95%.

is set up to vary on a monthly basis employing the UF exchange rate at the end of each month.[10] Real monthly wages were obtained by using the top-cap-defining UF value in each month and the UF value for December 28, 2021.

Real monthly wages were employed in both aggregate- and individual-level estimations. To estimate the effect of KIBS agglomeration on mining sector productivity at the municipal level, real wages were collapsed into municipality-level average monthly values, considering only those payments stemming from mining sector activities. To estimate at the individual level, data on wages were summed to obtain annual values for each individual. In order to fill gaps within years due to changes in workers' affiliation, the monthly average wage value was imputed. Wages for a given individual with more than one paying employer for a given month were averaged. Individuals lacking an open-ended contract were dropped. With respect to the definition of the upper limit for Tobit model estimations, the top-cap values were adjusted by using the same exchange rate employed when correcting wages, and these were extrapolated to annual values.

4.3 Independent variables

4.3.1 Agglomeration measures

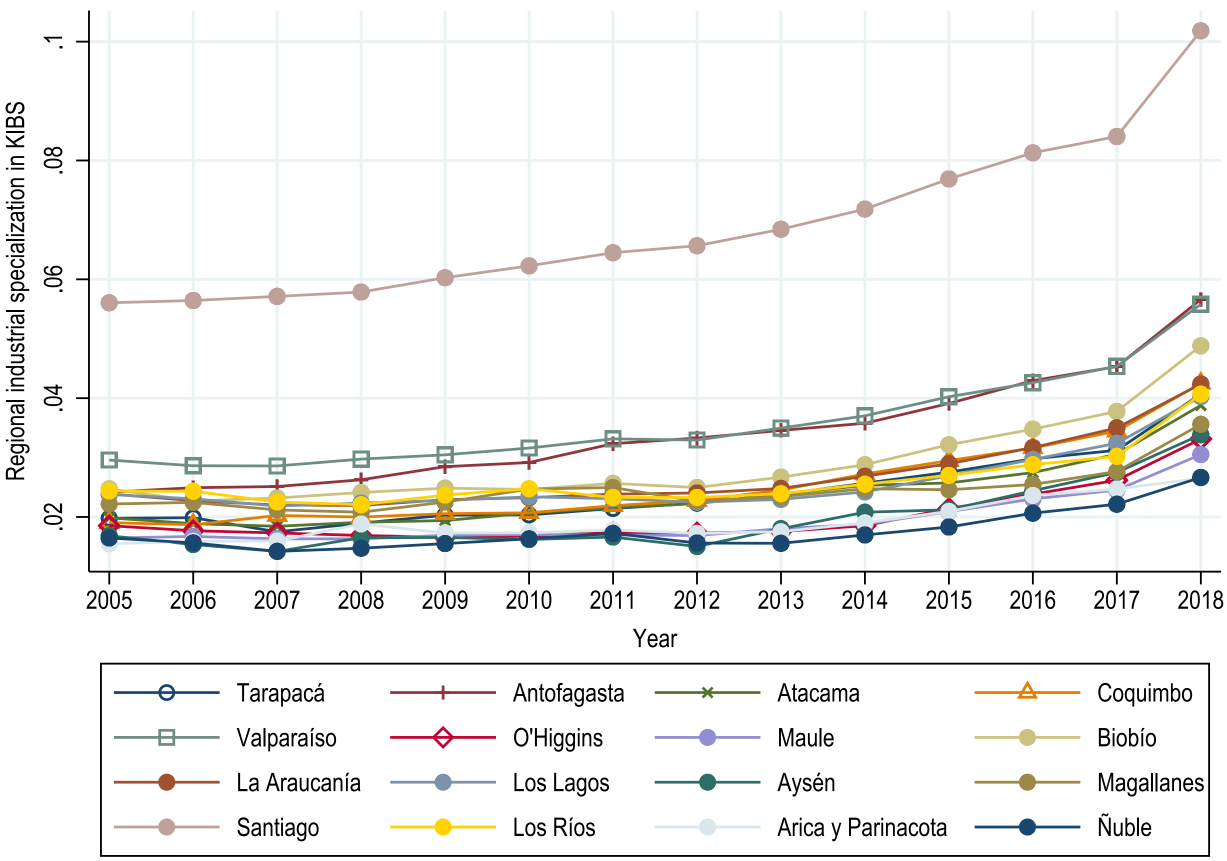
Annual data on companies by geographic zone and economic sector provided by the Chilean internal revenue service (SII) database allow for computing municipality-level agglomeration measures. This database encompasses all formal companies delivering a tax declaration in the corresponding fiscal year. Companies are classified by sector and subsectors, following the ISIC rev. 4 classification coding. The geographic location of each company is determined by the location of the headquarters. In order to identify those firms that can fulfill the definition of KIBS, we follow Miles et al. (2018). We consider NACE rev. 2 divisions classified by the author as professional services or P-KIBS, scientific and technical services or T-KIBS, and creativity-intensive services or C-KIBS. To look for the equivalent divisions between ISIC rev. 4 and NACE rev. 2, the correspondence tables provided by Eurostat Reference and Management of Nomenclatures (RAMON) were employed. Table A1 in the appendix shows the matching between these two classifications.

Municipality-level industrial specialization in KIBS is computed as the share of this type of company in each municipality over the number of total companies in the same geographical unit and this stands for our variable of interest. Likewise, this agglomeration measure is computed for

[10] *Unidad de Fomento* (UF) is a Chilean non-circulating currency created in 1967. The exchange rate between this and the Chilean Peso varies on a daily basis according to the inflation rate. The taxable cap until 2009 was UF 90.0, UF 97.1 for 2010, UF 99.0 for 2011, UF 101.1 for 2012, UF 105.4 for 2013, UF 108.5 for 2014, UF 109.8 for 2015, UF 111.4 for 2016, UF 113.5 for 2017, UF 117.5 for 2018, and UF 118.9 for 2019.

mining sector companies to control for potential localization economies. Figures 4 and 5 depict the behavior of the aforementioned agglomeration measures at the regional level for the period 2005-2018. It is worth noting that the Metropolitan Region exhibits a relatively greater concentration of KIBS-related companies for the whole period if compared to the rest of the country. This fact reflects the expected high agglomeration of knowledge-intensive activities and skilled human capital in metropolitan municipalities, followed by those in the Valparaiso Region—located in the Chilean central coast—and the Antofagasta Region. Conversely, following Figure 5, most of the northern regions, i.e., Antofagasta, Atacama, and Coquimbo, stand out from the rest of the country for their significantly higher levels of concentration of mining activity.

Figure 4: Industrial specialization in KIBS by region, 2005-2018.

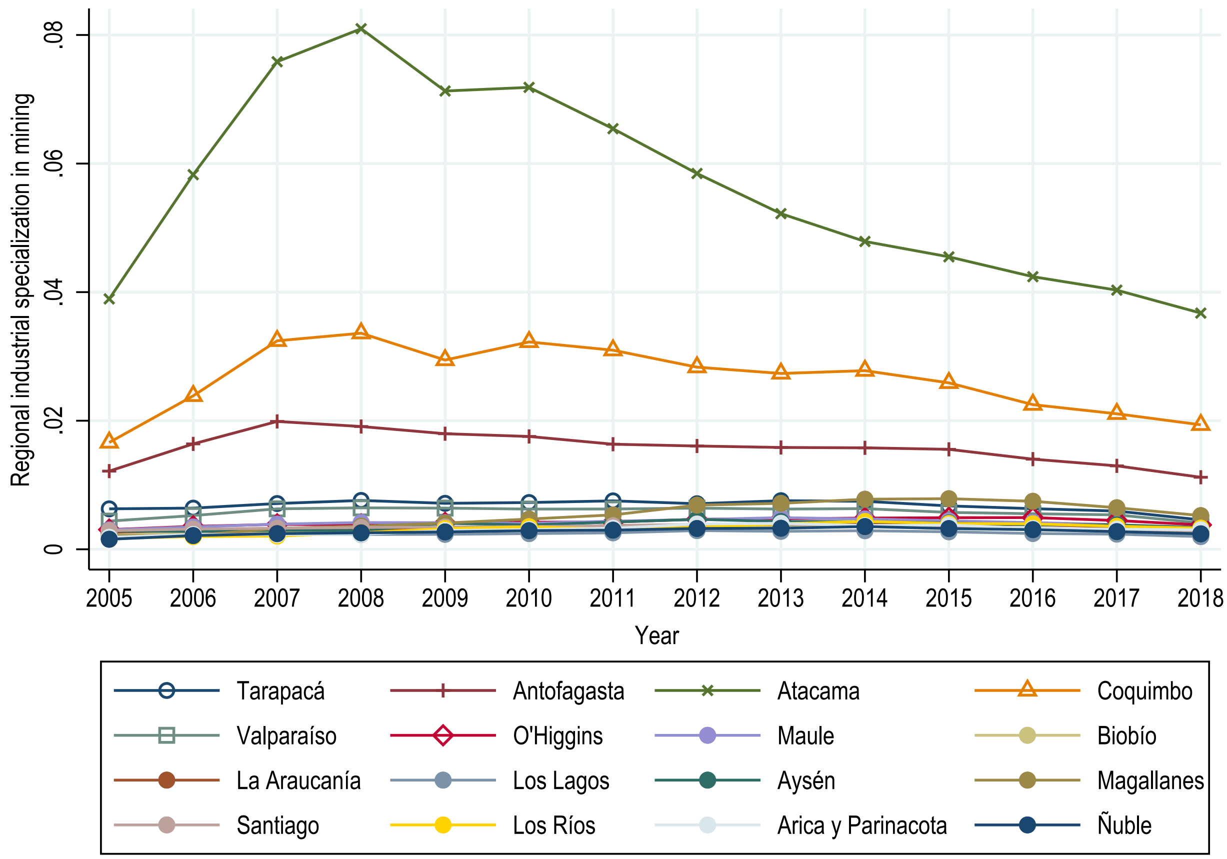


Source: Own elaboration, employing data on tax-filing companies obtained from SII.

4.3.2 Meso-level controls

In order to adjust our framework of estimation for local and regional effects, a number of variables at different spatial levels are included in the specification. To adjust for the effect of the regional labor market on income levels, the employment-to-population ratio is used. This ratio corresponds

Figure 5: Industrial specialization in Mining by region, 2005-2018.



Source: Own elaboration, employing data on tax-filing companies obtained from SII.

to the share of a region's working-age population with a job.[11]

Productivity is often associated with competitiveness and the exposure to the external sector is an important dimension to take into account. In order to capture the potential effects of international trade at the local scale, the province-level export-to-import ratio is computed. This variable is based on data provided annually by the national customs service. Customs data on export (FOB) and import (CIF) values are reported in US dollars by spatial unit.

Finally, to control for the wage gap associated with the firm size (see the survey by Oi and Idson (1999)), we have included the share of large firms at the municipal level as a regressor. This variable is based on the number of enterprises with 200 or more formal employees, extracted from the records of the PUI (*Superintendencia de Pensiones*).

[11]Data on this variable follows the former administrative division with 13 regions.

4.4 Descriptive statistics

Table 1 summarizes the variables explained in the analysis. For both types of estimations, the vector of meso-level controls $\boldsymbol{MC}_t$ includes the aforementioned employment-to-population ratio at the regional level (ETP_{rt}, where $r = \{1, ..., 16\}$ stands for regions), export-to-import ratio at province level (XTI_{pt}, where $p = \{1, ..., 56\}$ stands for provinces), and the share of large firms at the municipal level (LSF_{ct}, where $c = \{1, ..., 317\}$ stands for municipalities). For the municipality-level estimations, the variables referring to the demographic characteristics vector $\boldsymbol{DC}_{ct}$ in Equation 1, are the annual share of employees with tertiary education ($Educ^T_{ct}$), the share of female workers ($Female_{ct}$), and the share of foreign workers ($Foreign_{ct}$) for each municipality in year t, for workers in the mining sector, jointly with their annual mean age (Age_{ct}). For the estimation at the individual level, these demographic characteristics are treated as categorical, dichotomous variables, except age (Age_{it}), which is continuous. Table 2 presents a summary of the descriptive statistics of all the continuous variables mentioned in this section.

Table 1: Summary of variables.

Variable	Definition	Data source
Dependent variables		
Municipality-level real monthly wage (W_{ct})	Monthly average wage in mining sector at municipal level, adjusted for inflation, in Chilean peso.	SP
Real annual wage (W_{it})	Individual annual wage of mining sector workers adjusted for inflation, in Chilean peso.	SP
Agglomeration proxies		
Industrial Specialization in KIBS (ξ_{ct-1})	Share of KIBS-related companies on the total number of companies in the municipality. One-period lagged.	SII
Industrial Specialization in Mining (μ_{ct-1})	Share of mining sector companies on the total number of companies in the municipality. One-period lagged.	SII
Meso-level controls		
Employment-to-population ratio (ETP_{rt})	Share of employed working-age population in a region.	INE
Export-to-import ratio (XTI_{pt})	Province-level exports over province-level imports in US dollars	Aduanas
Large-sized firms (LSF_{ct})	Share of firms of 200 or more formal employees at the municipal level.	SP

Source: Own elaboration.

From Table 2 we can gain some insights of the characteristics of the Chilean mining industrial

Table 2: Descriptive statistics.

Municipality level dataset					
Variable	N	Mean	SD	Min	Max
W_{ct}	2,785	1,554,371	724,268.3	32,790.75	3,683,141
ξ_{ct-1}	2,639	0.0201	0.0207	0.0008	0.1856
μ_{ct-1}	2,557	0.0109	0.0241	0.0002	0.2636
ETP_{rt}	2,785	0.5682	0.0332	0.5060	0.7047
XTI_{pt}	2,785	11.8589	101.0197	0	2,906.09
LSF_{ct}	2,785	0.4183	0.0966	0.1197	0.9524
Age_{ct}	2,785	39.7812	5.9387	18	66
$Educ_{ct}^{T}$	2,785	0.1321	0.1849	0	1
$Female_{ct}$	2,785	0.0938	0.1375	0	1
$Foreign_{ct}$	2,785	0.0096	0.0330	0	1
Individual level dataset					
Variable	N	Mean	SD	Min	Max
W_{it}	145,211	23,283,083	12,380,616	0	44,197,686
ξ_{ct-1}	144,418	0.0357	0.0266	0.0008	0.1856
μ_{ct-1}	143,680	0.0187	0.0261	0.0002	0.2636
ETP_{rt}	145,211	0.5792	0.0240	0.5060	0.7047
XTI_{pt}	145,211	5.8496	30.8970	0	2,906.10
LSF_{ct}	145,211	0.5138	0.0874	0.1197	0.9524
Age_{it}	145,211	40.082	10.358	15	76

Source: Own elaboration. Monetary values in Chilean peso.

tissue and workforce. When employing the municipality-level dataset, the average (gross) real wage during the period 2010-2019 for mining sector workers was CLP$1,554,371 (US$1,824), while the annual average real wage in the individual-level dataset was CLP$23,283,083 (US$27,327.56).[12] Viewing the indicators for industrial specialization (in logarithms), it can be noticed that there is a high variability in the share of both KIBS and mining firms in total companies among municipalities. The maximum quota of KIBS in a municipality is equivalent to almost 20% of the total number of companies in a given year, whereas the minimum quota in the sample is roughly 0.08%. A similar picture emerges when analyzing the mining sector companies. This reflects relevant territorial differences in terms of industrial specialization at the municipality-level. Concerning the demographic characteristics, on average, mining workers are middle-aged males, lacking advanced education: the average age is roughly 40 years and only around 13% of the workforce have higher (tertiary) education. This could be a possible hindrance for the absorption of knowledge in new technology. In this sense, outsourcing might become an attractive alternative for mining companies in terms of costs for the adoption of innovation, when compared to the cost of training their own workforce.

[12] Values obtained employing exchange rate from December 31, 2021, that is, US$1 equals CLP$852.

5 Results

Estimations of KIBS agglomeration effects on mining productivity, both at the aggregate and individual level, were performed, followed by a series of extensions. Subsequently, the results from the exploratory spatial analyses were discussed.

5.1 Aggregate- and individual-level effect estimations

The evaluation of the effect of KIBS agglomeration on mining sector productivity at the aggregate level was conducted by estimating the fixed-effects model in Equation 2. After running a Hausman specification test, the results indicated that a fixed-effects specification was appropriate. The errors were clustered at the regional level, assuming the existence of spatial similarities among municipalities within greater geographic divisions.[13] Table 3 presents the estimates for the agglomeration measures within the model. Results in Columns 1, 2, and 3 refer to all of the country, while estimates in Columns 4, 5, and 6 encompass all the Chilean territory excluding the Santiago province. This last choice was driven by the concern to assess the relative impact of the capital city and surrounding municipalities on the estimates, given the high concentration of KIBS firms in the metropolitan area and the tendency of firm headquarters to locate there as well.

As presented in Table 3, the results from the estimation of the effect of KIBS firms agglomeration on mining productivity are inconclusive. These results hold when the Santiago province is excluded from the sample. One insight about this result refers to the composition of the workforce belonging to the mining sector. The significant heterogeneity of the workers in the mining sector in terms of education and technological complexity of tasks might lead KIBS agglomeration externalities not to spread, and, thus, diffuse at the aggregate level. Concerning the potential localization economies derived from the agglomeration of mining activity in each municipality, the results are inconclusive on the existence of these externalities. The latter is in line with the enclave setting in mining regions, as discussed in Arias et al. (2014).

To estimate the impact of KIBS agglomeration on the individual productivity (approximated by annual wages of mining sector workers) we applied a random-effects Tobit model, controlling for the top-capped wages reported in the records from the PUI. Results are presented in Table 4, where Columns 1, 2, and 3 contain the estimates employing the full sample, while the rest of the columns presents the coefficients obtained after excluding workers from the Santiago province.

[13]In order to take into account the clustered errors in the model specification test, we estimated the model presented in Equation 2 following a correlated random effects framework. Next, we tested whether the random effects hypothesis could be rejected. The results from this test for the coefficient for our variables of interest confirms the results from the Hausman specification test.

Table 3: Regression results: Fixed-effects models. Aggregate-level estimations

	Dependent variable: lnW_{ct}					
	(1)	(2)	(3)	(4)	(5)	(6)
ξ_{ct-1}	-4.004**	-3.099*	-2.419	-3.957*	-3.054	-2.660
	(1.559)	(1.713)	(1.643)	(2.109)	(2.411)	(2.064)
μ_{ct-1}		-1.524*	-1.432		-1.651*	-1.594
		(0.814)	(0.922)		(0.855)	(0.954)
Constant	13.89***	13.72***	12.93***	13.81***	13.65***	12.88***
	(0.0509)	(0.251)	(0.549)	(0.0587)	(0.260)	(0.572)
Observations	2,639	2,477	2,477	2,319	2,168	2,168
R-squared	0.235	0.226	0.272	0.219	0.208	0.256
Municipalities	309	290	290	277	258	258
Year	Yes	Yes	Yes	Yes	Yes	Yes
Stgo.	Yes	Yes	Yes	No	No	No
MC	No	Yes	Yes	No	Yes	Yes
DC	No	No	Yes	No	No	Yes
Cluster	Region	Region	Region	Region	Region	Region
Model	FE	FE	FE	FE	FE	FE
Period	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
MC (Meso-level controls): $lnETP_{rt}$ $lnXTI_{pt}$ $lnLSF_{ct}$
DC (Demographic characteristics): $lnEduc^{T}_{ct}$ $lnFemale_{ct}$ $lnForeign_{ct}$ $lnAge_{ct}$

Table 4: Regression results: Random-effects Tobit models. Individual-level estimations.

	Dependent variable: lnW_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
ξ_{ct-1}	5.290***	4.267***	4.642***	4.904***	4.139***	3.772***
	(0.147)	(0.142)	(0.141)	(0.224)	(0.220)	(0.219)
μ_{ct-1}		-2.430***	-2.583***		-2.390***	-2.527***
		(0.127)	(0.127)		(0.126)	(0.126)
Constant	16.16***	14.43***	14.08***	16.16***	14.49***	14.18***
	(0.00681)	(0.0309)	(0.0470)	(0.00754)	(0.0322)	(0.0481)
Observations	144,418	143,051	143,051	125,897	124,658	124,658
Number of ID	31,295	31,062	31,062	26,737	26,519	26,519
Right-censored	13,311	13,292	13,292	9,179	9,163	9,163
Year	Yes	Yes	Yes	Yes	Yes	Yes
Stgo.	Yes	Yes	Yes	No	No	No
IC	No	Yes	Yes	No	Yes	Yes
MC	No	No	Yes	No	No	Yes
Period	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
MC (Meso-level controls): $lnETP_{rt}$ $lnXTI_{pt}$ $lnLSF_{ct}$
IC (Individual characteristics): $Educ_i$ $Female_i$ $Foreign_i$ Age_{it} Age^2_{it}

In contrast to previous estimations, results from estimations at the individual level suggest that a higher presence of knowledge-intensive activities enhances mining sector productivity. These results hold when individuals located in the Santiago province are excluded from the sample to control for the spatial labor division in the mining sector, knowing that most firms' headquarters are located in the capital city (Phelps et al., 2015). Bearing in mind both estimations at the aggregate and individual level, it can be suggested that the principal channel by which KIBS externalities operate is associated with the workers' performance, but this effect diminishes at the aggregate level. With respect to the agglomeration of mining activity, the estimates suggest a negative association with mining workforce wages. In the absence of localization economies, this result might reflect the competition effects due to the higher concentration of this activity in the municipality, which increases the supply of this type of workers and, thus, lowers wages.

5.2 Extensions

5.2.1 Interaction between agglomeration measures

One extension of our baseline estimations consists of assessing whether the effect from the agglomeration of mining firms on our labor productivity proxy is affected by the concentration of KIBS firms in the municipality. One perception behind this effect is that spatial proximity between specialized service firms and mining companies might fuel productivity by enhancing processes intensive in physical capital. In turn, the competition effect on the mining labor market might become stronger. To determine this, we included an interaction term between these two measures. The outputs of these estimations are presented in Tables 5 and 6 for aggregate- and individual-level models, respectively.

In line with our baseline estimation of the aggregate-level model, the coefficient of our proxy for the agglomeration of mining companies has a negative sign (as in Table 5). This suggests the existence of competition effects in the mining labor market at the municipal level. An increase in the concentration of this type of firm and, thus, a thicker labor market in certain municipalities, is associated with a decrease in wages due to the higher supply of workers. When including the interaction term as a covariate, results suggest that an increase in the spatial concentration of KIBS suppliers intensifies the competition effect in the mining labor market. When focusing on the outputs of the individual-level model (Table 6), the coefficient of the interaction term is positive and significant only when Santiago is included in the sample. This suggests that competition effects from the agglomeration of mining activity on wages at the individual level are not necessarily affected by the concentration of KIBS suppliers. This provides insight about the mechanisms behind the impact of KIBS on our proxy for mining productivity. KIBS agglomeration is associated with a stronger competition effect in the mining labor market at the municipal level. Conversely, this agglomeration directly pushes individual productivity, as suggested by the baseline results (see Table 4).

Table 5: Extension: Aggregate level model estimation with interaction term between agglomeration measures.

	Dependent variable: lnW_{ct}			
	(1)	(2)	(3)	(4)
ξ_{ct-1}	-3.669**	-2.824	-3.744	-3.311
	(1.590)	(1.606)	(2.324)	(2.003)
μ_{ct-1}	-1.655**	-1.706*	-1.815**	-1.923*
	(0.724)	(0.868)	(0.768)	(0.900)
$\xi_{ct-1} \times \mu_{ct-1}$	1.219**	1.169**	1.380**	1.372**
	(0.400)	(0.450)	(0.497)	(0.576)
Observations	2,477	2,477	2,168	2,168
R-squared	0.225	0.273	0.208	0.257
Number of commune	290	290	258	258
Year	Yes	Yes	Yes	Yes
Stgo.	Yes	Yes	No	No
MC	No	Yes	No	Yes
DC	No	Yes	No	Yes
Cluster	Region	Region	Region	Region
Model	FE	FE	FE	FE
Period	2010-2019	2010-2019	2010-2019	2010-2019

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
MC (Meso-level controls): $lnETP_{rt}$ $lnXTI_{pt}$ $lnLSF_{ct}$
DC (Demographic characteristics): $lnEduc^{T}_{ct}$ $lnFemale_{ct}$ $lnForeign_{ct}$ $lnAge_{ct}$

5.2.2 Separated KIBS classifications

We estimate the aggregate- and individual-level effects of agglomeration of the different classifications of KIBS suggested by Miles et al. (2018) on mining labor productivity. Table 7 presents the estimates of the fixed-effects models as in Equation 1, but considering the shares of P-KIBS, T-KIBS, and C-KIBS in the computation of our agglomeration measures, labeling them as ξ^P, ξ^T, and ξ^C, respectively. Columns 1, 2, and 3 present the estimates for the full model with the whole sample, while the rest of the columns present the full specification excluding those municipalities belonging to the Santiago province.

In line with the previous estimations at the aggregate level, the results for the estimation of the effect of the agglomeration of KIBS on mining productivity are inconclusive, both when including and excluding the Santiago province from the sample. By applying this approach and replicating the model in Equation 2, we estimate the potential effects of the agglomeration of each class of KIBS firms on individual-level productivity for the mining sector. Table 8 presents the estimates of the full model specification, adopting a random-effects Tobit approach and excluding observations for the Santiago province in Columns 4, 5, and 6. The results are in line with those obtained in the individual-level specifications with all the KIBS firms as a whole. They suggest a positive association between each class of KIBS agglomeration and the individual productivity levels in the

Table 6: Extension: Individual level model estimation with interaction term between agglomeration measures.

	Dependent variable: lnW_{ct}			
	(1)	(2)	(3)	(4)
ξ_{ct-1}	4.803***	4.601***	4.252***	3.838***
	(0.146)	(0.142)	(0.225)	(0.218)
μ_{ct-1}	-3.138***	-2.232***	-2.989***	-2.180***
	(0.131)	(0.130)	(0.131)	(0.129)
$\xi_{ct-1} \times \mu_{ct-1}$	0.815***	0.157**	0.685***	0.0379
	(0.0722)	(0.0735)	(0.0732)	(0.0745)
Observations	172,535	172,505	150,059	150,029
Number of ID	34,809	34,798	29,589	29,578
Right-censored	14613	14613	10044	10044
Year	Yes	Yes	Yes	Yes
Stgo.	Yes	Yes	No	No
IC	No	Yes	No	Yes
MC	No	Yes	No	Yes
Period	2010-2019	2010-2019	2010-2019	2010-2019

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
MC (Meso-level controls): $lnETP_{rt}$ $lnXTI_{pt}$ $lnLSF_{ct}$
IC (Individual characteristics): $Educ_i$ $Female_i$ $Foreign_i$ Age_{it} Age^2_{it}

mining sector, which holds when Santiago is excluded from the sample. Although the coefficients seem higher for the estimations with the whole sample, a caveat must be taken into account: larger coefficients might be associated with the relatively small concentration of these classes of services in the local milieu.

5.3 Spatial analysis

5.3.1 Spatial structure exploratory analysis

The estimates of the aggregate-level models including the distance variables are presented in Table 9. Overall, results are heterogeneous among the three zones. We might interpret this heterogeneity as the existence of territorial patterns involving mining productivity following a polycentric structure. In other words, results suggest that Santiago cannot be considered as a unique center and there are several significant locations across Chile that play a role in enhancing the productivity of mining workers. Specifically, in the case of municipalities in the northern regions, the distance between each city and its regional capital is negatively associated with our proxy for mining productivity. Even if the estimation of the effect of the distance from Santiago is larger in absolute terms, its coefficient's significance is weaker. For municipalities in central regions, the distance towards the national capital shapes mining workers' productivity and exhibits a stronger influence

Table 7: Extension: Aggregate-level effect estimations, separated KIBS classifications.

	Dependent variable: lnW_{ct}					
	(1)	(2)	(3)	(4)	(5)	(6)
ξ^P_{ct-1}	-2.589			-0.929		
	(2.814)			(3.896)		
ξ^T_{ct-1}		-4.301			-4.719	
		(3.879)			(4.656)	
ξ^C_{ct-1}			-3.779			-7.061
			(7.105)			(8.099)
Constant	12.90***	12.93***	12.90***	12.86***	12.89***	12.87***
	(0.568)	(0.545)	(0.533)	(0.581)	(0.567)	(0.564)
Observations	2,477	2,477	2,477	2,168	2,168	2,168
R-squared	0.272	0.272	0.272	0.255	0.256	0.256
Municipalities	290	290	290	258	258	258
Year	Yes	Yes	Yes	Yes	Yes	Yes
Stgo.	Yes	Yes	Yes	No	No	No
MC	Yes	Yes	Yes	Yes	Yes	Yes
DC	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Region	Region	Region	Region	Region	Region
Model	FE	FE	FE	FE	FE	FE
Period	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
MC (Meso-level controls): $lnETP_{rt}$ $lnXTI_{pt}$ $lnLSF_{ct}$
DC (Demographic characteristics): $lnEduc^T_{ct}$ $lnFemale_{ct}$ $lnForeign_{ct}$ $lnAge_{ct}$

Table 8: Extension: Individual-level effect estimations, separated KIBS classifications.

	Dependent variable: lnW_{ct-1}					
	(1)	(2)	(3)	(4)	(5)	(6)
ξ^P_{ct-1}	7.247***			6.011***		
	(0.242)			(0.415)		
ξ^T_{ct-1}		9.401***			5.556***	
		(0.360)			(0.432)	
ξ^C_{ct-1}			16.02***			9.987***
			(0.607)			(0.799)
Constant	14.08***	14.21***	14.14***	14.17***	14.20***	14.17***
	(0.0471)	(0.0467)	(0.0470)	(0.0481)	(0.0481)	(0.0481)
Observations	143,051	143,051	143,051	124,658	124,658	124,658
Number of ID	31,062	31,062	31,062	26,519	26,519	26,519
Right-censored	13292	13292	13292	9163	9163	9163
Year	Yes	Yes	Yes	Yes	Yes	Yes
Stgo.	Yes	Yes	Yes	No	No	No
IC	Yes	Yes	Yes	Yes	Yes	Yes
MC	No	No	No	No	No	No
Period	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
MC (Meso-level controls): $lnETP_{rt}$ $lnXTI_{pt}$ $lnLSF_{ct}$
IC (Individual characteristics): $Educ_i$ $Female_i$ $Foreign_i$ Age_{it} Age^2_{it}

than regional capitals. This is consistent with the shorter distance between these municipalities and Santiago city. Finally, there are inconclusive results associating the distance either toward Santiago or the regional capital city with the aggregate labor productivity of mining workers in southern municipalities. This might be explained by the fact that these municipalities are quite distant both from the national capital and the regional ones. This is especially true for those in the southernmost regions, where mining activities linked to fossil fuels are located.

Table 9: Spatial structure evaluation: LSDV models. Municipality-level estimations.

	Dependent variable: lnW_{ct}					
	(1)	(2)	(3)	(4)	(5)	(6)
$lnDist_c^R$	-0.0344***		-0.150***		-0.110	
	(0.00289)		(0.0212)		(0.0546)	
$lnDist_c^N$		-0.892*		-1.115***		-4.709
		(0.283)		(0.157)		(2.343)
Constant	14.17***	26.84***	14.19***	27.02***	11.03***	73.77
	(1.588)	(3.776)	(0.523)	(1.441)	(0.257)	(31.39)
Observations	318	318	1,671	1,671	488	488
R-squared	0.952	0.952	0.845	0.845	0.708	0.708
Year	Yes	Yes	Yes	Yes	Yes	Yes
ξ_{ct-1}, μ_{ct-1}	Yes	Yes	Yes	Yes	Yes	Yes
MC	Yes	Yes	Yes	Yes	Yes	Yes
DC	Yes	Yes	Yes	Yes	Yes	Yes
Distance	Reg Cap	Santiago	Reg Cap	Santiago	Reg Cap	Santiago
Zone	North	North	Center	Center	South	South
Cluster	Region	Region	Region	Region	Region	Region
Model	LSDV	LSDV	LSDV	LSDV	LSDV	LSDV
Period	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
MC (Meso-level controls): $lnETP_{rt}$ $lnXTI_{pt}$ $lnLSF_{ct}$
DC (Demographic characteristics): $lnEduc_{ct}^T$ $lnFemale_{ct}$ $lnForeign_{ct}$ $lnAge_{ct}$

5.3.2 Spatial spillover analysis

For the exploratory analysis of spatial spillovers we exploit data at the aggregate level from 2019. In order to select the models that best fit the data, we followed the approach presented by Elhorst (2010). After estimating a non-spatial linear model, whose results are presented in Column 1 in Table 10, Moran's I is estimated, employing the two weight matrices specified in Section 3.3: a matrix for the k nearest neighbors, where k is equal 3 ($W_{k=3}$); and a matrix for the five-closest neighbors ($W_{k=5}$). These estimates are presented in Table A2 in the appendix. For both matrices, the results indicate positive and significant Moran's I, which suggests the existence of spatial correlations in favor of adopting the spatial approach. A Global Moran test adjusted for residuals from the linear model confirms the residual presence of spatial autocorrelation in both cases.

Regarding the choice of model, the results of robust Lagrange multiplier tests allow us to reject $H_0 : \rho = 0$, but they do not support rejection of $H_0 : \lambda = 0$. Therefore, an SDM model was estimated for each matrix. The results from the SDM model estimation employing matrices $W_{k=3}$ and $W_{k=5}$ are presented in Columns 2 and 4 from Table 10, respectively. However, following the sequential approach, after performing the likelihood ratio test to assess the existence of spatial lags, the result supports the SAR model as the most appropriate framework (LR test θ p-value $W_{k=3}$ = 0.467 and LR test θ p-value $W_{k=5}$ = 0.116). SAR model estimates using k-nearest neighbors matrices are presented in Columns 3 and 5 in Table 10. The estimates from employing the smaller neighborhood setting suggest a significant spatial dependency between mining productivity and the municipality-level industrial specialization in KIBS. Estimations using the five-neighbor matrix are only slightly significant. However, the share of large-sized firms, highly educated mining workers, and foreign workers, as well as the average age, exhibit significant coefficients with the two matrices. In order to correctly interpret the output of the SAR models, direct and indirect effects were computed and summarized in Figure 6. Following Floch and Le Saout (2018), we computed confidence intervals employing 1000 simulations from empirical distribution to assess the significance of those impacts. The values of the coefficients and confidence intervals employing matrices of 3- and 5-nearest neighbors are presented in Table A3 and A4, respectively.

Table 10: Spatial models: Estimation of spillover effects at municipality level, k-nearest neighbors matrices.

		$W_{k=3}$		$W_{k=5}$	
	(1)	(2)	(3)	(4)	(5)
Variables	OLS	SDM	SAR	SDM	SAR
ξ_{ct-1}	2.8615*	1.8738	2.4111**	2.3838	2.2884*
	(1.2144)	(1.5109)	(1.1918)	(1.4939)	(1.1931)
μ_{ct-1}	-0.0564	-1.1333	-0.1948	-1.3022	-0.2813
	(1.6005)	(1.9153)	(1.5420)	(2.0132)	(1.5397)
$lnETP_{rt}$	0.7781	2.4866	0.5983	1.8349	0.6431
	(0.5089)	(2.8996)	(0.4937)	(2.4754)	(0.4966)
$lnXTI_{pt}$	-0.0114	0.0003	-0.0071	-0.0015	-0.0065
	(0.0282)	(0.0429)	(0.0272)	(0.0419)	(0.0271)
LSF_{ct}	2.3908***	1.9651***	2.1096***	1.8754***	2.0418***
	(0.4487)	(0.5460)	(0.4434)	(0.5386)	(0.4459)
$lnEduc^T_{ct}$	1.1891***	1.0979***	1.1024***	1.0630***	1.0888***
	(0.2140)	(0.2094)	(0.2070)	(0.2082)	(0.2068)
$lnAge_{ct}$	-0.6359**	-0.6397***	-0.6562***	-0.6654***	-0.6292***
	(0.1918)	(0.1895)	(0.1848)	(0.1849)	(0.1846)
$lnForeign_{ct}$	1.3057*	1.3452***	1.2754**	1.1837**	1.2740**
	(0.5149)	(0.5078)	(0.4964)	(0.5014)	(0.4960)
$lnFemale_{ct}$	0.1514	0.0937	0.0917	0.0371	0.0636
	(0.2394)	(0.2353)	(0.2312)	(0.2334)	(0.2313)
Intercept	16.0070***	14.8850***	13.6815***	14.2047***	12.9455***
	(0.7879)	(1.9110)	(1.2374)	(2.2474)	(1.3880)
$\hat{\rho}$		0.1344*	0.1699***	0.1403	0.2181***
		(0.0779)	(0.0678)	(0.0967)	(0.0798)
$\hat{\theta}, \xi_{ct-1}$		0.3674		-1.9738	

Standard errors in parenthesis. For tests, p-value is indicated.
*** p<0.01, ** p<0.05, * p<0.1

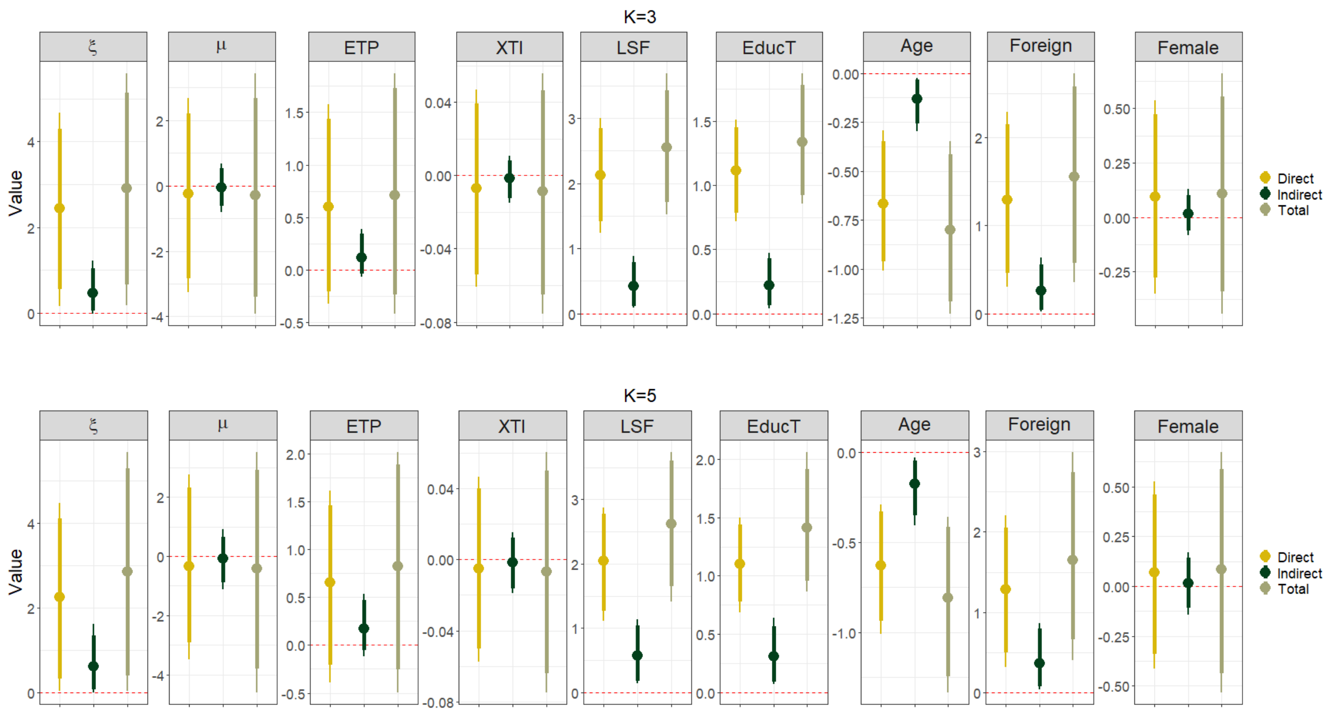
Table 10 – continued from previous page

		$W_{k=3}$		$W_{k=5}$	
	(1)	(2)	(3)	(4)	(5)
Variables	OLS	SDM	SAR	SDM	SAR
		(1.9685)		(2.3876)	
$\hat{\theta}, \mu_{ct-1}$		2.2858		2.8329	
		(2.4671)		(2.8057)	
$\hat{\theta}, lnETP_{rt}$		-1.9460		-1.0424	
		(2.9248)		(2.5843)	
$\hat{\theta}, lnXTI_{pt}$		-0.0012		0.0264	
		(0.0511)		(0.0534)	
$\hat{\theta}, lnLSF_{ct}$		-0.0431		-0.2636	
		(0.7588)		(0.8664)	
$\hat{\theta}, lnEduc^{T}_{ct}$		0.3548		1.2612**	
		(0.3758)		(0.5007)	
$\hat{\theta}, lnAge_{ct}$		-0.2111		0.0210	
		(0.3450)		(0.4110)	
$\hat{\theta}, lnForeign_{ct}$		-0.3433		-1.2515	
		(0.9264)		(1.2585)	
$\hat{\theta}, lnFemale_{ct}$		0.2011		0.5186	
		(0.4484)		(0.5534)	
Observations	253	253	253	253	253
AIC	279.49	289.80	274.66	284.02	274.03
Adjusted R^2	0.3347				
LR Test Resid Auto		0.1003	0.2513	0.8117	0.4254
LR Test θ		0.4674		0.1156	

Standard errors in parenthesis. For tests, p-value is indicated.
*** p<0.01, ** p<0.05, * p<0.1

Analyzing direct, indirect, and total impacts from the SAR models when using k-nearest neighbors matrices, results reveal the existence of spatial effects of municipality-level agglomeration of KIBS on surrounding municipalities. This implies that changes in the proxy of local-level industrial specialization of one municipality could have positive impacts on mining labor productivity in all the other closest municipalities. Moreover, the results suggest significant impacts of the shares of highly educated workforce, large-sized firms, and foreign workers, as well as mean age, when employing both neighborhood settings. This would indicate that local mining productivity is affected by these productive factors located in surrounding municipalities, and, therefore, space matters when analyzing mining productivity determinants at the local level. The choice of the model that best fits the data is based on Akaike's Information Criterion (AIC) (Akaike, 1973), where the lower scores are better. Under this criterion, the SAR model adopting matrix $W_{k=5}$ is the most appropriate.

Figure 6: Direct, indirect, and total impacts, SAR models with $\boldsymbol{W} : k = 3$ and $k = 5$.



Source: Own elaboration. Empirical confidence intervals at 90% and 95% are represented by thick and thin lines, respectively.

6 Concluding remarks

In this study, we have provided evidence to the extent to which the Chilean mining industry can benefit from the spatial concentration of knowledge-intensive business services (KIBS) firms at the local level in terms of productivity. The idea is that these specialized firms operate as facilitators and co-producers of innovation. The suggested channel is related to the knowledge spillovers stemming from innovative firms that trigger productivity in mining companies through outsourcing and geographic proximity. In particular, we assume that the concentration of KIBS firms at the municipality level has a positive impact on labor productivity of the Chilean mining sector. In order to approximate this channel, we analyzed the effect of the share of knowledge-intensive firms on mining sector labor productivity approximated by the level of wages at the municipal level. This analysis was run both at aggregate and individual level, employing average monthly income at the municipal level and workers' annual wages, respectively. This dual approach allows us to gain insight into the level at which the spatial proximity to KIBS suppliers play a role in mining productivity. However, the particular mechanisms by which these externalities take place remain an objective for future studies.

Our results suggest that the high presence of knowledge-intensive activities has a beneficial effect over mining sector productivity at the individual level. However, the results about the direct effect on aggregate-level productivity are inconclusive. We interpret that spatial spillovers are effective at the worker level because such features are likely to target labor productivity improvements at the individual level, but they fade away at the aggregate level. One potential explanation for this is related to the degree of heterogeneity within the mining labor force and their job tasks, which makes the diffusion of these externalities quite complicated. In this regard, our outcomes are partially in line with the current literature on the existence of agglomeration economies derived from spatial concentration of knowledge-intensive activities. The first extension for these baseline estimations allows us to dig deeper into the interaction between sectors, suggesting that the spatial concentration of KIBS intensifies the competition effects derived from the agglomeration of mining on our proxy for labor productivity. Hence, spatial proximity of agglomeration of knowledge-intensive service suppliers might promote productivity, enhancing processes related to capital investments. Results from the second extension of the baseline estimations allow us to conclude that positive externalities on workers' productivity stemming from KIBS firms agglomeration spread across professional, technical, and creative knowledge-intensive services firms.

Concerning the exploratory spatial analysis, estimates suggest the existence of heterogeneous spatial structures throughout the territory regarding mining productivity. The estimates for assessing the spatial structure in northern municipalities suggest that the distance from each regional capital has a stronger effect on average wages at the aggregate level than the distance to the national capital. This points out to the predominance of a polycentric-type spatial structure. In the case of the central zone, the national capital exerts a stronger influence on productivity outcomes as farther distances toward Santiago are associated with reductions in mining productivity. Estimations for southern municipalities, in turn, do not show conclusive results on spatial effects. Furthermore, the results from spatial models exploiting cross-sectional data suggest the existence of spatial dependencies among municipalities, both involving the impacts of the agglomeration of KIBS at the municipal level and the impacts from covariates, mostly related to demographic characteristics. The selected measure for KIBS agglomeration at the municipal level exhibits direct and indirect impacts when using spatial matrices based on each municipality's three and five nearest localities, where the latter corresponds to the setting that best fits our data. However, to determine the basin of influence of these spillovers is left for further research.

Policy implications that can be derived from the results of this study point to the need for building precise local development strategies, primarily in the case of regions that are well-endowed with natural resources. In light of our results, policymakers should target attracting highly skilled human capital into resource-rich localities and encourage the creation of knowledge-intensive service firms at the local level. This would strengthen the creation of productive networks and the generation of innovation, leading to improvements in productivity. Moreover, the agglomeration and proximity of knowledge-intensive activities might spur the creation of new specialized services, fueled by the symbiotic relation or synergies between contractors and client firms (den Hertog, 2000). A higher concentration of knowledge and specialized economic agents encourages territorial competitiveness to export specialized services, which could pave the transition toward a knowledge-based economy supported by natural resources (Marin et al., 2015). However, policymakers should also face the challenge to encourage networking with the local environment for these knowledge-generating activities mostly dominated by foreign capital in the Chilean mining sector. In addition, guaranteeing fair labor conditions for third-party employees is a crucial need when encouraging outsourcing. Unfortunately, the loss of classic employment conditions and increasing labor precariousness have been a visible symptom of this growing practice since its rise during the dictatorship (Leiva, 2009).

Finally, as discussed in Miles et al. (2018), the insufficient level of disaggregation of industrial classifications is a repetitive burden for empirical studies, and this study is not exempt. As long as industrial classification systems are output-oriented, they will not allow for working exclusively with data on KIBS for the mining sector, and we are approximating it with the total number of KIBS. Therefore, more disaggregated data would help in proposing a more precise path forward on the role of KIBS in the mining industry. Additionally, this type of data would open new roads for future research to study the specific mechanisms by which KIBS promote innovation at the regional level and their spatial area of influence on other extractive industries.

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A Appendix

A.1 Correspondence table for KIBS-related activities

Table A1: KIBS divisions and correspondence between NACE rev. 2 and ISIC rev. 4.

	NACE rev. 2		ISIC rev. 4	
P-KIBS	69.1:	Legal activities.	691:	Legal activities
	69.2:	Accounting, bookkeeping and auditing activities; tax consultancy.	692:	Accounting, bookkeeping and auditing activities; tax consultancy.
	70.21:	Public relations and communication activities.	7020:	Management consultancy activities.
	70.22:	Business and other management consultancy activities.	701:	Activities of head offices.
	70.1:	Activities of head offices.		
T-KIBS	62.01:	Computer programming activities.	6201:	Computer programming activities.
	62.02:	Computer consultancy activities	6202:	Computer consultancy and computer facilities management activities
	62.03:	Computer facilities management activities		
	62.09:	Other information technology and computer service activities	6209:	Other information technology and computer service activities
	71.11:	Architectural activities	7110:	Architectural and engineering activities and related technical consultancy
	71.12:	Engineering activities and related technical consultancy		
	71.2:	Technical testing and analysis	712:	Technical testing and analysis
	72.1:	Research and experimental development on natural sciences and engineering	721:	Research and experimental development on natural sciences and engineering
	72.2:	Research and experimental development on social sciences and humanities	722:	Research and experimental development on social sciences and humanities
C-KIBS	73.1:	Advertising	731:	Advertising
	73.2:	Market research and public opinion polling	732:	Market research and public opinion polling
	74.1:	Specialised design activities	741:	Specialised design activities
	74.2:	Photographic activities	742:	Photographic activities

Source: Miles et al. (2018), NACE rev. 2-ISIC rev. 4 Correspondence Tables, available at: `https://ec.europa.eu/eurostat/ramon/relations/index.cfm?TargetUrl=LST_REL`

A.2 Tests for spatial correlation

Table A2: Tests for spatial correlation

Test	(1) $W_{k=3}$	(2) $W_{k=5}$
Moran's I	0.3041***	0.2814***
	(0.0000)	(0.0000)
Moran test for residuals	0.1024***	0.0819***
	(0.005)	(0.003)
LM_λ Test	4.629**	4.842**
	(0.0314)	(0.0278)
LM_ρ Test	8.206***	8.982***
	(0.0042)	(0.0027)
Robust LM_λ Test	0.5462	0.4085
	(0.4599)	(0.5227)
Robust LM_ρ Test	4.124**	4.548**
	(0.0423)	(0.033)

P-values in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

A.3 Direct, indirect, and total impacts

Table A3: Direct, indirect, and total impacts from SAR model estimations. $\boldsymbol{W}: k = 3$

Parameter	Direct	Indirect	Total
ξ_{ct-1}	2.4334	0.4735	2.9069
	[0.1521; 4.6785]	[-0.0168; 1.2121]	[0.1751; 5.5938]
	(0.5549; 4.2962)	(0.0438; 1.0430)	(0.6693; 5.1467)
μ_{ct-1}	-0.2335	-0.0474	-0.2810
	[-3.2642; 2.6817]	[-0.8120; 0.6628]	[-3.9133; 3.4359]
	(-2.8372; 2.2118)	(-0.6301; 0.5260)	(-3.4010; 2.6634)
$lnETP_{rt}$	0.5983	0.1165	0.7148
	[-0.3239; 1.5726]	[-0.0659; 0.3909]	[-0.4163; 1.8719]
	(-0.2036; 1.4399)	(-0.0354; 0.3448)	(-0.2379; 1.7320)
$lnXTI_{pt}$	-0.0071	-0.0014	-0.0086
	[-0.0609; 0.0470]	[-0.0149; 0.0107]	[-0.0755; 0.0559]
	(-0.0539; 0.0395)	(-0.0123; 0.0083)	(-0.0651; 0.0464)
$lnLSF_{ct}$	2.1288	0.4199	2.5487
	[1.2437; 2.9987]	[0.0881; 0.8797]	[1.5270; 3.6892]
	(1.4194; 2.8443)	(0.1207; 0.7901)	(1.7158; 3.4298)
$lnEduc^{T}_{ct}$	1.1117	0.2230	1.3346
	[0.7211; 1.5133]	[0.0391; 0.4716]	[0.8589; 1.8725]
	(0.7865; 1.4495)	(0.0637; 0.4299)	(0.9250; 1.7827)
$lnAge_{ct}$	-0.6660	-0.1323	-0.7983
	[-1.0103; -0.2914]	[-0.2947; -0.0235]	[-1.2285; -0.3458]
	(-0.9619; -0.3479)	(-0.2569; -0.0327)	(-1.1666; -0.4143)
$lnForeign_{ct}$	1.2931	0.2577	1.5508
	[0.3034; 2.2870]	[0.0256; 0.6346]	[0.3582; 2.7293]
	(0.4635; 2.1525)	(0.0436; 0.5591)	(0.5711; 2.5747)
$lnFemale_{c}t$	0.0925	0.0174	0.1099
	[-0.3517; 0.5371]	[-0.0813; 0.1294]	[-0.4430; 0.6611]
	(-0.2764; 0.4740)	(-0.0626; 0.1007)	(-0.3413; 0.5537)

Empirical confidence intervals of 1000 MCMC simulations are presented in brackets (quantiles at 2.5% and 97.5%) and parentheses (quantiles at 5% and 95%).

Table A4: Direct, indirect, and total impacts from SAR model estimations. $\boldsymbol{W}: k = 5$

Parameter	Direct	Indirect	Total
ξ_{ct-1}	2.2463	0.6090	2.8553
	[0.0263; 4.4800]	[0.0001; 1.6084]	[0.0364; 5.6845]
	(0.3188; 4.1152)	(0.0637; 1.3413)	(0.3967; 5.3047)
μ_{ct-1}	-0.3331	-0.0842	-0.4172
	[-3.4955; 2.7626]	[-1.1194; 0.9011]	[-4.5999; 3.5229]
	(-2.9059; 2.3295)	(-0.8831; 0.6546)	(-3.8074; 2.9124)
$lnETP_{rt}$	0.6515	0.1722	0.8237
	[-0.3876; 1.6167]	[-0.1144; 0.5360]	[-0.4944; 2.0188]
	(-0.2039; 1.4616)	(-0.0552; 0.4734)	(-0.2569; 1.8835)
$lnXTI_{pt}$	-0.0052	-0.0014	-0.0066
	[-0.0577; 0.0468]	[-0.0190; 0.0155]	[-0.0748; 0.0606]
	(-0.0500; 0.0399)	(-0.0161; 0.0122)	(-0.0641; 0.0500)
$lnLSF_{ct}$	2.0501	0.5670	2.6172
	[1.1118; 2.8722]	[0.1379; 1.1380]	[1.4058; 3.7405]
	(1.2731; 2.7787)	(0.1819; 1.0367)	(1.6561; 3.6041)
$lnEduc^T_{ct}$	1.1031	0.3104	1.4136
	[0.6879; 1.4983]	[0.0729; 0.6363]	[0.8668; 2.0619]
	(0.7761; 1.4396)	(0.0927; 0.5640)	(0.9535; 1.9166)
$lnAge_{ct}$	-0.6307	-0.1786	-0.8093
	[-1.0081; -0.2925]	[-0.4076; -0.0308]	[-1.3336; -0.3615]
	(-0.9381; -0.3294)	(-0.3520; -0.0493)	(-1.2459; -0.4145)
$lnForeign_{ct}$	1.2818	0.3625	1.6443
	[0.3135; 2.2013]	[0.0412; 0.8642]	[0.4033; 2.9958]
	(0.4926; 2.0556)	(0.0737; 0.7969)	(0.6583; 2.7392)
$lnFemale_{ct}$	0.0677	0.0170	0.0847
	[-0.4132; 0.5265]	[-0.1442; 0.1690]	[-0.5328; 0.6736]
	(-0.3400; 0.4615)	(-0.1090; 0.1434)	(-0.4369; 0.5878)

Empirical confidence intervals of 1000 MCMC simulations are presented in brackets (quantiles at 2.5% and 97.5%) and parentheses (quantiles at 5% and 95%).

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